

Rational Disposition Effects: Theory and Evidence

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Abstract

The disposition effect is a longstanding puzzle in financial economics. This paper demonstrates that it is not intrinsically at odds with rational behavior. In a rational expectations model with asymmetrically informed investors, trading strategies as predicted by the disposition effect can arise as an optimal response to dynamic changes in the information structure. The model generates several novel predictions: the disposition behavior of unsophisticated investors should weaken after events that reduce information asymmetries and should be concentrated in stocks with weak price momentum. The data, trading records of 30,000 clients at a German discount brokerage firm from 1995 to 2000, are consistent with these predictions.

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I. Introduction

Recent empirical studies have documented a number of regularities in the behavior of investors that seem to be at odds with the rational expectations paradigm. One of the most striking patterns is the tendency of investors to sell their winning investments sooner than their losing investments. This reluctance to realize losses, which has been termed the “disposition effect” by Shefrin and Statman (1985), has been uncovered in a variety of data sets and time periods.¹ While such behavior is more pronounced among less sophisticated investors, it has also been found in the trading of mutual fund managers (Frazzini (2006)) and professional futures traders (Locke and Mann (2005)).

Although the existence of the disposition effect seems undisputed, economists and investment professionals have not agreed on an explanation for this phenomenon. The empirical literature favors a behavioral explanation suggested by Shefrin and Statman (1985) that combines the ideas of mental accounting (Thaler (1985)) and prospect theory (Kahneman and Tversky (1979)). Despite its prominence, this explanation has received little formal scrutiny. An exception is a recent paper by Barberis and Xiong (2009) that analyzes the trading behavior of an investor with prospect-theory type preferences in a dynamic setting. They find that the link between these preferences and the disposition effect is not as obvious as previously thought. While prospect theory does indeed predict a disposition effect in some cases, in others it predicts the opposite.

This paper explores theoretically and empirically whether informational differences across investors can provide a rational alternative. We first present a simple rational expectations model that allows us to analyze how dynamic changes in the degree of information asymmetry between better-informed and less-informed investors affect their trading behavior. We then confront the model’s key predictions with actual trading records of 30,000 clients at a German

¹The disposition effect has been documented for individual investors in the U.S. (Odean (1998), Dhar and Zhu (2006)), Finland (Grinblatt and Keloharju (2001)), Israel (Shapira and Venezia (2001)), China (Feng and Seasholes (2005)), and Australia (Brown et al. (2002)).

discount brokerage firm over a 5 1/2-year period.

Our theoretical analysis leads to two main findings. First, the trading strategies predicted by the disposition effect can indeed be a rational response of less-informed investors to changes in the information structure. In particular, we show that these traders prefer to sell their winning stocks rather than their losing stocks when the information asymmetry increases over time. When the information asymmetry decreases over time, however, less-informed investors exhibit a reverse disposition effect: they keep their winners and sell their losers. In this case, it is better-informed investors who display the disposition effect.

While differences in information among investors have long been recognized as a possible explanation (Lakonishok and Smidt (1986)), the superior subsequent return of winners that are sold, compared with losers that are not sold, has led empirical studies to reject an information-based explanation (Odean (1998), Brown et al. (2002)). Our second main finding suggests that this conclusion is not always correct. Risk-averse investors can rationally exhibit the disposition effect even though past winners continue to outperform past losers in subsequent periods. Thus, in contrast to Grinblatt and Han (2005) who show that irrational “disposition investors” can cause price momentum, we demonstrate that both the disposition effect and price momentum can arise in a world with fully rational agents.

The basic intuition for our results is as follows. Consider a dynamic model where in each period a fraction of investors receive private information concerning, say, a future earnings announcement and where liquidity shocks prevent prices from fully revealing this information. In such a framework, the informational advantage of privately informed agents can either increase or decrease over time, depending on the precision of their signals and the magnitude of liquidity shocks in each period. If the information disparity increases over time, uninformed investors learn very little about the new information obtained by informed investors from the observed price. They rely more heavily on information revealed by past prices and are reluctant to revise their optimal stock holdings in response to the current price change. Put differently, the demand of uninformed investors is less sensitive to news about changes

in the asset value than that of informed investors. When new information suggests higher-than-expected payoffs, market clearing implies that the price will increase until the amount of shares that uninformed investors are willing to sell equals the amount that informed investors want to buy. The reverse is true when new information indicates lower-than-expected payoffs. In this case, the price will drop until uninformed investors are willing to buy shares from informed investors. In equilibrium, uninformed investors will therefore find it optimal to follow a contrarian strategy: they tend to decrease their stock holdings when good news drives prices up (“sell their winners”) and to increase their stock holdings when bad news forces prices down (“hold on to their losers”).

The opposite effect is observed when the information asymmetry between investors decreases over time. In this case, new information about the asset value has a stronger impact on the beliefs of uninformed investors. Not knowing the signals received by informed investors in previous periods, uninformed investors learn more from this new signal and, hence, respond more aggressively to new information, forcing informed traders to pursue a contrarian investment strategy. In other words, uninformed investors “overreact” to new information from the perspective of informed investors.

The relationship between information asymmetry and disposition effect generates novel testable predictions about the investors’ trading behavior. In particular, our model suggests that the disposition behavior of less-informed investors is more pronounced prior to public news releases. Our empirical results indicate that the tendency to sell winners and hold on to losers indeed weakens substantially after events such as earnings announcements or periods of high turnover, which are likely associated with a decrease in the information asymmetry across investors. Consistent with the model, this pattern is stronger for stocks with greater earnings surprises and for investors deemed less likely to be informed.

The model further predicts that the disposition behavior of less-informed investors is concentrated primarily in stocks with weak price momentum. Intuitively, selling winners and holding on to losers is a less detrimental strategy for uninformed investors when stock returns

are serially uncorrelated. The data are consistent with this prediction as well. In particular, we find that investors with smaller and less diversified portfolios are more likely to hold on to losing stocks with weak price momentum.

Our empirical results do not imply that the disposition effect is a fully rational phenomenon. Behavioral biases as outlined by prospect theory may also contribute to this particular pattern of trading. These biases, however, fail to explain the documented changes in disposition behavior around news events and the stronger disposition behavior of uninformed investors in stocks with weak price momentum.

The remainder of this paper is organized as follows. Section II presents the model, provides closed-form solutions for prices and quantities, and derives the model's empirical implications. Section III describes the data and reports the results of the hypothesis tests. Section IV concludes the paper. All proofs are contained in the Appendix.

II. A Model of Time-Varying Information Asymmetry

A. Description of the Model

The economic setting we use extends the rational expectations model developed by Grossman and Stiglitz (1980) to two trading periods. However, unlike other dynamic versions of that model in which information is dispersed among many market participants, we maintain the strictly hierarchical information structure of Grossman and Stiglitz's original framework to highlight our ideas in as simple a setting as possible.² In this respect, our approach is similar to Wang (1993, 1994), who studies the optimal trading strategies of asymmetrically informed investors and the resulting price dynamics in an infinite-horizon setting. While in some aspects more restrictive than Wang (1993, 1994), our two-period model allows us to characterize equilibrium demands and prices in closed form and to derive conditions for the

²See, e.g., Grundy and McNichols (1989), Brown and Jennings (1989), and He and Wang (1995) for a dynamic setting with a single risky asset, and Brennan and Cao (1997) and Zhou (1998) for the multiple-asset case.

disposition behavior of various investor groups.³

A.1. Assets

There are two assets available for trading in the market: a riskless bond and a risky stock. The bond is in perfectly elastic supply. For simplicity, we normalize its interest rate to zero.

Each share of the stock pays a liquidation value of P_2 at date 2 that is drawn from a normal distribution with mean zero and variance one, and is unknown to investors prior to date 2. Shares of the stock are infinitely divisible and are traded competitively in the stock market. The price of the stock at date $t = 0, 1$ is denoted by P_t . The aggregate supply of the stock is random and equals z_0 at date 0 and $z_0 + z_1$ at date 1. Such supply shocks are a typical ingredient of rational expectations models. The noise that they create prevents equilibrium prices from fully revealing the informed agents' private information.⁴ For simplicity, we assume that z_0 and z_1 are normally distributed with mean zero and variances $\sigma_{z_0}^2$ and $\sigma_{z_1}^2$, respectively, and are independent of each other and all other random variables.⁵

The assumption that all uncertainty is resolved by date 2 is not crucial for our results. In a more realistic setting, the payment of the liquidating dividend could be interpreted as any public announcement (such as an earnings announcement) that temporarily eliminates, or at least reduces, informational differences between investors. As long as information is made public in the form of discrete news events, rather than continuously, the introduction of an infinite series of public announcements would not alter our basic conclusions.⁶

³In the more general setting of Wang (1994), analytical expressions for the equilibrium price functions in terms of exogenous model parameters are not available (see the proof of Proposition 1 in Appendix A).

⁴The assumption of a stochastic stock supply is equivalent to assuming the presence of liquidity traders who have inelastic demands of $-z_0$ and $-z_1$ shares of the stock, for reasons that are exogenous to the model.

⁵Normalizing the expected stock supply to zero can be done without loss of generality. Introducing a positive mean supply would cause the unconditional risk premium to be nonzero, but would not alter our basic results.

⁶See Holden and Subrahmanyam (2002) for a formalization of this approach.

A.2. Investors

Our economy is populated by two types of market participants: informed investors who possess private information about the stock's payoff, and uninformed investors.

In each period, informed investors receive a private signal that is related to the stock's payoff as follows:

$$S_t = P_2 + \epsilon_t, \quad \text{for } t = 0, 1, \quad (1)$$

where the error terms $\{\epsilon_t\}_{t=0,1}$ are independently and normally distributed with mean zero and variance $\sigma_{\epsilon_t}^2$, conditional on P_2 . Thus, the investors' signals are unbiased forecasts of P_2 . Uninformed investors do not observe S_0 and S_1 directly but can infer some of the informed agents' private information from market prices.

For tractability, we assume that informed and uninformed investors behave competitively. They take equilibrium prices as given even though their aggregate trades affect market prices. Such behavior can be justified by assuming that investors are individually infinitesimal, so that no single trader can influence the price. More precisely, we assume that there is a continuum of informed (uninformed) investors whose set has measure M (N). Because the mass of each investor type is not crucial for our main results, we treat M and N as exogenous and normalize $M + N = 1$. Thus, M (N) can be interpreted as the proportion of informed (uninformed) investors.⁷

Following Grossman and Stiglitz (1980), we assume that both informed and uninformed investors have negative exponential utility over terminal wealth W , with a common risk aversion coefficient γ , that is, $U(W) = -e^{-\gamma W}$. Besides allowing us to derive linear equilibria in closed form, this utility function has the advantage that income effects play no role in the agents' portfolio choice.⁸ This ensures that the disposition effect is not driven by the agents'

⁷The proportion of informed investors can easily be endogenized by introducing a fixed cost that investors must incur in order to receive the signals S_0 and S_1 .

⁸See, e.g., Huang and Litzenberger (1988).

need to rebalance their portfolios as a result of price changes.⁹ It is also common knowledge that the endowment of every trader is equal to zero.

B. Equilibrium

In this section, we solve for the equilibrium of the economy defined above. The equilibrium concept we use is that of a rational expectations equilibrium (REE), developed by Grossman (1976), Hellwig (1980), and Bray (1981). Formally, an REE is defined by prices P_0 and P_1 , and by demand functions of informed and uninformed investors, such that: (i) for each price-taking investor, the trades specified by her demand function at a given date maximize her expected utility of consumption, subject to a budget constraint and available information, including past and current market prices; and (ii) for every combination of signals and supply shocks, markets clear.

Given the well-known properties of CARA preferences under normal distributions of payoffs, signals, and supply shocks, we restrict our attention to linear equilibria. Thus, we postulate that the prices are linear functions of the private signals and the supply shocks to date, such that:

$$P_0 = a S_0 + b z_0, \tag{2}$$

$$P_1 = c S_0 + d S_1 + e z_0 + f z_1. \tag{3}$$

In the ensuing analysis, we derive a linear equilibrium in which this conjecture is confirmed to be correct. Although the aggregate stock supply is independent of the stock's payoff P_2 , it enters the price functions because it affects the number of shares held by investors and, hence, the total risk that the economy has to bear.

⁹If, for example, the utility function exhibited constant relative risk aversion, investors would respond to large price increases by selling some of their shares in order to restore the initial proportions of wealth invested in the risky and the riskless asset.

B.1. Optimal Demand of Informed Investors

The optimal demand of informed investors can be derived using backward induction. Each investor's final wealth at date 2 is given by:

$$W_I = x_0(P_2 - P_0) + x_1(P_2 - P_1), \quad (4)$$

where x_t denotes the investor's (net) demand at date t . Because W_I is normally distributed, conditional on the informed investor's date 1 information set $\mathcal{F}_1^I = \{S_0, S_1, P_0, P_1, z_0, z_1\}$, one can use the mean-variance framework to show that the optimal demand for shares at date 1 is equal to:¹⁰

$$x_1 = \frac{E[P_2 | \mathcal{F}_1^I] - P_1}{\gamma \text{Var}[P_2 | \mathcal{F}_1^I]} - x_0 = \frac{\lambda_0 S_0 + \lambda_1 S_1 - P_1}{\gamma \tau_I} - x_0, \quad (5)$$

where the values of the constants λ_0 , λ_1 , and τ_I (which are provided in the Appendix) can be calculated from the projection theorem.¹¹ The right-hand side of this equation shows the familiar result that CARA preferences under normal distributions of payoffs lead to linear optimal demand functions.

When making their portfolio decisions at date 0, informed investors can use their signal S_0 and the observed market price P_0 to predict future returns, i.e., $\mathcal{F}_0^I = \{S_0, P_0, z_0\}$. The following lemma shows that the date 0 demand of informed investors, x_0 , is linear in the expected date 1 price change, $E[P_1 - P_0 | \mathcal{F}_0^I]$, and in the expected date 2 price change, $E[P_2 - P_1 | \mathcal{F}_0^I]$.

Lemma 1 *At date 0, the optimal demand of informed investors is given by:*

$$x_0 = \frac{E[P_1 | \mathcal{F}_0^I] - P_0}{\gamma G_{11}^I} + \frac{G_{11}^I - \lambda_1 G_{12}^I}{G_{11}^I} \frac{E[P_2 - P_1 | \mathcal{F}_0^I]}{\gamma \tau_I}, \quad (6)$$

¹⁰The information set contains the current price P_1 , because investors can submit their demands as a function of the price. Moreover, knowing S_0 and S_1 , informed investors can infer the supply shocks z_0 and z_1 from equilibrium prices.

¹¹See, e.g., Anderson (1984), chapter 2.

where G_{11}^I and G_{12}^I are functions of the price coefficients d and f .

Note that the second component of the demand function is proportional to the investor's expected optimal stock holdings at date 1, $E[x_0 + x_1 | \mathcal{F}_0^I]$: on the one hand, informed investors attempt to exploit the expected price appreciation across dates 0 and 1; on the other hand, they hedge in advance the expected demand at date 1. The constant $(G_{11}^I - \lambda_1 G_{12}^I)/G_{11}^I$ represents the degree to which informed traders hedge their expected date 1 demand in advance. In fact, it is easy to show that this coefficient lies between zero and one, and increases (decreases) with the precision of the date 0 (date 1) signal S_0 (S_1). The coefficient equals one if either S_0 fully reveals P_2 (i.e., if $\sigma_{\epsilon_0} = 0$) or if S_1 contains no additional information (i.e., if $\sigma_{\epsilon_1} = \infty$).

B.2. Optimal Demand of Uninformed Investors

At date 1, an uninformed investor faces the following optimization problem:

$$\max_{y_1} E[-\exp\{-\gamma(y_0(P_2 - P_0) + y_1(P_2 - P_1))\} | \mathcal{F}_1^U], \quad (7)$$

where y_t denotes her (net) demand at date t . Because uninformed investors do not observe the signals S_0 and S_1 , their only source of information about the payoff P_2 is past and current market prices, i.e., $\mathcal{F}_1^U = \{P_0, P_1\}$. Given the linearity of the equilibrium pricing relationships, the random variables P_0 , P_1 , and P_2 are jointly normally distributed, which implies that the investor's terminal wealth conditional on \mathcal{F}_1^U is normally distributed as well. Therefore, one can use the standard mean-variance analysis to show that the uninformed investor's optimal date 1 demand is given by:

$$y_1 = \frac{E[P_2 | \mathcal{F}_1^U] - P_1}{\gamma \text{Var}[P_2 | \mathcal{F}_1^U]} - y_0 = \frac{\kappa_0 P_0 + (\kappa_1 - 1) P_1}{\gamma \tau_U} - y_0. \quad (8)$$

The conditional moments of P_2 can again be calculated from the projection theorem (see equations (26) and (27) in the Appendix).

At date 0, uninformed investors can infer information about P_2 from the observed market price P_0 , i.e., $\mathcal{F}_0^U = \{P_0\}$. Lemma 2 shows that their demand, y_0 , is linear in $E[P_1 - P_0 \mid \mathcal{F}_0^U]$ and $E[P_2 - P_1 \mid \mathcal{F}_0^U]$ and, hence, in P_0 .

Lemma 2 *At date 0, the optimal demand of uninformed investors is given by:*

$$y_0 = \frac{E[P_1 \mid \mathcal{F}_0^U] - P_0}{\gamma G_U} + \frac{1 - \kappa_1}{G_U} \frac{E[P_2 - P_1 \mid \mathcal{F}_0^U]}{\gamma \tau_U}, \quad (9)$$

where G_U is a function of the price coefficients a, b, c, d, e , and f .

Note that the optimal demand of uninformed traders, like that of informed traders, consists of two components: the first component exploits the price change in the first period, and the second hedges in advance the expected demand in the second period.

B.3. Characterization of Linear Equilibrium

Solving for a rational expectations equilibrium entails determining values for the price coefficients a, b, c, d, e , and f , such that the market clearing conditions:

$$M x_t + (1 - M) y_t = z_t, \quad \text{for } t = 0, 1, \quad (10)$$

are satisfied with probability one. The following lemma shows that a linear rational expectations equilibrium exists and provides sufficient condition for its uniqueness (among the class of linear REE).

Lemma 3 *There exists a linear REE in which equilibrium prices are as in (2) and (3); the equilibrium price coefficients are given in the Appendix. The linear REE is unique if:*

$$M \left(3(2 + M) \sigma_{\epsilon_1}^2 + 4(1 + 2M + 2\sigma_{\epsilon_1}^2) \sigma_{\epsilon_0}^2 \right) > \sigma_{\epsilon_1}^2 \quad (11)$$

Depending on the parameter values, there may be multiple linear equilibria in our economy. However, as the proof of Lemma 3 demonstrates, the set of parameter values for which these additional equilibria can be sustained is very limited. They only exist if the information asymmetry between informed and uninformed investors is sufficiently large at date 0. We will therefore focus our analysis on the unique linear REE that exists for all parameter specifications.¹²

C. Trading Behavior and Price Dynamics

This section describes the trading behavior of informed and uninformed investors and its relationship to equilibrium price dynamics. We show that, depending on how the degree of information asymmetry between informed and uninformed investors changes over time, both types of investors can exhibit the disposition effect.

C.1. Trading Behavior of Informed Investors

There are two reasons why we might expect informed investors to exhibit the disposition effect. First, selling stocks at high prices (likely winners) and buying stocks at low prices (likely losers) always seems a good idea when some investors trade for noninformational motives.¹³ The second reason is related to differences between the informed and uninformed investors' information about the asset payoff P_2 . Specifically, informed investors may exhibit the disposition effect if their informational advantage over uninformed investors decreases over time. For example, consider the extreme scenario where the signal S_1 is made public at date 1, and suppose that informed traders purchased the stock on the basis of favorable information

¹²The proof of Lemma 3 shows that these additional equilibria have some undesirable features: first, the uninformed investors' demand at date 1 is increasing in the stock price P_1 ; second, the equilibrium price P_1 is negatively correlated with the signal S_1 ; third, the risk premium associated with the supply shock z_1 is negative. These properties, although no reason to discard the equilibria on theoretical grounds, are clearly counterintuitive.

¹³In our model, changes in the aggregate supply of the stock are independent of the stock's date 2 payoff. Interpreting these supply shocks as the result of liquidity trading activity, we would expect rational risk-averse investors to absorb these shocks by providing liquidity at an appropriate risk premium.

at date 0. If S_1 is good news as well, both informed and uninformed investors will revise their expectations about the payoff P_2 upwards and will demand higher stock holdings at date 1. This drives up the price P_1 . Although both types of investors respond to good news by demanding more shares, they do so with different intensities. Not knowing S_0 , uninformed investors learn more from the signal S_1 than informed investors do. In other words, the announcement of S_1 has a much stronger impact on the uninformed investors' expectations about P_2 and, hence, on their optimal demand. In equilibrium, informed investors will therefore find it optimal to sell part of their stock holdings to uninformed investors at a price that exceeds their private valuations. To put it differently, from the informed investors' perspective, the price increase is not justified by the new information S_1 , so they decide to sell shares. If, on the other hand, S_1 signals a low payoff, both informed and uninformed investors want to sell shares. Again, however, uninformed investors, not knowing the favorable signal S_0 , are more eager to do so. The price will drop until informed investors are willing to buy shares from uninformed investors despite the bad signal S_1 and the market clears. This implies that, on average, informed investors react to a price increase by selling some of their shares and to a price decrease by buying even more shares.

The intuition for this extreme scenario where S_1 is publicly announced carries over to the more general case in which the price P_1 reveals S_1 with sufficient precision and thereby reduces the information asymmetry between informed and uninformed investors. This happens when the variance of the date 1 supply shock z_1 is low relative to that of the date 0 shock z_0 , the precision of the signal S_1 is high relative to that of the signal S_0 , and the fraction of informed traders, M , is high.

Proposition 1 *Suppose:*

$$\sigma_{\epsilon_1} \sigma_{z_1} < \frac{M \sigma_{\epsilon_0} \sigma_{z_0}}{\sqrt{M^2 (1 + \sigma_{\epsilon_0}^2) + \gamma^2 \sigma_{\epsilon_0}^4 \sigma_{z_0}^2}} \equiv \sigma_{crit}. \quad (12)$$

Then, informed investors are more likely to sell their winning stocks than their losing stocks, *i.e.*,

$$Pr(x_1 < 0 \mid x_0 > 0, \Delta P_1 > 0) > Pr(x_1 < 0 \mid x_0 > 0, \Delta P_1 < 0), \quad (13)$$

where ΔP_1 denotes the date 1 price change $P_1 - P_0$.

Note that, since the random variables x_0 , x_1 , and ΔP_1 are jointly normally distributed with mean zero, it follows immediately that Proposition 1 applies to short sales as well. If informed investors initially have a short position in the stock, they are more likely to buy back shares when the price goes down than when the price goes up, given that $\sigma_{\epsilon_1} \sigma_{z_1} < \sigma_{crit}$.¹⁴

C.2. Trading Behavior of Uninformed Investors

Using wealth, age, and trading experience as proxies for investor sophistication, recent empirical studies indicate that less sophisticated investors are more susceptible to the disposition effect.¹⁵ If one is willing to accept the premise that inexperienced investors face higher information production (or processing) costs and are therefore less informed, our analysis suggests that these investors rationally exhibit the disposition effect when the information asymmetry between investors increases prior to public announcements.

Proposition 2 *Uninformed investors are more likely to sell their winning stocks than their losing stocks, i.e.,*

$$Pr(y_1 < 0 \mid y_0 > 0, \Delta P_1 > 0) > Pr(y_1 < 0 \mid y_0 > 0, \Delta P_1 < 0), \quad (14)$$

if and only if $\sigma_{\epsilon_1} \sigma_{z_1} > \sigma_{crit}$.

¹⁴In fact, this symmetry holds for all of our results and so, from now on, we will present them only from the perspective of an investor who holds a long position at date 0.

¹⁵See, e.g., Dhar and Zhu (2006) and Feng and Seasholes (2005). In fact, Dhar and Zhu find that about one-fifth of the investors in their sample exhibit a “reverse disposition effect.” These are typically older and wealthier investors who classify themselves as professionals.

The intuition behind the above proposition is as follows. Suppose that the signal S_0 contains no information at all.¹⁶ In this case, informed and uninformed investors hold identical portfolios at date 0, absorbing the supply shock z_0 . At date 1, the stock price increases, if one of two things happens: (i) informed traders receive good news and, hence, revise their expectations about P_2 upwards, or (ii) the aggregate stock supply drops. Not being able to distinguish these two possible causes, uninformed investors respond to the observed price increase by selling (some of) their shares. The reverse is true if the price drops at date 1. In this case, uninformed investors optimally buy shares, hoping that the price depreciation is due to a positive supply shock and not to bad news about P_2 .

C.3. Ex Post Returns

Whenever the aggregate stock supply varies over time and these variations are independent of the fundamentals, homogeneously informed investors will follow a contrarian strategy and will sell shares when the price is up and buy shares when the price is down. In such a symmetric information model, the period 2 price change $\Delta P_2 = P_2 - P_1$ will, on average, be higher for losing stocks that investors hold on to than for winning stocks that investors decide to sell. In fact, this argument has been used in empirical studies (see, e.g., Odean (1998) and Brown et al. (2002)) to take the superior “ex post return” of winners that are sold, compared with losers that are not sold, as evidence against an information-based explanation for the disposition effect. Odean concludes that the investors’ preference for selling winners and holding on to losers “is not justified by subsequent portfolio performance.” The following proposition shows that this conclusion is not always correct. Investors may rationally sell their winners and hold on to their losers even though the expected future return of winners exceeds that of losers. While our subsequent discussion focuses on the behavior of uninformed investors, a similar result can be obtained for informed investors.

¹⁶In this case, the condition in Proposition 2 is satisfied for all $\sigma_{\epsilon_1}, \sigma_{z_1} \in \mathbb{R}_+$, because σ_{crit} converges to zero as σ_{ϵ_0} goes to infinity.

Proposition 3 *There exists a $\sigma^* > \sigma_{crit}$ such that for all $\sigma_{\epsilon_1}\sigma_{z_1} \in (\sigma_{crit}, \sigma^*)$, the expected period 2 (dollar) return of winning stocks that uninformed investors sell exceeds that of losing stocks that they buy, i.e.,*

$$E[\Delta P_2 \mid y_0 > 0, \Delta P_1 > 0, y_1 < 0] > E[\Delta P_2 \mid y_0 > 0, \Delta P_1 < 0, y_1 > 0]. \quad (15)$$

From the previous section, we know that uninformed investors exhibit the disposition effect if the informational advantage of informed investors increases across dates 0 and 1. In fact, if the information revealed through the price P_1 is sufficiently noisy, uninformed investors' date 1 trades are perfectly negatively correlated with the price change ΔP_1 .¹⁷ Thus, a necessary condition for the above result is that the price changes ΔP_1 and ΔP_2 be positively correlated. There are two opposing effects influencing the serial correlation. The first effect is that the risk premium required by investors to absorb the supply shock z_0 is gradually reduced over time as investors become better informed. Put differently, the negative effect a positive supply shock has on the price at date 0 is only partially reversed at date 1. This gradual decrease in the risk premium introduces persistence into price changes. However, the shock z_1 is reversed by date 2, causing a price reversal, on average (as in a standard inventory model). If the date 1 supply shock and/or the residual uncertainty at date 1 are small, then the former effect dominates, and we get positive serial correlation in returns.¹⁸

While a small supply shock at date 1 is a necessary condition for price continuation, a sufficiently large shock is required for P_1 not to convey too much information, so that uninformed investors prefer to sell winners and buy losers, hoping to benefit from liquidity trades. Our analysis shows that there exists a nonempty set of parameter values for which both effects are present: (i) the information revealed by P_1 is noisy enough to make uninformed

¹⁷See the proof of Proposition 1.

¹⁸This result is consistent with the momentum effect documented by Jegadeesh and Titman (1993). We further discuss the relationship between price momentum and the disposition effect in Section II.C.4.

investors follow a contrarian strategy, and (ii) the reversal of the conditional risk premium due to z_1 is small enough to cause a positive autocorrelation in price changes. As a result, we obtain the empirically observed phenomenon that uninformed investors sell their winning stocks even though the subsequent return of these stocks is, on average, higher than that of losing stocks that they keep in their portfolios.¹⁹

C.4. Price Momentum

The consistent profitability of momentum strategies, i.e., strategies that buy stocks that performed well in the past and sell stocks that performed poorly, remains one of the most puzzling anomalies in finance. Jegadeesh and Titman (1993) show that past winners continue to outperform past losers by about 1% per month over the subsequent 3 to 12 months. Recent empirical evidence indicates that momentum profits cannot be explained by Fama–French factors, industry effects, or cross-sectional differences in expected returns.²⁰

Holden and Subrahmanyam (2002) show that price continuations can arise in a rational expectations model when private information is received sequentially by risk-averse agents. In this case, the risk borne by the market decreases over time. This effect causes a positive autocorrelation in the conditional risk premium and thus leads to price momentum.

As pointed out in the previous section, the same effect is at work in our model.²¹ The risk premium related to the supply shock z_0 decreases across dates 0 and 1 as (some) investors observe the signal S_1 , and it further decreases across dates 1 and 2 as prices approach full revelation. This gradual decrease introduces persistence into price changes. On the other hand, the additional risk premium due to the shock z_1 at date 1 reverses by date 2, causing a price reversal, on average. If this additional date 1 risk premium is small—either because

¹⁹Notice that Proposition 3 only makes a statement about the relationship between expected returns and *changes* in the uninformed investors’ stock portfolios. In particular, it does not say that period 2 returns are negatively correlated with the investors’ optimal date 1 stock holdings.

²⁰See Fama and French (1996), Moskowitz and Grinblatt (1999), Grundy and Martin (2001), Jegadeesh and Titman (2001, 2002), and Lewellen (2002).

²¹In fact, the two-period model of Holden and Subrahmanyam (2002) corresponds to the special case $\sigma_{\epsilon_0} = \infty$ of our model.

the average date 1 supply shock is small, or the residual uncertainty is low (which is the case when the mass of informed investors is large, the noise variance of S_1 is small, and/or the variance of the date 1 supply shock is small)—the first effect dominates, resulting in positive serial correlation in returns.

Proposition 4 *The price changes $\Delta P_1 = P_1 - P_0$ and $\Delta P_2 = P_2 - P_1$ are positively correlated if and only if:*

$$\sigma_{\epsilon_1} \sigma_{z_1} < \sqrt{\frac{M \sigma_{\epsilon_0}^2 \sigma_{z_0}^2 (M + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2)}{M^2 (1 + \sigma_{\epsilon_0}^2) + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2 (M + \sigma_{\epsilon_0}^2)}}. \quad (16)$$

Grinblatt and Han (2005) link price momentum to the disposition effect. In their model, a fraction of homogeneously informed investors are assumed to have a higher demand for losing stocks than for winning stocks, other things being equal. Grinblatt and Han show that such a demand perturbation tends to generate short-term price underreaction to public information and, hence, price continuation.²² This is in stark contrast to our result. While Grinblatt and Han take the trading strategies of “disposition investors” as given, and show that such a behavioral bias can cause momentum, we demonstrate that both the disposition effect and price momentum can arise in a world with fully rational agents. In fact, since σ_{crit} satisfies the inequality in Proposition 4, our model shows that both scenarios—informed investors exhibiting the disposition effect, and uninformed investors exhibiting the disposition effect—are consistent with price continuation. We want to point out, however, that there is no causal relationship between these two effects. In fact, when the expected date 1 supply shock is sufficiently large, both informed and uninformed investors will sell their winners and hold on to their losers, even though—or rather because—price changes are negatively correlated.

²²Using data on stock holdings of mutual funds, Frazzini (2006) finds empirical support for the hypothesis that the presence of disposition investors leads to positive serial correlation in stock returns.

C.5. Empirical Implications

Our theoretical analysis has shown that depending on how the degree of information asymmetry changes over time, both informed and uninformed investors can exhibit the disposition effect.²³ Of course, in real financial markets we cannot expect the information asymmetry to constantly increase or decrease over time. There will be periods when corporate announcements—such as earnings announcements, bond rating changes, analyst up- or downgrades, etc.—reduce the differences in information across investors. However, there will also be periods without any public news releases. In these periods, investors can gain an informational advantage over their peers by acquiring firm-specific information that is not (yet) publicly available.

The relationship between information asymmetry and disposition effect suggests new empirical tests to distinguish our rational explanation from the behavioral explanation offered by Shefrin and Statman (1985). While both theories can explain the average investor behavior documented by empirical studies, prospect theory does not link the investors' preference for selling winners rather than losers to changes in the information structure. We would therefore not expect to find significant differences in measures of the disposition effect before and after corporate announcements. In contrast, our analysis predicts a relationship between the disposition effect and public news releases that reduce information asymmetries between investors.

If one is willing to accept the premise that less-sophisticated investors face higher information production (or processing) costs and are therefore, on average, less informed, our analysis suggests that the disposition behavior of less-sophisticated traders is more pronounced prior to corporate announcements, whereas the disposition behavior of more-sophisticated traders

²³While our model can generate a disposition effect for the average investor, we want to point out that informed and uninformed investors will typically not exhibit such behavior at the same time. When informed investors sell their winners, uninformed investors will, on average, buy these winners, and vice versa. This is a consequence of the market clearing condition and is not specific to our model. Unless investors constantly leave and (re)enter the market, we cannot expect all investors to follow disposition strategies all the time.

is more pronounced immediately after corporate announcements. In our empirical study, we measure the disposition effect by calculating the difference between the proportion of gains realized (PGR) and the proportion of losses realized (PLR).²⁴ This leads to the following hypothesis.

HYPOTHESIS 1: *The difference between PGR and PLR of less-experienced investors should decrease immediately after corporate announcements, whereas the PGR/PLR ratio of more-experienced investors should increase.*

Further empirical predictions concerning the relationship between price momentum and the disposition effect can be obtained through numerical computations. Not surprisingly, we find that the correlation between ΔP_1 and ΔP_2 is decreasing in σ_{z_1} , and thus, for a given information structure, is lower for values of $\sigma_{\epsilon_1}\sigma_{z_1}$ that exceed σ_{crit} . This implies that the disposition behavior of less-informed investors is concentrated primarily in relation to stocks with weak momentum.²⁵ Put differently, the propensity of less-informed investors to sell winners and hold on to losers, measured by the difference between PGR and PLR, is inversely related to the persistence in stock returns.

HYPOTHESIS 2: *The difference between PGR and PLR of less-experienced investors should be higher for stocks with weak price momentum than for stocks with strong price momentum.*

²⁴We will provide a more detailed description of our methodology in Section III.

²⁵We cannot make an analogous statement for (better-)informed investors, because they exhibit disposition behavior for small values of σ_{z_1} , as well as for large values of σ_{z_1} (the condition $\sigma_{\epsilon_1}\sigma_{z_1} < \sigma_{crit}$ is sufficient but not necessary). In the former case they primarily benefit from uninformed trend followers, in the latter case from supply shocks.

III. Empirical Results

A. The Data

The empirical analysis draws on complete daily transaction records for a sample of 30,000 clients at one of the three largest German discount brokers between January 1995 and May 2000. The broker is labeled as a discount broker because no investment advice is given. The transaction records are complete in that they contain all transactions of a client from the account opening date until the account closing date or May 31, 2000, whichever comes earlier. This allows us to reconstitute the entire portfolio of each client at the end of each day during the sample period. In contrast to the data used in many other studies of the disposition effect (see, e.g., Odean (1998) and Grinblatt and Keloharju (2001)), purchase prices are known for all positions in the sample which allows us to unambiguously classify all positions as winners or losers (relative to the value-weighted average purchase price) on any given day. Moreover, capital gains were essentially not taxable during the sample period which removes the potentially confounding effects of tax-loss selling.

The client sample was drawn randomly from the entire population of active and former clients who opened their accounts sometime between January 1995 and June 1999. As of the end of 1999, the sample represents close to 5% of the entire German discount brokerage population, which is the largest in Europe (Van Steenis and Ossig (2000)). The aggregate trading volume during the sample period amounts to DEM 5.5 billion in more than 1,000 German stocks (roughly USD 3 billion at the average DEM/USD exchange rate during the sample period). Dorn, Huberman, and Sengmueller (2008) report that, during the subperiod from February 1998 to May 2000, the aggregate order imbalance across a similar sample of investors represents close to 1% of the market-wide trading volume in the average stock. Moreover, the sample is likely representative of the broader population of retail clients at German discount brokers. This population represents a substantial fraction of the total number of retail brokerage accounts in Germany. At the end of 2000, roughly 2 million retail

accounts were held at the five largest German discount brokers compared with an estimated 6 million retail investors with exposure to individual stocks (see Deutsches Aktieninstitut (2003)).

A.1. Informed versus Uninformed Traders

The hypotheses developed in Section II distinguish between the trading behavior of traders who possess private information about future prices (informed traders) and those who do not (uninformed traders).

Identifying informed traders is challenging. One possibility is to classify the entire sample as uninformed. In a study of 60,000 U.S. discount brokerage clients during the period from 1991 to 1996, Barber and Odean (2000) report that most clients underperform the market, especially those who trade aggressively. In a study of the Taiwanese stock market, Barber, Lee, Liu, and Odean (2009) report that individual investors systematically and substantially underperform institutional investors. This is intuitive; the individual investors typically lack the resources to compete with professional investors.

Another possibility is to classify investors as informed based on characteristics that may be associated with their ability or cost to gather information about future prices, such as wealth, trading experience, portfolio size, and portfolio diversification. Feng and Seasholes (2005), using portfolio diversification at account opening as a proxy for investor sophistication, report that less sophisticated Chinese households exhibit a stronger disposition effect. In a related study, Dhar and Zhu (2006) report that investors with lower incomes display a stronger disposition effect. As an alternative to treating the entire sample as uninformed, we therefore classify sample investors as uninformed if their account is less well-diversified or smaller than the typical (median) portfolio at the end of the first month after account opening.

Accounts are ranked by the size of the associated German stock portfolio at the end of the first month after account opening. To make the account values of early and late account openers comparable, account values are measured in constant 1994 DEM (account values

for given month are divided by the German consumer price index for that month, with 1 corresponding to the level on December 31, 1994). Similarly, accounts are ranked by their Herfindahl-Hirschmann Index (HHI) at that time. Since portfolio size and diversification are measured right after account opening, the classification of investors as informed and uninformed is not affected by their trading behavior during the sample period (see Feng and Seasholes (2005)). We choose median cutoffs as opposed to finer cutoffs such as quartiles to ensure that both the informed and the uninformed group contain a sizable number of investors. According to this classification, roughly three quarters of the sample is deemed uninformed.

Table I contrasts portfolio and personal characteristics of informed and uninformed investors. By definition, the portfolios of informed investors are much larger and consist of more positions than those of uninformed investors. The portfolio value of informed investors, measured at the end of the first month after account opening and in 1994 DEM, averages DEM 73,000, compared to DEM 20,000 for investors classified as uninformed. The initial HHI of informed investors averages 0.38, which corresponds to an equally-weighted portfolio of between two and three stocks; the average initial HHI of uninformed investors is 0.89 (see Panel A of Table I).

To gauge the performance of the two investor groups, monthly raw returns for each group are computed in two steps: first, each member's portfolio return is computed; then, the equally-weighted group average is taken. To calculate monthly benchmark returns for an investor, a value-weighted benchmark portfolio based on the investor's beginning-of-the-month holdings is formed as follows. In a given month, each stock is assigned an equally-weighted portfolio of German stocks within the same size decile and book-to-market quintile at the end of the previous month. The monthly excess return is the difference between the portfolio return and the return on the benchmark portfolio, assuming that the securities are held throughout the month.

Monthly excess returns after trading costs are calculated as follows. If an investor bought

200 shares at a price of DEM 50 per share (this is the actual transaction price, i.e., it reflects the bid-ask spread and any price impact), paid a commission of DEM 90, and the Datastream closing price for the stock on the trading date were 49, then the associated trading costs would be $\text{DEM } 90 + 200(50 - 49) = 290$. The difference between transaction and closing price proxies for the effective spread and market impact of the trade, as noted by Barber and Odean (2000). To obtain excess returns net of trading costs, we sum the trading costs across all transactions for a given investor and month, divide this sum by the average actual portfolio value during the month, and subtract this ratio from monthly excess returns.

Informed investors appear to outperform uninformed investors before and after transaction costs, though the return differences between the two groups are not statistically significant at conventional levels (assuming that excess returns are independent over time, but not across investors in a group). Portfolio turnover among the two groups is similar, although trading seems to be relatively more costly for uninformed investors, presumably because of their smaller order size.

A subset of 1,300 investors also participated in a survey at the end of the sample period (see Dorn and Huberman (2005) for a detailed description of the survey). For these investors, detailed demographic and socio-economic information is available and summarized in Panel B of Table I. Investors classified as informed appear to be older, better educated, wealthier, as well as more likely to be self-employed, to earn higher incomes, and to have longer stock market experience. The differences in age, income, wealth, and stock market experience are statistically significant.

The two definitions of being informed proposed here are simple, appear to be consistent with other investor attributes and results reported in several earlier studies, and are available for the entire sample. Of course, other definitions of what constitutes uninformed investors are conceivable. Depending on preferences and information cost functions, it is possible that some investors decide to become informed only about a few stocks, as argued by van Nieuwerburgh and Veldkamp (2008) and Ivković, Sialm, and Weisbenner (2008). In unreported results,

investors with large and concentrated—as opposed to diversified—initial portfolios in our sample fail to outperform their peers. Moreover, Dorn and Huberman (2005) document a positive association between portfolio diversification and measures of financial knowledge for the survey subsample; investors who judge themselves better informed than their peers and those who display a better grasp of basic financial concepts tend to hold better diversified portfolios.

A.2. Summary Statistics on the Disposition Effect

Portfolio-Level Statistics

Starting with Odean (1998), many studies use the following trade-based measure of the disposition effect. Every time an investor sells a stock, all stocks in her portfolio are classified either as a realized gain, realized loss, paper gain, or paper loss. Realized positions are those that are sold on the date in question; all other positions are considered paper positions. Gains are positions for which the current price is above the share-weighted average purchase price; all other positions are considered losses. Realized gains, paper gains, realized losses, and paper losses are then summed across investors and sale dates. The proportion of gains realized (PGR) is the number of realized gains divided by the sum of realized gains and paper gains. The proportion of losses realized (PLR) is the number of realized losses divided by the sum of realized losses and paper losses. A positive difference $PGR - PLR$, or a ratio of PGR/PLR greater than one, is interpreted as evidence of the disposition effect.

Panel A, Column (1), of Table II reports the average PGR and PLR for the entire sample period (January 1995 to May 2000) and all German stocks for which Datastream provides the total return index values necessary to calculate average purchase prices. In the full sample, PGR is 22.3% and PLR is 14.7%; in other words, investors are 50% more likely to realize a winner than a loser. The relative magnitude of the disposition effect for German discount brokerage clients, the ratio between PGR and PLR of 1.52, is almost identical to the ratio of

1.51 reported for U.S. discount brokerage clients (see Table I in Odean (1998)).

PGR and PLR are higher in our sample than in Odean (1998), who reports a PGR of 14.8% and a PLR of 9.8% for his full sample, primarily because we focus on positions in German stocks and exclude holdings of foreign stocks and stock mutual funds. Focusing on a subset of securities increases PGR and PLR mechanically. A simple example helps to illustrate this. Suppose that an investor holds two German stocks and a foreign stock. On a given day, she sells one of the German stocks. If we focus on the German stock portfolio, we will record one realized gain or loss (for the German stock sold) and one paper gain or loss (for the German stock held). If we include foreign stocks, we will record one realized gain or loss (for the German stock sold), but *two* paper gains or losses (one for the German stock held and one for the foreign stock held).

Panel A, Columns (2)-(3), of Table II report PGR and PLR measures separately for investors classified as informed and uninformed. Both groups exhibit the disposition effect, although the effect appears to be stronger for uninformed investors. This is consistent with Feng and Seasholes (2005) and Dhar and Zhu (2006) who report stronger disposition effects for less sophisticated Chinese and U.S. brokerage customers (relative to their more sophisticated peers).

Stock-Level Statistics

The disposition effect can also be defined at the stock level. For each stock-trading day combination, one can classify the positions of all investors who own the stock either as a realized gain, a paper gain, a realized loss, or a paper loss (depending on whether the position is sold and whether the current price exceeds the share-weighted average purchase price). Contrary to the portfolio-level calculations described above, paper positions are positions of other investors in the same stock rather than positions of other stocks held by the same investor. Realized gains, paper gains, realized losses, and paper losses are then summed across all stock-trading day observations. As before, PGR is calculated as the number of

realized gains divided by the sum of realized gains and paper gains and PLR as the number of realized losses divided by the sum of realized losses and paper losses.

The main difference between the the stock-level calculation just described and the portfolio-level calculation above lies in the conditioning on trading. The portfolio-level calculation answers the question “Conditional on selling, is an investor more likely to sell a winner?” and thus offers a clean control for the trading needs of the investor. The stock-level calculation answers the question “Are investors more likely to sell winners?” and thus captures the intuition that people who are subject to a disposition effect are unconditionally more likely to sell a winner (see also Grinblatt and Han (2005) and Frazzini (2006)).

One could also aggregate realized gains, paper gains, realized losses, and paper losses defined at the portfolio level for each stock-day (see Kumar (2008)). An example helps to distinguish between these two approaches. Suppose that on a given trading day, stock A is held by 20 investors, 10 of whom have a paper gain, and 10 of whom have a paper loss. Further, suppose that two of the investors realize a gain and one investor realizes a loss on that day. At the stock level, this translates into a difference between PGR and PLR for stock A of $2/10 - 1/10 = 1/10$. At the portfolio level, the difference between PGR and PLR may be negative, zero, or positive, depending on how many of the remaining 17 investors in stock A trade on that day (a stock other than A). If the other 17 investors do not trade at all on that day, the difference between PGR and PLR would be zero ($= 2/2 - 1/1$). If, of the remaining 17 investors, one investor with a capital gain and one investor with a capital loss in stock A traded stocks other than stock A, the difference between PGR and PLR for stock A would be $2/(2+1) - 1/(1+1) = 1/6$. If, of the remaining 17 investors, three investors with a capital gain and one investor with a capital loss in stock A traded stocks other than stock A, the difference between PGR and PLR for stock A would be $2/(2+3) - 1/(1+1) = -1/10$.

For the purpose of testing our hypotheses, the stock-level estimation of the disposition effect offers three advantages over the portfolio-level estimation described above. First, whether a stock position is counted as a paper gain or loss does not depend on the trading of other

stocks. Under the portfolio-level calculation, by contrast, an investor's holding of a winning or losing position in stock A is only classified as a paper gain or loss during a given period if the investor sells some other stock B during that period.

Second, when paper gains and losses are calculated at the portfolio level (i.e., only on dates when the investor trades some other stock) and subsequently aggregated for a given stock-period, PGR and PLR often take on the extreme value of one or cannot be calculated at all, especially for short periods. The reason is that investors typically hold between one and two stocks and trade once per month. Conditional on observing a trade in a given stock and month, the typical stock is held by 32 sample investors and traded by 4 investors during that month. If the remaining 28 investors do not trade at all, which is not unusual given that they typically own only one or two stocks, the difference between PGR and PLR is either zero (if capital gains and losses are realized) or cannot be calculated at all (if only capital gains or only capital losses are realized). Moreover, the portfolio-level methodology proposed by Odean (1998) discards all trades in portfolios consisting of a single stock, a substantial portion of our (and his) sample.

Third, the portfolio-level estimation of PGR and PLR overweights active investors. Because an investor needs to sell a stock during a given period in order for her other holdings to be counted as paper gains or losses during that period, active investors generate a disproportionate number of observations.

Summary statistics for PGR and PLR resulting from stock-level calculations are reported in Panel B of Table II. Across all stock-days, there are more than 33 million realized gains, paper gains, realized losses, and paper losses. The disposition effect is evident at the stock level as well, with an average PGR of 0.65% and an average PLR of 0.48%. An average PGR of 0.65%, for example, means that investors sell winners in 0.65% of the situations in which they had an opportunity to do so. The magnitude of both PGR and PLR is lower than that reported in Panel A of Table II. This is to be expected because positions of non-traders are now also classified as paper gains or losses. However, the relative magnitude of the disposition

effect—a PGR/PLR ratio of roughly 1.4—is similar to that of 1.5 estimated at the portfolio level.

B. Hypotheses Tests

B.1. Disposition Effect and Changes in Information Asymmetry

Hypothesis 1 states that the difference between PGR and PLR of less-informed investors should decrease immediately after corporate announcements that reduce the information asymmetry. Conversely, the difference between PGR and PLR of better-informed investors should increase in this case.

Earnings Announcements as Proxies for Changes in Information Asymmetry

Patell and Wolfson (1979) report that option implied volatilities for individual stock returns tend to increase during the month before an earnings announcement and sharply drop with the announcement. Similar time-series volatility patterns in conjunction with important scheduled macroeconomic and firm-specific announcements have been reported more recently for Treasury bond futures (Ederington and Lee (1996)) and equities (Dubinsky and Johannes (2005)). Thus, it seems reasonable to think of periods just before an earnings announcement as periods of high information asymmetry and periods immediately after an announcement as periods of low information asymmetry.

Data on earnings announcements for German stocks are taken from I/B/E/S. We manually merge actual earnings announcement dates with stock holdings and Datastream return information. The difference between PGR and PLR is computed during the week before the earnings announcement and compared to the difference between PGR and PLR during the week after the earnings announcement. We use the difference between PGR and PLR rather than the ratio PGR/PLR to avoid having to exclude periods with PLR equal to zero (that is, no realized losers). A relatively short period of one week is chosen as the pre- and

post-event window based on the evidence in Patell and Wolfson (1979) and Dubinsky and Johannes (2005); in addition, we consider a four-week window. To avoid that the results are driven by stocks held by very few investors—which tend to generate extreme PGR and PLR differences—we require that a stock is held by an average of at least four investors during the pre- and post-event period. This is the case for roughly 90% of the observations. The results reported below appear qualitatively robust to this filter.

Panel A, Columns (1) and (2), of Table III report the baseline results. Consistent with the model’s prediction—if one accepts the classification of the entire sample as being uninformed—the difference between PGR and PLR is significantly larger during the week before an earnings announcement than during the week after the announcement. The difference between PGR and PLR during the week before an earnings announcement averages 0.3% versus 0.02% during the week after the announcement. The magnitudes of both PGR and PLR around earnings announcements are higher than their unconditional averages reported in Table II, which is consistent with the increased trading activity around announcements reported by Kandel and Pearson (1995) and Lamont and Frazzini (2007). The change in the disposition effect appears to be concentrated in the two weeks surrounding the announcement; the difference between PGR-PLR during the four weeks before and after the announcement is indistinguishable from zero (see Panel B, Columns (1) and (2)).

The market’s reaction to earnings announcements allows us to further refine Hypothesis 1. A larger earnings surprise indicates a potentially larger decrease in the information asymmetry between informed and uninformed investors through the announcement. In contrast, if the information content of the announcement is already reflected in prices, there is presumably little change in information asymmetry. One would therefore expect that the change in disposition behavior is more pronounced for stocks with larger earnings surprises. Following Brandt et al. (2008), we use the stock’s abnormal return during the three-day period centered around the announcement date as a proxy for the magnitude of the earnings surprise. The abnormal return is calculated as the stock’s return minus the return of the broad German

market index DAX 100 (similar results obtain when the benchmark is a portfolio containing stocks in the same size tercile and book-to-market tercile as the announcement stock; these results are not reported).

Columns (3)-(6) of Table III report the results for two subsets of observations: the subset of above-median earnings surprises (Columns (3) and (4)) and the subset of below-median earnings surprises (Columns (5) and (6)). Both PGR and PLR are much higher, corresponding to higher trading activity, surrounding greater earnings surprises. More importantly, the reduction in the disposition effect among the sample investors is only negative and significant for the subset of above-median surprises (the difference between PGR-PLR across the two subsets is significant as well, though only at the 10% level).

Peak Turnover Days as Proxies for Changes in Information Asymmetry

Rather than using earnings announcements, one can use daily turnover (i.e., the number of shares traded on a given day across all German stock exchanges divided by the number of shares outstanding as reported by Datastream) to identify important events that reduce the information asymmetry between informed and uninformed investors.

A turnover-based identification strategy overcomes two limitations of earnings announcements. First, there are news events besides earnings announcements that presumably reduce the information asymmetry between informed and uninformed investors *and* that are associated with above-average turnover. For example, Womack (1996) reports that trading volume for U.S. stocks on recommendation days is at least twice the normal trading volume. Second, because I/B/E/S covers only a subset of the stocks in the sample, and because many firms in the sample only report earnings once a year, the number of observations based on earnings announcements is relatively small.

We divide the sample period into calendar quarters and identify the peak trading day within each quarter; we exclude “triple witching days”²⁶—the third Friday in March, June,

²⁶On these days, three categories of Eurex options expire: futures and options on the European Stoxx

September, and December—since turnover in large stocks typically spikes on these days even without important news releases. However, the results reported below are robust to including triple witching days. A quarterly frequency is chosen because at least one important news release, the quarterly earnings announcement, occurs at that frequency for larger stocks. If two peak turnover days lie fewer than two event windows apart, we divide the trading days between them equally into a post- and a pre-release period. As above, one- and four-week event windows are considered and only stocks that are held by an average of at least four investors during the pre- and post-event window are included.

Columns (1) and (2) of Table IV summarize the PGR and PLR before and after peak turnover days for pre- and post-event windows of one week (Panel A) and four weeks (Panel B). Consistent with our hypothesis, we find that the difference between PGR and PLR is significantly larger during the week before a peak turnover day than during the week after a peak turnover day. The difference between PGR and PLR during the week before a peak turnover event averages 0.47% versus 0.33% during the week after a peak turnover event. In contrast to earnings announcements, the reduction in the disposition effect is similar and statistically significant for a four-week horizon. It is possible that information asymmetries decrease more gradually around peak turnover days than around earnings announcements. Consider the effect of a takeover announcement on the information asymmetry between informed and uninformed investors of the target, for example. The information asymmetry will not only decrease as a result of the initial announcement, but also in response to subsequent news about deal details such as the premium and likelihood of completion.

Robustness Checks

Given that PGR and PLR are a function of the sample investors' turnover of the stock (either explicitly when using peak turnover days or implicitly when using earnings announcements), one might be concerned that the difference between PGR and PLR is mechanically

indices, futures and options on the DAX, and individual equity options.

correlated with stock turnover. For example, even if the PGR/PLR ratio remained the same before and after the information event, a higher turnover during the pre-event window than during the post-event window would translate into a decreased difference between PGR and PLR ²⁷. A quick glance at Tables III and IV, however, suggests that trading activity is not systematically higher during periods of high information asymmetry. A way to further address this issue is to compute the PGR/PLR ratio before and after the peak turnover day and to consider the difference $\ln(\text{PGR}_t/\text{PLR}_t) - \ln(\text{PGR}_{t-1}/\text{PLR}_{t-1})$. The computation of this statistic requires that at least one investor realizes a loss and at least one investor realizes a gain before and after the information event; hence, the number of observations is smaller when compared with the number of observations underlying the baseline results. The thrust of the results, however, is the same. Table V confirms statistically significant decreases in PGR/PLR during the first week after the information event (earnings announcement or peak turnover day).

Another concern is that the decrease in the disposition effect merely reflects a time trend unrelated to information events. For example, if the disposition effect were due to a bias, people might learn to shed this bias as they become more experienced or the sample composition may shift towards less biased investors. If this were the case, one would expect to see decreases in the difference between PGR and PLR around arbitrary points in time that are similar in magnitude to those associated with earnings announcements or peak turnover days. To gauge the validity of this story, we compute the difference between PGR and PLR for all stock-weeks in the sample and take first differences. The resulting mean across all observations is indeed negative (-0.05% with a standard deviation of 5% across more than 62,000 stock-weeks). However, the hypothesis that the average change in PGR-PLR surrounding earnings announcements or peak turnover days equals the average weekly change in PGR-PLR can be rejected at the 1% level.

²⁷Consider the following example: $\text{PGR}_{t-1} = 1.5\%$, $\text{PLR}_{t-1} = 1\%$, $\text{PGR}_t = 1.2\%$, $\text{PLR}_t = 0.8\%$. These measures translate into a difference of $\text{PGR}_t - \text{PLR}_t - (\text{PGR}_{t-1} - \text{PLR}_{t-1}) = -0.1\% < 0$.

Disposition Effects of Informed and Uninformed Investors

Our model predicts that the disposition behavior of uninformed investors is more pronounced prior to public news releases, whereas the disposition behavior of informed investors is more pronounced immediately after public news releases. To examine this prediction, we repeat the baseline analysis separately for investors classified as more likely to be informed (clients with relatively large and better diversified initial portfolios) and those classified as less likely to be informed (clients with relatively small or poorly diversified initial portfolios). The results are reported in Table VI.

Consistent with the model's prediction, the reduction in the disposition effect surrounding news events appears to be more pronounced for the group of investors classified as uninformed. For a weekly event window, for example, the change in PGR-PLR surrounding peak turnover days averages -0.18% for uninformed investors (which is significantly less than zero) and -0.04% for informed investors (which is not significantly different from zero). In general, however, the differences in disposition patterns between informed and uninformed investors are not statistically significant. This lack of significance could be due to the sample containing few genuinely informed investors whose trading is obscured by other investors mistakenly classified as informed.

B.2. Return Momentum and the Disposition Effect

Our second hypothesis predicts that the difference between the proportion of gains and losses realized by uninformed investors should be greater in stocks with weak price momentum. In the context of our model, a stock exhibits strong momentum if its period-1 price change ΔP_1 is strongly positively correlated with its period-2 price change ΔP_2 .

To test this hypothesis, we start by sorting all stocks into monthly return quintiles; the first quintile contains the stocks with the lowest returns and the fifth quintile contains the stocks with the highest returns during a given month. Stocks are classified as weak momentum

stocks if they are in the lowest quintile in one month and in the highest quintile in the next month. Stocks are classified as strong momentum stocks if they are in the lowest return quintile or in the highest return quintile in two consecutive months. All stocks not classified as weak or strong momentum stocks are considered intermediate momentum stocks. Finally, we compute the average and the standard deviation of the difference between PGR and PLR for each stock category across all observations in a category. The unit of observation is a stock-period, where the period encompasses two consecutive months.

Table VII reports the PGR-PLR statistic by momentum category for three samples of investors: the full sample, the subsample of investors classified as informed, and the subsample of investors classified as uninformed. Consistent with the model’s prediction, the difference in the average PGR-PLR statistic between weak and strong momentum stocks is positive for the full sample and significantly positive for the subsample of investors classified as uninformed.

Given that the model does not pin down the test specification precisely, we consider several variations of the above specification. Panel A of Table VIII reports results that correspond to those in Table VII when stocks are sorted into return terciles each month instead of return quintiles. The results are qualitatively similar. Panels B and C of Table VIII report the corresponding results when stocks are sorted into return quintiles using sorting periods of three months (Panel B) and six months (Panel C) as opposed to one month in Table VII. Again, the results are qualitatively similar.

IV. Conclusion

This paper presents a dynamic rational expectations model that generates trading patterns as predicted by the disposition effect. Our focus is on analyzing how time-varying information asymmetry influences the investors’ behavior. Consistent with the empirical evidence, we find that less-informed investors may prefer to sell their winning investments rather than their losing investments even though past winners continue to outperform past losers

in the future. This is typically the case when the information asymmetry between investors increases over time. When the information asymmetry decreases over time, however, less-informed investors exhibit a reverse disposition effect: they keep their winners and sell their losers. In this case, it is better-informed investors who exhibit a disposition effect.

The relationship between information asymmetry and disposition effect generates novel testable implications that can help to distinguish our rational explanation from the behavioral explanation advanced by Shefrin and Statman (1985). In particular, our model predicts that unsophisticated investors are more prone to the disposition effect prior to public news releases, whereas sophisticated investors are more likely to exhibit such behavior immediately after public news releases. It further suggests that the disposition behavior of unsophisticated investors is concentrated primarily in stocks with weak price momentum. The data, trading records of 30,000 clients at a German discount brokerage firm from 1995 to 2000, are consistent with these predictions.

Of course, investors may also exhibit prospect-theory type preferences, or irrationally believe in mean-reverting prices. It is not our intention to insist that all investors are rational. We merely wanted to develop a model that does not rely on the opposite assumption and to show that the data are consistent with its predictions. Our empirical study is not designed to assess the relative importance of rational and behavioral explanations for the disposition effect. Rather, it highlights some systematic patterns in the trading behavior of individual investors that have not yet been documented. At a minimum, these patterns suggest that it might be premature to dismiss an information-based explanation.

V. Appendix

The following lemma is a standard result on multivariate normal random variables (see, e.g., Bray (1981) or Marin and Rahi (1999)) and is used to derive the optimal date 0 demand of investors:

Lemma 4 *Let $\mathbf{x} \in \mathbb{R}^n$ be a normally distributed random vector with mean (vector) $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. Then:*

$$E \left[e^{\mathbf{x}^T \mathbf{A} \mathbf{x} + \mathbf{b}^T \mathbf{x} + c} \right] = |\mathbf{I} - 2\boldsymbol{\Sigma} \mathbf{A}|^{-\frac{1}{2}} \exp \left\{ c + \mathbf{b}^T \boldsymbol{\mu} + \boldsymbol{\mu}^T \mathbf{A} \boldsymbol{\mu} + \frac{1}{2} (\mathbf{b} + 2\mathbf{A} \boldsymbol{\mu})^T (\boldsymbol{\Sigma}^{-1} - 2\mathbf{A})^{-1} (\mathbf{b} + 2\mathbf{A} \boldsymbol{\mu}) \right\} \quad (17)$$

where \mathbf{A} is a symmetric $n \times n$ matrix, \mathbf{b} is an n -vector, and c is a scalar.

Note that (17) is only well-defined if $\mathbf{I} - 2\boldsymbol{\Sigma} \mathbf{A}$ is positive definite.

Furthermore, in order to calculate the conditional probabilities and expectations in Section II, we use the following results on normally distributed random variables (see David (1953) and Kamat (1953)):

Lemma 5 *Let $\{x_i\}_{i=1,2,3}$ be jointly normally distributed random variables with mean zero and correlation $\{\rho_{ij}\}_{i,j=1,2,3}$. Then:*

$$Pr(x_1 > 0, x_2 > 0) = \frac{1}{2\pi} (\pi - \arccos \rho_{12}) \quad (18)$$

and:

$$Pr(x_1 > 0, x_2 > 0, x_3 > 0) = \frac{1}{4\pi} (2\pi - \arccos \rho_{12} - \arccos \rho_{13} - \arccos \rho_{23}). \quad (19)$$

Lemma 6 *Let x_1 and x_2 be jointly normally distributed random variables with mean zero, variance one, and correlation ρ , and let $[m, n]$ denote the “incomplete moment” given by:*

$$[m, n] = \int_0^\infty \int_0^\infty x_1^m x_2^n f(x_1, x_2) dx_1 dx_2, \quad (20)$$

where $f(x_1, x_2)$ denotes the joint probability-density function. Then:

$$[1, 0] = \frac{1 + \rho}{2\sqrt{2\pi}}, \quad (21)$$

$$[2, 0] = \frac{1}{2\pi} \left(\pi - \arccos \rho + \rho\sqrt{1 - \rho^2} \right), \quad (22)$$

$$[1, 1] = \frac{1}{2\pi} \left(\rho(\pi - \arccos \rho) + \sqrt{1 - \rho^2} \right). \quad (23)$$

For incomplete moments of the trivariate normal distribution, we refer the reader to Kamat (1953).

Conditional Moments of P_2

The expected value and the variance of P_2 conditional on the informed investors' date 1 information set, \mathcal{F}_1^I , are given by:

$$\begin{aligned} E [P_2 | \mathcal{F}_1^I] &= E[P_2 | S_0, S_1] \\ &= \frac{\sigma_{\epsilon_1}}{\underbrace{\sigma_{\epsilon_0} + \sigma_{\epsilon_1} + \sigma_{\epsilon_0}\sigma_{\epsilon_1}}_{\equiv \lambda_0}} S_0 + \frac{\sigma_{\epsilon_0}}{\underbrace{\sigma_{\epsilon_0} + \sigma_{\epsilon_1} + \sigma_{\epsilon_0}\sigma_{\epsilon_1}}_{\equiv \lambda_1}} S_1, \end{aligned} \quad (24)$$

$$Var [P_2 | \mathcal{F}_1^I] = Var[P_2 | S_0, S_1] = \frac{\sigma_{\epsilon_0}\sigma_{\epsilon_1}}{\sigma_{\epsilon_0} + \sigma_{\epsilon_1} + \sigma_{\epsilon_0}\sigma_{\epsilon_1}} \equiv \tau_I. \quad (25)$$

Similarly, the conditional moments of P_2 based on the uninformed investors' date 1 information set, \mathcal{F}_1^U , are given by:

$$E [P_2 | \mathcal{F}_1^U] = \frac{a\sigma_{P_1}^2 - (c+d)\sigma_{P_0, P_1}}{\underbrace{\sigma_{P_0}^2\sigma_{P_1}^2 - \sigma_{P_0, P_1}^2}_{\equiv \kappa_0}} P_0 + \frac{(c+d)\sigma_{P_0}^2 - a\sigma_{P_0, P_1}}{\underbrace{\sigma_{P_0}^2\sigma_{P_1}^2 - \sigma_{P_0, P_1}^2}_{\equiv \kappa_1}} P_1, \quad (26)$$

$$Var [P_2 | \mathcal{F}_1^U] = 1 - \frac{a^2\sigma_{P_1}^2 + (c+d)^2\sigma_{P_0}^2 - 2a(c+d)\sigma_{P_0, P_1}}{\sigma_{P_0}^2\sigma_{P_1}^2 - \sigma_{P_0, P_1}^2} \equiv \tau_U, \quad (27)$$

where:

$$\sigma_{P_0}^2 \equiv Var[P_0] = a^2(1 + \sigma_{\epsilon_0}^2) + b^2\sigma_{z_0}^2, \quad (28)$$

$$\sigma_{P_1}^2 \equiv Var[P_1] = c^2(1 + \sigma_{\epsilon_0}^2) + d^2(1 + \sigma_{\epsilon_1}^2) + 2cd + e^2\sigma_{z_0}^2 + f^2\sigma_{z_1}^2, \quad (29)$$

$$\sigma_{P_0, P_1} \equiv Cov[P_0, P_1] = ac(1 + \sigma_{\epsilon_0}^2) + ad + be\sigma_{z_0}^2. \quad (30)$$

Proof of Lemma 1

Let us define $\mathcal{J}_I(x_0)$ to be an informed trader's maximum expected utility from date 2 consumption given that her date 0 stock holding is x_0 , that is:

$$\mathcal{J}_I(x_0) = \max_{x_1} E \left[-\exp \{ -\gamma (x_0(P_2 - P_0) + x_1(P_2 - P_1)) \} \mid \mathcal{F}_1^I \right]. \quad (31)$$

At date 0, each informed investor faces the following optimization problem:

$$\max_{x_0} E \left[\mathcal{J}_I(x_0) \mid \mathcal{F}_0^I \right], \quad (32)$$

where the investor's date 0 information set is given by $\mathcal{F}_0^I = \{S_0, P_0, z_0\}$. Substituting the investor's optimal date 1 demand given by (5) into equation (31), we can rewrite the investor's date 1 value function as:

$$\begin{aligned} \mathcal{J}_I(x_0) &= -\exp \left\{ -\gamma \left(x_0(P_1 - P_0) + \frac{(\lambda_0 S_0 + \lambda_1 S_1 - P_1)^2}{2\gamma\tau_I} \right) \right\} \\ &= -\exp \left\{ \gamma P_0 x_0 - \frac{1}{2\tau_I} \lambda_0^2 S_0^2 - \underbrace{\left(\begin{array}{c} \gamma x_0 - \frac{1}{\tau_I} \lambda_0 S_0 \\ \frac{1}{\tau_I} \lambda_0 \lambda_1 S_0 \end{array} \right)^T \left(\begin{array}{c} P_1 \\ S_1 \end{array} \right)}_{\equiv \mathbf{b}_I^T} \right. \\ &\quad \left. - \left(\begin{array}{c} P_1 \\ S_1 \end{array} \right)^T \underbrace{\frac{1}{2\tau_I} \left(\begin{array}{cc} 1 & -\lambda_1 \\ -\lambda_1 & \lambda_1^2 \end{array} \right)}_{\equiv \mathbf{A}_I} \left(\begin{array}{c} P_1 \\ S_1 \end{array} \right) \right\}. \end{aligned} \quad (33)$$

Given the conjectured equilibrium price function in (3), P_1 and S_1 are jointly normally distributed with respect to the date 0 information set, \mathcal{F}_0^I . Thus, it follows from Lemma 4 that maximizing (32) with respect to x_0 is equivalent to maximizing:²⁸

$$\mathbf{b}_I^T \boldsymbol{\mu}_I - \frac{1}{2} (\mathbf{b}_I + 2\mathbf{A}_I \boldsymbol{\mu}_I)^T \underbrace{(\boldsymbol{\Sigma}_I^{-1} + 2\mathbf{A}_I)^{-1}}_{\equiv \mathbf{G}_I} (\mathbf{b}_I + 2\mathbf{A}_I \boldsymbol{\mu}_I) - \gamma P_0 x_0, \quad (36)$$

²⁸The determinant of the matrix $\mathbf{I} - 2\boldsymbol{\Sigma}_I \mathbf{A}_I$ is given by:

$$\left(1 + \frac{1}{\sigma_{\epsilon_0}^2} + \frac{1}{\sigma_{\epsilon_1}^2} \right) \left(d^2 \sigma_{\epsilon_1}^2 + (1-d)^2 \frac{\sigma_{\epsilon_0}^2}{1 + \sigma_{\epsilon_0}^2} + f^2 \sigma_{z_1}^2 \right) \quad (35)$$

This expression is strictly positive for all price coefficients d and f and, hence, the investor's optimization problem at date 0 is well-defined.

where $\boldsymbol{\mu}_I$ denotes the expectation and $\boldsymbol{\Sigma}_I$ the variance of the random vector $(P_1, S_1)^T$, conditional on \mathcal{F}_0^I :

$$\boldsymbol{\mu}_I \equiv E \left[\begin{pmatrix} P_1 \\ S_1 \end{pmatrix} \middle| \mathcal{F}_0^I \right] = \begin{pmatrix} \left(c + \frac{d}{1+\sigma_{\epsilon_0}^2} \right) S_0 + e z_0 \\ \frac{1}{1+\sigma_{\epsilon_0}^2} S_0 \end{pmatrix}, \quad (37)$$

$$\begin{aligned} \boldsymbol{\Sigma}_I &\equiv \text{Var} \left[\begin{pmatrix} P_1 \\ S_1 \end{pmatrix} \middle| \mathcal{F}_0^I \right] \\ &= \begin{pmatrix} \frac{d^2(\sigma_{\epsilon_0}^2 + \sigma_{\epsilon_1}^2 + \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^2)}{1+\sigma_{\epsilon_0}^2} + f^2 \sigma_{z_1}^2, & d \left(\frac{\sigma_{\epsilon_0}^2}{1+\sigma_{\epsilon_0}^2} + \sigma_{\epsilon_1}^2 \right) \\ d \left(\frac{\sigma_{\epsilon_0}^2}{1+\sigma_{\epsilon_0}^2} + \sigma_{\epsilon_1}^2 \right), & \frac{\sigma_{\epsilon_0}^2}{1+\sigma_{\epsilon_0}^2} + \sigma_{\epsilon_1}^2 \end{pmatrix}. \end{aligned} \quad (38)$$

Substituting the expressions for \mathbf{A}_I and \mathbf{b}_I from (33) into (36), we derive the first-order condition for a maximum with respect to x_0 as:

$$x_0 = \frac{E[P_1 | \mathcal{F}_0^I] - P_0}{\gamma G_{11}^I} + \frac{G_{11}^I - \lambda_1 G_{12}^I}{G_{11}^I} \frac{\lambda_0 S_0 + \lambda_1 E[S_1 | \mathcal{F}_0^I] - E[P_1 | \mathcal{F}_0^I]}{\gamma \tau_I} \quad (39)$$

$$= \frac{E[P_1 | \mathcal{F}_0^I] - P_0}{\gamma G_{11}^I} + \frac{G_{11}^I - \lambda_1 G_{12}^I}{G_{11}^I} \frac{E[P_2 - P_1 | \mathcal{F}_0^I]}{\gamma \tau_I}, \quad (40)$$

where G_{ij}^I are the elements of the matrix \mathbf{G}_I . It is easily verified that the demand defined by (40) is the unique maximum, because (36) is strictly concave in x_0 .²⁹ ■

Proof of Lemma 2

The optimal date 0 stock holdings of uninformed investors are found by solving the problem:

$$\max_{y_0} E[\mathcal{J}_U(y_0) | \mathcal{F}_0^U], \quad (42)$$

²⁹The second derivative of (36) is equal to $-\gamma^2 G_{11}^I$. If we let $\sigma_{S_1}^2$ denote the variance of S_1 , $\sigma_{P_1}^2$ the variance of P_1 , and ρ_{P_1, S_1} the correlation between P_1 and S_1 , conditional on \mathcal{F}_0^I , we can rewrite G_{11}^I as follows:

$$G_{11}^I = \frac{\lambda_1^2 (1 - \rho_{P_1, S_1}^2) \sigma_{P_1}^2 \sigma_{S_1}^2 + \tau_I \sigma_{S_1}^2}{\lambda_1^2 \sigma_{P_1}^2 - 2\lambda_1 \rho_{P_1, S_1} \sigma_{P_1} \sigma_{S_1} + \sigma_{S_1}^2 + \tau_I} \quad (41)$$

This expression clearly shows that G_{11}^I is strictly positive and, hence, that (36) is a concave function of x_0 .

where $\mathcal{J}_U(y_0)$ is the uninformed investors' date 1 value function:

$$\mathcal{J}_U(y_0) = \max_{y_1} E \left[-\exp \{ -\gamma (y_0(P_2 - P_0) + y_1(P_2 - P_1)) \} \mid \mathcal{F}_1^U \right] \quad (43)$$

$$= -\exp \left\{ -\gamma \left(y_0(P_1 - P_0) + \frac{(\kappa_0 P_0 + (\kappa_1 - 1)P_1)^2}{2\gamma\tau_U} \right) \right\}. \quad (44)$$

The only random variable in (42) is the date 1 price P_1 , which is normally distributed given \mathcal{F}_0^U . Therefore, we can use Lemma 4 to rewrite the uninformed investors' objective as:

$$\max_{y_0} \gamma(\mu_U - P_0) y_0 - \frac{1}{2} G_U \left(\gamma y_0 + \frac{\kappa_1 - 1}{\tau_U} (\kappa_0 P_0 + (\kappa_1 - 1)\mu_U) \right)^2, \quad (45)$$

where G_U is a positive constant equal to $(1/\Sigma_U + (\kappa_1 - 1)^2/\tau_U)^{-1}$ and μ_U and Σ_U denote the conditional expectation and variance of P_1 :

$$\mu_U \equiv E [P_1 \mid \mathcal{F}_0^U] = \frac{\sigma_{P_0, P_1}}{\sigma_{P_0}^2} P_0, \quad (46)$$

$$\Sigma_U \equiv Var [P_1 \mid \mathcal{F}_0^U] = \sigma_{P_1}^2 - \frac{\sigma_{P_0, P_1}^2}{\sigma_{P_0}^2}, \quad (47)$$

where $\sigma_{P_0}^2$, $\sigma_{P_1}^2$, and σ_{P_0, P_1} are defined in (28) – (30). The unique³⁰ optimum of this quadratic maximization problem is given by:

$$y_0 = \frac{E [P_1 \mid \mathcal{F}_0^U] - P_0}{\gamma G_U} + \frac{1 - \kappa_1}{G_U} \frac{\kappa_0 P_0 + (\kappa_1 - 1)E [P_1 \mid \mathcal{F}_0^U]}{\gamma \tau_U} \quad (48)$$

$$= \frac{E [P_1 \mid \mathcal{F}_0^U] - P_0}{\gamma G_U} + \frac{1 - \kappa_1}{G_U} \frac{E [P_2 - P_1 \mid \mathcal{F}_0^U]}{\gamma \tau_U}. \quad (49)$$

■

³⁰The second derivative with respect to y_0 is $-\gamma^2 G_U$, which is clearly negative.

Proof of Lemma 3

First, we demonstrate that the following price coefficients constitute a rational expectations equilibrium:

$$a = \frac{M}{D_0} (M + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2), \quad (50)$$

$$b = -\frac{\gamma \sigma_{\epsilon_0}^2}{M} a, \quad (51)$$

$$c = \frac{M \sigma_{\epsilon_1}^2}{D_1} (M + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2)(M^2 + \gamma^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2), \quad (52)$$

$$d = \frac{M \sigma_{\epsilon_0}^2}{D_1} (M^2 + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2)(M + \gamma^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2), \quad (53)$$

$$e = -\frac{\gamma \sigma_{\epsilon_0}^2}{M} c, \quad (54)$$

$$f = -\frac{\gamma \sigma_{\epsilon_1}^2}{M} d, \quad (55)$$

with:

$$D_0 = M^2(1 + \sigma_{\epsilon_0}^2) + \gamma^2(M + \sigma_{\epsilon_0}^2) \sigma_{\epsilon_0}^2 \sigma_{z_0}^2, \quad (56)$$

$$\begin{aligned} D_1 = & \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^2 \delta_0 \delta_1 + M(\sigma_{\epsilon_0}^2 + \sigma_{\epsilon_1}^2) \delta_0 \delta_1 + M^2(\sigma_{\epsilon_0}^2(1 + \sigma_{\epsilon_1}^2) \delta_0 + \sigma_{\epsilon_1}^2(1 + \sigma_{\epsilon_0}^2) \delta_1) \\ & + M^3(\sigma_{\epsilon_1}^2 \delta_0 + \sigma_{\epsilon_0}^2 \delta_1) + M^4(\sigma_{\epsilon_0}^2 + \sigma_{\epsilon_1}^2 + \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^2), \end{aligned} \quad (57)$$

where $\delta_0 = \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2$ and $\delta_1 = \gamma^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2$.

In order to prove that the above price functions form an REE, we have to show that they clear the market for all possible realizations of S_0 , S_1 , z_0 , and z_1 . The market clearing condition at date 0 is given by:

$$M x_0 + (1 - M) y_0 = z_0. \quad (58)$$

Substituting the equilibrium price coefficients a , b , c , d , e , and f into the expressions for the conditional moments $\boldsymbol{\mu}_I$, $\boldsymbol{\Sigma}_I$, μ_U , and Σ_U given by (37), (38), (46), and (47), we can rewrite the investors' date 0 demand functions as follows:

$$x_0 = \frac{1}{\gamma} \left(\frac{1}{\sigma_{\epsilon_0}^2} S_0 - \left(1 + \frac{1}{\sigma_{\epsilon_0}^2} \right) P_0 \right), \quad (59)$$

$$y_0 = - \left(\frac{1}{\gamma} + \frac{\gamma \sigma_{\epsilon_0}^2 \sigma_{z_0}^2}{M} \right) P_0. \quad (60)$$

Thus, the stock market clears at date 0, if:

$$\frac{M}{\gamma \sigma_{\epsilon_0}^2} \left(S_0 - (1 + \sigma_{\epsilon_0}^2) P_0 \right) - \frac{(1 - M) \gamma \sigma_{\epsilon_0}^2 \sigma_{z_0}^2}{M + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2} P_0 = z_0, \quad (61)$$

or, equivalently, if:

$$P_0 = \frac{M (M + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2)}{M^2 (1 + \sigma_{\epsilon_0}^2) + \gamma^2 (M + \sigma_{\epsilon_0}^2) \sigma_{\epsilon_0}^2 \sigma_{z_0}^2} \left(S_0 - \frac{\gamma \sigma_{\epsilon_0}^2}{M} z_0 \right). \quad (62)$$

This expression is identical to the price function defined above.

Similarly, the market clearing condition at date 1 is given by:

$$M x_1 + (1 - M) y_1 = z_1, \quad (63)$$

or, in terms of total stock holdings, by:

$$M (x_0 + x_1) + (1 - M) (y_0 + y_1) = z_0 + z_1. \quad (64)$$

From (5), (24), and (25), it follows that an informed investor's optimal stock holdings are given by:

$$x_0 + x_1 = \frac{1}{\gamma} \left(\frac{1}{\sigma_{\epsilon_0}^2} S_0 + \frac{1}{\sigma_{\epsilon_1}^2} S_1 - \left(1 + \frac{1}{\sigma_{\epsilon_0}^2} + \frac{1}{\sigma_{\epsilon_1}^2} \right) P_1 \right). \quad (65)$$

The optimal date 1 stock holdings of an uninformed investor are given by (8). Substituting the equilibrium price coefficients a , b , c , d , e , and f into the expressions for the conditional expectation and variance of P_2 given by (26) and (27), we have:

$$\begin{aligned} y_0 + y_1 &= \frac{\gamma M^2 ((1 + \sigma_{\epsilon_0}^2) \sigma_{\epsilon_1}^2 \sigma_{z_1}^2 - \sigma_{\epsilon_0}^2 \sigma_{z_0}^2) + \gamma^3 \sigma_{\epsilon_0}^4 \sigma_{\epsilon_1}^2 \sigma_{z_0}^2 \sigma_{z_1}^2}{(M^2 + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2) (M + \gamma^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2) \sigma_{\epsilon_0}^2} (P_0 - P_1) \\ &\quad - \left(\frac{1}{\gamma} + \frac{\gamma \sigma_{\epsilon_0}^2 \sigma_{z_0}^2}{M} \right) P_0. \end{aligned} \quad (66)$$

Substituting (65) and (66) into (64), replacing P_0 by $a S_0 + b z_0$, and solving for P_1 , we get:

$$\begin{aligned} P_1 &= \frac{M \sigma_{\epsilon_1}^2}{D_1} (M + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2) (M^2 + \gamma^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2) \left(S_0 - \frac{\gamma \sigma_{\epsilon_0}^2}{M} z_0 \right) \\ &\quad + \frac{M \sigma_{\epsilon_0}^2}{D_1} (M^2 + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2) (M + \gamma^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2) \left(S_1 - \frac{\gamma \sigma_{\epsilon_1}^2}{M} z_1 \right), \end{aligned} \quad (67)$$

where D_1 is defined in (57). This proves that the price functions specified above clear the market.

Next, we derive sufficient conditions for the above equilibrium to be the unique linear REE. Suppose that the uninformed investors' optimal date 1 stock holdings, which were shown to be linear in P_0 and P_1 in Section II.B, are given by $y_0 + y_1 = \beta_0 P_0 + \beta_1 P_1$. Furthermore, let $\phi = b/a$ and consider the following linear transformations of the equilibrium prices:

$$\theta_0 \equiv \frac{1}{a} P_0, \quad (68)$$

$$\theta_1 \equiv \frac{\gamma \tau_I}{M \lambda_0} \left(\left(\frac{M}{\gamma \tau_I} - (1 - M) \beta_1 \right) P_1 - (1 - M) \beta_0 P_0 \right) - \frac{1}{a} P_0. \quad (69)$$

Then, $\theta_0 = S_0 + \phi z_0$. Moreover, from the date 1 market clearing condition:

$$\frac{M}{\gamma \tau_I} (\lambda_0 S_0 + \lambda_1 S_1 - P_1) + (1 - M) (\beta_0 P_0 + \beta_1 P_1) = z_0 + z_1, \quad (70)$$

we have:

$$\begin{aligned} \frac{\gamma \tau_I}{M \lambda_0} \left(\left(\frac{M}{\gamma \tau_I} - (1 - M) \beta_1 \right) P_1 - (1 - M) \beta_0 P_0 \right) \\ = S_0 + \frac{\lambda_1}{\lambda_0} S_1 - \frac{\gamma \tau_I}{M \lambda_0} (z_0 + z_1). \end{aligned} \quad (71)$$

Thus:

$$\theta_1 = S_0 + \frac{\lambda_1}{\lambda_0} S_1 - \frac{\gamma \tau_I}{M \lambda_0} (z_0 + z_1) - (S_0 + \phi z_0) \quad (72)$$

$$= \frac{\sigma_{\epsilon_0}^2}{\sigma_{\epsilon_1}^2} S_1 - \left(\frac{\gamma \sigma_{\epsilon_0}^2}{M} + \phi \right) z_0 - \frac{\gamma \sigma_{\epsilon_0}^2}{M} z_1. \quad (73)$$

Note that θ_0 and θ_1 are informationally equivalent to P_0 and P_1 . Thus, the uninformed investors' demand function can be written as:

$$y_0 + y_1 = \frac{E[P_2 | \theta_0, \theta_1] - P_1}{\gamma \text{Var}[P_2 | \theta_0, \theta_1]}. \quad (74)$$

Applying the projection theorem, we get:

$$y_0 + y_1 = \frac{\hat{\kappa}_0 \theta_0 + \hat{\kappa}_1 \theta_1 - P_1}{\gamma \hat{\tau}_U}, \quad (75)$$

where the coefficients $\hat{\kappa}_0$, $\hat{\kappa}_1$, and $\hat{\tau}_U$ are functions of γ , M , σ_{ϵ_0} , σ_{ϵ_1} , σ_{z_0} , σ_{z_1} , and ϕ . Substituting this demand function and the demand function of informed investors given by (65) into the market clearing condition and solving for P_1 yields:

$$P_1 = c S_0 + d S_1 + e z_0 + f z_1, \quad (76)$$

where the coefficients c , d , e , and f depend on γ , M , σ_{ϵ_0} , σ_{ϵ_1} , σ_{z_0} , σ_{z_1} , and ϕ .

These price coefficients can now be used to express the informed investors' optimal date 0 demand function given by (6) in terms of S_0 , P_0 , the model primitives γ , M , σ_{ϵ_0} , σ_{ϵ_1} , σ_{z_0} , σ_{z_1} , and the price coefficient ϕ :

$$x_0 = \alpha_S S_0 + \alpha_P P_0. \quad (77)$$

Let $y_0 = \psi P_0$ denote the uninformed investors' date 0 demand, where ψ is a function of ϕ . Then the date 0 market clearing condition, which is given by:

$$M (\alpha_S S_0 + \alpha_P P_0) + (1 - M) \psi P_0 = z_0, \quad (78)$$

implies that:

$$a = -\frac{M \alpha_S}{M \alpha_P + (1 - M) \psi}, \quad (79)$$

$$b = \frac{1}{M \alpha_P + (1 - M) \psi}. \quad (80)$$

Thus, the price coefficients a , b , c , d , e , and f constitute an equilibrium, if and only if ϕ satisfies the cubic equation:

$$\phi = -\frac{1}{M \alpha_S}. \quad (81)$$

Fortunately, this equation can be written as the product of a linear term and a quadratic term in ϕ :

$$(\gamma \sigma_{\epsilon_0}^2 + M \phi) (h_0 + h_1 \phi + h_2 \phi^2) = 0, \quad (82)$$

where:

$$h_0 = \sigma_{\epsilon_0}^4 \left(M^3 (\sigma_{\epsilon_0}^2 + \sigma_{\epsilon_1}^2 + \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^2) + \gamma^4 \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^4 \sigma_{z_1}^2 (\sigma_{z_0}^2 + \sigma_{z_1}^2) \right. \\ \left. + \gamma^2 M \sigma_{\epsilon_1}^2 (\sigma_{\epsilon_0}^2 \sigma_{z_1}^2 + (M \sigma_{\epsilon_0}^2 + (1 + \sigma_{\epsilon_0}^2) \sigma_{\epsilon_1}^2) (\sigma_{z_0}^2 + \sigma_{z_1}^2)) \right), \quad (83)$$

$$h_1 = \gamma \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^2 \sigma_{z_0}^2 (2 M^2 (\sigma_{\epsilon_0}^2 + \sigma_{\epsilon_1}^2 + \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^2) + \gamma^2 (1 + M) \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2), \quad (84)$$

$$h_2 = \sigma_{z_0}^2 (M^2 (\sigma_{\epsilon_0}^2 + \sigma_{\epsilon_1}^2) + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2) \\ \times (M (\sigma_{\epsilon_0}^2 + \sigma_{\epsilon_1}^2 + \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^2) + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2). \quad (85)$$

This shows that $\phi = -\gamma \sigma_{\epsilon_0}^2 / M$ is indeed an equilibrium. Moreover, if $M \left(3(2 + M) \sigma_{\epsilon_1}^2 + 4(1 + 2M + 2\sigma_{\epsilon_1}^2) \sigma_{\epsilon_0}^2 \right) > \sigma_{\epsilon_1}^2$, then $h_1^2 < 4h_0 h_2$ and, hence, $h_0 + h_1 \phi + h_2 \phi^2 > 0$ for all $\phi \in \mathbb{R}$. In other words, the equation $h_0 + h_1 \phi + h_2 \phi^2 = 0$ does not have real roots. This proves that if this condition is satisfied, the equilibrium specified above is the unique linear REE.

Furthermore, it can be shown that, if equation (82) has three real roots, the other two roots result in a negative price coefficient d and a positive price coefficient f :

$$d = -\frac{M^2}{\gamma^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2} \quad (86)$$

$$f = \frac{M}{\gamma \sigma_{z_1}^2} \quad (87)$$

Thus, for these other solutions of (82), the equilibrium price P_1 is negatively correlated with the signal S_1 and positively correlated with the supply shock z_1 . Moreover, the negative price coefficient d and the market clearing condition (70) imply that $\beta_1 > 0$, i.e., the uninformed investors' demand at date 1 is increasing in P_1 . ■

Proof of Proposition 1

The proof consists of two parts. First, we show that y_1 and ΔP_1 are perfectly positively correlated, if $\sigma_{\epsilon_1} \sigma_{z_1} < \sigma_{crit}$. Then, we demonstrate that this implies that the probability of an informed investor selling a winner (loser) is greater (less) than $\frac{1}{2}$.

From (60) and (66), it follows immediately that an uninformed investor's stock demand at date 1 can be written as:

$$y_1 = -\frac{\gamma M^2 \left((1 + \sigma_{\epsilon_0}^2) \sigma_{\epsilon_1}^2 \sigma_{z_1}^2 - \sigma_{\epsilon_0}^2 \sigma_{z_0}^2 \right) + \gamma^3 \sigma_{\epsilon_0}^4 \sigma_{\epsilon_1}^2 \sigma_{z_0}^2 \sigma_{z_1}^2}{(M^2 + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2) (M + \gamma^2 \sigma_{\epsilon_1}^2 \sigma_{z_1}^2) \sigma_{\epsilon_0}^2} \Delta P_1. \quad (88)$$

Thus, y_1 is linearly increasing (decreasing) in ΔP_1 , if and only if $\sigma_{\epsilon_1} \sigma_{z_1}$ is less (greater) than:

$$\sigma_{crit} = \frac{M \sigma_{\epsilon_0} \sigma_{z_0}}{\sqrt{M^2(1 + \sigma_{\epsilon_0}^2) + \gamma^2 \sigma_{\epsilon_0}^4 \sigma_{z_0}^2}}. \quad (89)$$

Next, we show that this linear relationship between y_1 and ΔP_1 puts a lower bound on the probability that an informed investor sells a winning stock. Using the market clearing condition, we have:

$$Pr(x_1 < 0 \mid x_0 > 0, \Delta P_1 > 0) = Pr(z_1 < (1 - M) y_1 \mid x_0 > 0, \Delta P_1 > 0) \quad (90)$$

$$> Pr(z_1 < 0 \mid x_0 > 0, \Delta P_1 > 0), \quad (91)$$

where the inequality follows from the fact that a price increase implies an increase in the uninformed investors' stock holdings (i.e., $y_1 > 0$), if $\sigma_{\epsilon_1} \sigma_{z_1} < \sigma_{crit}$. Because x_0 , ΔP_1 , and z_1 are jointly normally distributed with zero means, Lemma 5 allows us to rewrite the conditional probability as:

$$\begin{aligned} Pr(z_1 < 0 \mid x_0 > 0, \Delta P_1 > 0) \\ &= \frac{2\pi - \arccos \rho_{x_0, \Delta P_1} - \arccos(-\rho_{x_0, z_1}) - \arccos(-\rho_{z_1, \Delta P_1})}{2(\pi - \arccos \rho_{x_0, \Delta P_1})} \end{aligned} \quad (92)$$

$$= \frac{1}{2} - \frac{\arcsin \rho_{z_1, \Delta P_1}}{\pi + 2 \arcsin \rho_{x_0, \Delta P_1}}, \quad (93)$$

where $\rho_{x_0, \Delta P_1}$ denotes the correlation between x_0 and ΔP_1 , $\rho_{z_1, \Delta P_1}$ the correlation between z_1 and ΔP_1 , and ρ_{x_0, z_1} the correlation between x_0 and z_1 . The second equality follows from the fact that x_0 and z_1 are uncorrelated (i.e., $\arccos(-\rho_{x_0, z_1}) = \frac{\pi}{2}$), that $\arcsin(-\rho) = -\arcsin \rho$, and that $\arcsin \rho + \arccos \rho = \frac{\pi}{2}$. Thus, the probability of an informed investor selling a winner exceeds $\frac{1}{2}$, if $\arcsin \rho_{z_1, \Delta P_1} < 0$ or, equivalently, if $Cov[z_1, \Delta P_1] = f \sigma_{z_1}^2 < 0$. This inequality obviously holds, because a positive supply shock increases the required risk premium and thus reduces the date 1 price (i.e., the coefficient f is negative).

Similarly, the conditional probability that an informed investor sells a losing stock can be shown to be less than $\frac{1}{2}$.

$$Pr(x_1 < 0 \mid x_0 > 0, \Delta P_1 < 0) = Pr(z_1 < (1 - M) y_1 \mid x_0 > 0, \Delta P_1 < 0) \quad (94)$$

$$< Pr(z_1 < 0 \mid x_0 > 0, \Delta P_1 < 0) \quad (95)$$

$$= \frac{1}{2} + \frac{\arcsin \rho_{z_1, \Delta P_1}}{\pi - 2 \arcsin \rho_{x_0, \Delta P_1}} \quad (96)$$

Thus, the probability is bounded above by $\frac{1}{2}$, because $Cov[z_1, \Delta P_1] < 0$. This proves that informed investors are more likely to sell their winning stocks than their losing stocks, if $\sigma_{\epsilon_1} \sigma_{z_1} < \sigma_{crit}$. ■

Proof of Proposition 2

As shown in the proof of Proposition 1, y_1 and ΔP_1 are perfectly negatively correlated, if $\sigma_{\epsilon_1} \sigma_{z_1} > \sigma_{crit}$. This implies that:

$$Pr(y_0 > 0, \Delta P_1 < 0, y_1 < 0) = 0, \quad (97)$$

and, hence, that uninformed investors are more likely to sell their winning stocks than their losing stocks. If, on the other hand, $\sigma_{\epsilon_1} \sigma_{z_1} < \sigma_{crit}$, y_1 and ΔP_1 are perfectly positively correlated and:

$$Pr(y_0 > 0, \Delta P_1 > 0, y_1 < 0) = 0. \quad (98)$$

Thus, in this case, uninformed investors are more likely to sell their losers. This proves that the inequality $\sigma_{\epsilon_1} \sigma_{z_1} > \sigma_{crit}$ is a necessary and sufficient condition for the result that uninformed investors prefer to sell winning stocks. ■

Proof of Proposition 3

First, recall that y_0 , y_1 , and ΔP_2 are jointly normally distributed and that the uninformed investors' optimal date 1 stock holdings, $y_0 + y_1$, are linearly increasing in $E[P_2 - P_1 | \mathcal{F}_1^U]$, where \mathcal{F}_1^U contains y_0 and ΔP_1 . Thus:

$$E[\Delta P_2 | y_0, \Delta P_1, y_1] = E[P_2 - P_1 | y_0 + y_1, \Delta P_1, y_1] \quad (99)$$

$$= E[P_2 - P_1 | y_0 + y_1] \quad (100)$$

$$= \alpha (y_0 + y_1), \quad (101)$$

for some positive constant α .

Kamat (1953) has shown that incomplete moments of trivariate normally distributed random variables are continuous functions of the respective variances and covariances. Thus, the conditional expectations $E[y_0 + y_1 | y_0 > 0, \Delta P_1 > 0, y_1 < 0]$ and $E[y_0 + y_1 | y_0 > 0, \Delta P_1 < 0, y_1 > 0]$ are continuous in σ_{z_1} . In order to prove Proposition 3, it therefore suffices to show that the expected-returns inequality holds in the limit as σ_{z_1} approaches $\underline{\sigma}_{z_1} \equiv \sigma_{crit}/\sigma_{\epsilon_1}$ from above. From the proof of Proposition 1, we know that y_1 converges to

zero in this case. Hence:

$$\lim_{\sigma_{z_1} \downarrow \underline{\sigma}_{z_1}} E[y_0 + y_1 \mid y_0 > 0, \Delta P_1 \underset{(<)}{>} 0, y_1 \underset{(>)}{(<)} 0] = \lim_{\sigma_{z_1} \downarrow \underline{\sigma}_{z_1}} E[y_0 \mid y_0 > 0, \Delta P_1 \underset{(<)}{(>)} 0]. \quad (102)$$

We are therefore left to show that:

$$\lim_{\sigma_{z_1} \downarrow \underline{\sigma}_{z_1}} E[y_0 \mid y_0 > 0, \Delta P_1 > 0] > \lim_{\sigma_{z_1} \downarrow \underline{\sigma}_{z_1}} E[y_0 \mid y_0 > 0, \Delta P_1 < 0]. \quad (103)$$

From Lemmas 5 and 6, it follows immediately that a sufficient condition for this inequality to hold is that $\lim_{\sigma_{z_1} \downarrow \underline{\sigma}_{z_1}} Cov[y_0, \Delta P_1] > 0$. In fact, it is straightforward to show that y_0 and ΔP_1 are positively correlated for all $\underline{\sigma}_{z_1} \leq \sigma_{z_1} < \bar{\sigma}_{z_1}$, where:

$$\bar{\sigma}_{z_1} = \frac{1}{\sigma_{\epsilon_1}} \sqrt{\frac{M \sigma_{\epsilon_0}^2 \sigma_{z_0}^2 (M + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2)}{M^2 (1 + \sigma_{\epsilon_0}^2) + \gamma^2 \sigma_{\epsilon_0}^2 \sigma_{z_0}^2 (M + \sigma_{\epsilon_0}^2)}}. \quad (104)$$

Using again the fact that $y_0 + y_1$ is linearly increasing in $E[\Delta P_2 \mid \mathcal{F}_1^U]$, we have:

$$Cov[y_0 + y_1, \Delta P_1] = \beta E[E[\Delta P_2 \mid \mathcal{F}_1^U] \Delta P_1] = \beta Cov[\Delta P_1, \Delta P_2], \quad (105)$$

for some positive constant β . Because $Cov[\Delta P_1, \Delta P_2] > 0$ for all $\sigma_{z_1} < \bar{\sigma}_{z_1}$ (see Proposition 4), this implies that $Cov[y_0 + y_1, \Delta P_1] > 0$, and because:

$$Cov[y_0, \Delta P_1] = Cov[y_0 + y_1, \Delta P_1] - Cov[y_1, \Delta P_1], \quad (106)$$

that $Cov[y_0, \Delta P_1] > 0$ for all $\underline{\sigma}_{z_1} \leq \sigma_{z_1} < \bar{\sigma}_{z_1}$, because for these parameter values, y_1 is linearly decreasing in ΔP_1 (see the proof of Proposition 1). This proves the existence of a $\sigma^* > \sigma_{crit}$ such that for all $\sigma_{\epsilon_1} \sigma_{z_1} \in (\sigma_{crit}, \sigma^*)$, the expected period 2 return of winning stocks uninformed investors sell is higher than that of losing stocks they buy. ■

Proof of Proposition 4

The covariance of ΔP_1 and ΔP_2 is equal to:

$$\begin{aligned} Cov[\Delta P_1, \Delta P_2] &= Cov[(c-a)S_0 + dS_1 + (e-b)z_0 + fz_1, \\ &\quad P_2 - cS_0 - dS_1 - ez_0 - fz_1] \end{aligned} \quad (107)$$

$$\begin{aligned} &= (c-a)(1-c(1+\sigma_{\epsilon_0}^2) - d) + d(1-c-d(1+\sigma_{\epsilon_1}^2)) \\ &\quad - e(e-b)\sigma_{z_0}^2 - f^2\sigma_{z_1}^2 \end{aligned} \quad (108)$$

$$\begin{aligned} &= K\left(M^2(\sigma_{\epsilon_0}^2\sigma_{z_0}^2 - (1+\sigma_{\epsilon_0}^2)\sigma_{\epsilon_1}^2\sigma_{z_1}^2) \right. \\ &\quad \left. + \gamma^2\sigma_{\epsilon_0}^2\sigma_{z_0}^2(M\sigma_{\epsilon_0}^2\sigma_{z_0}^2 - (M+\sigma_{\epsilon_0}^2)\sigma_{\epsilon_1}^2\sigma_{z_1}^2)\right), \end{aligned} \quad (109)$$

where K is a strictly positive function of γ , M , σ_{ϵ_0} , σ_{ϵ_1} , σ_{z_0} , and σ_{z_1} . Thus, the price changes are positively correlated, if and only if:

$$\sigma_{\epsilon_1}^2\sigma_{z_1}^2 < \frac{M\sigma_{\epsilon_0}^2\sigma_{z_0}^2(M + \gamma^2\sigma_{\epsilon_0}^2\sigma_{z_0}^2)}{M^2(1 + \sigma_{\epsilon_0}^2) + \gamma^2\sigma_{\epsilon_0}^2\sigma_{z_0}^2(M + \sigma_{\epsilon_0}^2)}. \quad (110)$$

■

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Table I: Summary Statistics – Sample Investors

Statistics are reported for three samples: the full sample of investors, the subsample of investors classified as uninformed, and the subsample of investors classified as informed. Investors are classified as informed if their portfolios have CPI-adjusted initial values above the median and an initial HHI below the median. The remaining investors are classified as uninformed. Initial CPI-adjusted portfolio value is the value of the investor's portfolio at the end of the first month after account opening divided by the German consumer price index at that date (with the index normalized to 1 as of 12/31/1994). Portfolio value is reported in Deutsche Mark [DEM]; during the sample period, one U.S. Dollar [USD] corresponds to roughly DEM 1.7. Initial HHI is the Herfindahl-Hirschmann Index of the investor's portfolio at the end of the first month after account opening. Monthly raw return is the monthly portfolio return averaged first across investors for a given month and then across months. Excess returns are investor's portfolio returns in excess of a size- and book-to-market-matched benchmark portfolio (averaged first across investors for a given month and then across months). Excess returns net of trading costs are portfolio excess returns for a given month minus the sum of dollar trading commissions, spreads, and price impact as a fraction of average portfolio value during that month. Investor characteristics are available for a subsample of 1,300 investors who participate in a survey administered by the brokerage at the end of the sample period. ***/**/* in Column (4) indicate that the attribute means or proportions in Columns (2) and (3) are significantly different at the 1%/5%/10% level.

	(1)	(2)	(3)	(4)
	Full sample	Investors classified as Uninformed	Informed	(2)-(3)
Number of investors	29,938	21,620	8,318	
Portfolio characteristics				
Initial CPI-adjusted portfolio value	34,915	20,078	73,482	***
Initial HHI of individual stockholdings	75%	89%	38%	***
Monthly raw returns	1.52%	1.49%	1.57%	
Returns in excess of benchmark stocks (match by size decile, book-to-market quintile)	0.11%	0.09%	0.14%	
Excess returns net of trading costs	-0.22%	-0.27%	-0.09%	
Average monthly turnover	14%	14%	14%	
Investor characteristics (available for survey respondents only)				
Male [1=male, 0=female]	84%	84%	83%	
Age [years]	39	37	42	***
College [1=yes, 0=no]	69%	69%	72%	
Self-employed [1=yes, 0=no]	16%	15%	17%	
Income [DEM '000s]	93	90	100	***
Wealth [DEM '000s]	350	305	472	***
Length of stock market experience [years]	7.4	7.0	8.5	***

Table II: Summary Statistics – Disposition Effect

Every time an investor sells a stock, all stocks in his portfolio are classified either as a realized gain, paper gain, realized loss, or paper loss. Realized gains, paper gains, realized losses, and paper losses are then summed across all sales dates and all investors (Panel A, Column (1)), investors classified as uninformed (Panel A, Column (2)), and investors classified as informed (Panel A, Column (3)). The proportion of gains realized (PGR) is the number of realized gains divided by the sum of realized gains and paper gains. The proportion of losses realized (PLR) is the number of realized losses divided by the sum of realized losses and paper losses. To obtain PGR and PLR reported in Panel B, each stock-day we classify the position of each holder of that stock either as a realized gain, paper gain, realized loss, or a paper loss. Realized gains, paper gains, realized losses, and paper losses are then summed across all stock-days and all investors (Column (1)), investors classified as uninformed (Column (2)), or investors classified as informed (Column (3)).

Disposition Effect	(1)	(2)	(3)
Panel A: Portfolio-level calculations			
	Full sample	Uninformed	Informed
Number of observations	973,787	513,104	460,683
PGR	22.3%	25.8%	18.6%
PLR	14.7%	16.5%	12.6%
PGR-PLR	7.7%	9.3%	6.0%
PGR/PLR	1.52	1.56	1.48
Panel B: Stock-level calculations			
	Full sample	Uninformed	Informed
Number of observations	33,560,645	19,498,193	14,082,092
PGR	0.65%	0.66%	0.63%
PLR	0.48%	0.48%	0.46%
PGR-PLR	0.17%	0.18%	0.17%
PGR/PLR	1.36	1.36	1.36

Table III: Disposition Effect Surrounding Earnings Announcements

Realized gains, paper gains, realized losses, and paper losses are computed for each stock-day (see also Panel B of Table II). PGR and PLR are then computed for a given period (1 week in Panel A and 4 weeks in Panel B) before and after earnings announcements as reported by I/B/E/S. Columns (1) and (2) report the results for all observations. Columns (3) and (4) report the results for above-median earnings surprises; Columns (5) and (6) report the results for below-median earnings surprises. An earnings surprise is defined as the absolute value of the stock's cumulative return in excess of the market's return from the trading day before the announcement day until the first trading day after the announcement day. $t - 1$ indicates the period before the earnings announcement; t indicates the period after the earnings announcement. ******/******/***** indicate that the null hypothesis of $(PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1}) = 0$ can be rejected against the alternative hypothesis of $(PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1}) < 0$ at the 1%/5%/10% level, assuming that the observations are independent across stocks and over time. All values are in percent.

	(1)	(2)	(3)	(4)	(5)	(6)
	All Observations		Above-Median Surprise		Below-Median Surprise	
	Before	After	Before	After	Before	After
	Earnings Announcement		Earnings Announcement		Earnings Announcement	
Panel A: 1 week						
PGR [%]	1.06	0.96	1.29	1.16	0.71	0.66
PLR [%]	0.76	0.94	0.95	1.26	0.48	0.45
PGR-PLR [%]	0.30	0.02	0.34	-0.11	0.23	0.21
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]		-0.27**		-0.45**		-0.02
σ_D [%]		5.52		6.71		2.91
Nobs		1,273		765		508
Panel B: 4 weeks						
PGR [%]	1.18	0.94	1.40	1.05	0.85	0.78
PLR [%]	0.97	0.68	1.15	0.78	0.70	0.54
PGR-PLR [%]	0.21	0.26	0.25	0.26	0.16	0.25
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]		0.04		0.01		0.09
σ_D [%]		3.80		0.05		0.02
Nobs		1,381		834		547

Table IV: Disposition Effect Surrounding Peak Turnover Days

Realized gains, paper gains, realized losses, and paper losses are computed for each stock-day (see also Panel B of Table II). PGR and PLR are then computed for each stock-quarter for a given period (1 week in Panel A and 4 weeks in Panel B) before and after the highest turnover day during the quarter as reported by Datastream (datatype 'VZ'). Triple witching days on the third Fridays of the months March, June, September, and December are excluded. If peak turnover days in adjacent quarters lie fewer than two periods apart, the trading days between them are divided equally into a before- and an after-peak period. $t - 1$ indicates the period before the peak turnover day; t indicates the period after the peak turnover day. *****/**/*** indicate that the null hypothesis of $(PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1}) = 0$ can be rejected against the alternative hypothesis of $(PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1}) < 0$ at the 1%/5%/10% level, assuming that the observations are independent across stocks and over time. All values are in percent.

	(1)	(2)
	Before	After
	Peak turnover day in quarter	
Panel A: 1 week		
PGR [%]	1.14	1.18
PLR [%]	0.67	0.84
PGR-PLR [%]	0.47	0.33
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]		-0.13*
σ_D [%]		6.40
Nobs		4,301
Panel B: 4 weeks		
PGR [%]	0.99	0.89
PLR [%]	0.66	0.72
PGR-PLR [%]	0.33	0.18
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]		-0.15***
σ_D [%]		3.77
Nobs		4,684

Table V: Disposition Effect Surrounding Information Events – Alternative Measure of the Disposition Effect

Realized gains, paper gains, realized losses, and paper losses are computed for each stock-day (see also Panel B of Table II). PGR and PLR are then computed for a given period (1 week in Panel A and 4 weeks in Panel B) before and after earnings announcements as reported by I/B/E/S (Columns (1) and (2)) as well as before and after peak turnover days as reported by Datastream (Columns (3) and (4)). $t - 1$ indicates the period before the earnings announcement or peak turnover day; t indicates the period after the earnings announcement or peak turnover day. ***/**/* indicate that the null hypothesis of $\ln(PGR_t/PLR_t) - \ln(PGR_{t-1}/PLR_{t-1}) = 0$ can be rejected against the alternative hypothesis of $\ln(PGR_t/PLR_t) - \ln(PGR_{t-1}/PLR_{t-1}) < 0$ at the 1%/5%/10% level, assuming that the observations are independent across stocks and over time. All values are in percent.

	(1)	(2)	(3)	(4)
	Before	After	Before	After
Panel A: 1 week	Earnings announcement		Peak turnover day in quarter	
$\ln(PGR/PLR)$	0.13	0.01	0.28	0.16
$\Delta \equiv \ln(PGR_t/PLR_t) - \ln(PGR_{t-1}/PLR_{t-1})$		-0.11*		-0.12***
σ_Δ		1.12		1.09
Nobs		202		567
Panel B: 4 weeks				
$\ln(PGR/PLR)$	0.24	0.25	0.34	0.25
$\Delta \equiv \ln(PGR_t/PLR_t) - \ln(PGR_{t-1}/PLR_{t-1})$		0.01		-0.09***
σ_Δ		0.94		1.09
Nobs		493		1,239

Table VI: Disposition Effect Surrounding Information Events – Uninformed Versus Informed Investors

Realized gains, paper gains, realized losses, and paper losses are computed for each stock-day (see also Panel B of Table II). PGR and PLR are then computed for windows of one week and four weeks before and after each earnings announcement (Panel A and B) and peak turnover day (Panel C and D) separately for investors classified as uninformed and those classified as informed (see also Columns (2) and (3) of Table I). $t - 1$ indicates the period before the peak turnover day; t indicates the period after the peak turnover day. ***/**/* indicate that the null hypothesis of $(PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1}) = 0$ can be rejected against the alternative hypothesis of $(PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1}) < 0$ at the 1%/5%/10% level, assuming that the observations are independent across stocks and over time. All values are in percent.

	(1)	(2)	(3)	(4)
	Uninformed		Informed	
	Before	After	Before	After
Panel A: 1 week, earnings announcement				
PGR [%]	1.13	1.09	1.11	1.03
PLR [%]	0.87	1.10	0.78	0.92
PGR-PLR [%]	0.26	-0.01	0.33	0.11
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	-0.27		-0.22	
σ_D [%]	7.78		5.75	
Nobs	1,001		1,000	
Panel B: 4 weeks, earnings announcement				
PGR [%]	1.37	0.96	1.16	0.96
PLR [%]	1.08	0.74	1.08	0.79
PGR-PLR [%]	0.29	0.21	0.08	0.17
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	-0.08		0.09	
σ_D [%]	3.59		5.37	
Nobs	1,098		1,108	
Panel C: 1 week, peak turnover day				
PGR [%]	1.17	1.21	0.94	1.10
PLR [%]	0.72	0.94	0.73	0.94
PGR-PLR [%]	0.45	0.26	0.20	0.17
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	-0.18*		-0.04	
σ_D [%]	6.60		6.57	
Nobs	3,471		3,682	
Panel D: 4 weeks, peak turnover day				
PGR [%]	1.02	1.00	0.86	0.86
PLR [%]	0.69	0.85	0.65	0.71
PGR-PLR [%]	0.33	0.15	0.22	0.15
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	-0.18**		-0.06	
σ_D [%]	4.91		3.93	
Nobs	3,757		3,997	

Table VII: Disposition Effect in Weak Versus Strong Momentum Stocks

Every two months, stocks are sorted into quintiles by their returns during month $t - 1$ and during month t . Stocks are classified as weak momentum stocks during $(t - 1, t)$ if they are in the lowest quintile during one month and in the highest quintile during the other month. Stocks are classified as strong momentum stocks if they are in the lowest return quintile or in the highest return quintile during both months. All stocks not classified as weak or strong momentum stocks are considered intermediate momentum stocks. Reported below are the average and the standard deviation of the difference PGR-PLR for each stock category across all observations in a category – the unit of observation is a stock-period where the period encompasses months $t - 1$ and t . ***/**/* indicate that the average difference between PGR and PLR for the weak momentum category is significantly different from the average difference between PGR and PLR for the strong momentum category at the 1%/5%/10% level, assuming that all stock-periods are independent observations. All values are in percent.

	Momentum			Weak - Strong
	Weak	Intermediate	Strong	
Average PGR-PLR	0.80	0.36	0.60	0.20
Std PGR-PLR	3.16	3.56	4.66	
Nobs	876	6,889	807	
Average Uninformed PGR-PLR	1.00	0.50	0.29	0.71***
Std Uninformed PGR-PLR	3.95	4.78	4.05	
Nobs	794	6,062	729	
Average Informed PGR-PLR	0.48	0.26	0.54	-0.06
Std Informed PGR-PLR	2.85	3.70	4.75	
Nobs	814	6,413	765	

Table VIII: Disposition Effect in Weak Versus Strong Momentum Stocks – Robustness Checks

Every two periods (months in Panel A, quarters in Panel B, and half-years in Panel C), stocks are sorted into quantiles (terciles in Panel A, quintiles in Panels B and C) by their returns during period $t - 1$ and during period t . Stocks are classified as weak momentum stocks during $(t - 1, t)$ if they are in the lowest quantile during one month and in the highest quantile during the other month. Stocks are classified as strong momentum stocks if they are in the lowest return quantile or in the highest return quantile during both months. All stocks not classified as weak or strong momentum stocks are considered intermediate momentum stocks. Reported below are the average and the standard deviation of the difference PGR-PLR for each stock category across all observations in a category – the unit of observation is a stock-period where the period encompasses months $t - 1$ and t . ***/**/* indicate that the average difference between PGR and PLR for the weak momentum category is significantly different from the average difference between PGR and PLR for the strong momentum category at the 1%/5%/10% level, assuming that all stock-periods are independent observations. All values are in percent.

Panel A: Monthly sort into return terciles				
	Weak	Momentum Intermediate	Strong	Weak - Strong
Average PGR-PLR	0.59	0.26	0.47	0.12
Std PGR-PLR	3.48	3.59	4.12	
Nobs	2,148	3,695	1,965	
Average Uninformed PGR-PLR	0.80	0.37	0.43	0.36***
Std Uninformed PGR-PLR	4.03	4.84	4.48	
Nobs	1,922	3,229	1,756	
Average Informed PGR-PLR	0.40	0.20	0.31	0.09
Std Informed PGR-PLR	3.58	3.43	4.75	
Nobs	2,028	3,421	1,843	
Panel B: Quarterly sort into return quintiles				
	Weak	Intermediate	Strong	Weak - Strong
Average PGR-PLR	0.70	0.46	0.58	0.12
Std PGR-PLR	1.47	3.00	3.31	
Nobs	201	2,271	333	
Average Uninformed PGR-PLR	1.14	0.50	0.88	0.27
Std Uninformed PGR-PLR	2.66	2.52	4.36	
Nobs	181	2,082	310	
Average Informed PGR-PLR	0.38	0.35	0.41	-0.03
Std Informed PGR-PLR	1.52	3.35	2.57	
Nobs	195	2,163	320	
Panel C: Semi-annual sort into return quintiles				
	Weak	Intermediate	Strong	Weak - Strong
Average PGR-PLR	0.68	0.49	0.41	0.27
Std PGR-PLR	2.05	4.12	1.58	
Nobs	83	883	146	
Average Uninformed PGR-PLR	1.15	0.70	0.38	0.77**
Std Uninformed PGR-PLR	4.05	4.51	0.92	
Nobs	81	826	136	
Average Informed PGR-PLR	0.31	0.37	0.40	-0.09
Std Informed PGR-PLR	0.82	4.03	1.94	
Nobs	79	851	143	