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 predicts that the disposition behavior of less-informed investors weakens after events that reduce information asymmetries and are concentrated in stocks with weak return persistence. The data, trading records of 50,000 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),[1] has been uncovered in a variety of data sets and time periods.[2] While such behavior appears to be 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.[3]

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 trading records of 50,000 clients at a German discount brokerage firm

[1]We use the term "disposition effect" in the sense of Shefrin and Statman's (1985) original meaning to refer to investors' "disposition to sell winners too early and ride losers too long." We want to point out, however, that some authors have since used the term in a broader sense that encompasses related phenomena such as the weakening of this effect over the tax year.

[2]The 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, Chappel, da Silva Rosa, and Walter, 2002).

[3]Analyzing trading records of Finish retail investors, Kaustia (2010) reports that the empirical pattern of return realizations cannot be generated by reasonable parameterizations of prospect theory.

over a 5 1/2-year period.

Our theoretical analysis, developed in Section II, 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. Our second main finding suggests that risk-averse investors can rationally exhibit the disposition effect even though past winners continue to outperform past losers in subsequent periods. Thus, we demonstrate that both the disposition effect and price momentum can arise in a world with rational agents.

The basic intuition for our theoretical 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 uninformed investors is more pronounced prior to public news releases. The empirical results, reported in Section III, indicate that the tendency to sell winners and hold on to losers indeed drops sharply after events that reduce the informational gap between investors, such as earnings announcements. In fact, we observe a reverse disposition effect up to one week after an earnings announcement. The disposition effect reappears in the second week after the announcement, indicating that disposition behavior changes markedly around earnings releases. Consistent with the model, this pattern is stronger for stocks with greater earnings surprises.

Earlier studies of the disposition effect pay scant attention to its dynamic properties. One regularity, reported by Odean (1998) and Grinblatt and Keloharju (2001) is a greater willingness to part with losers in December, which is presumably driven by tax-loss selling. Figure 1 plots the ratio of the proportion of gains realized (PGR) to the proportion of losses realized (PLR) for our German sample stocks as a function of the calendar month. A ratio greater than one indicates the presence of a disposition effect. The figure shows that the magnitude of the effect is U-shaped over the calendar year: it averages 1.6 between October and February and drops to an average of 1.1 between May and July. During the sample period, capital gains were effectively tax-free for our sample investors, which can explain the absence of a December low. Figure 1 contrasts the PGR/PLR ratio with the number of earnings announcements per calendar month. Most German firms use the calendar year as their fiscal year and report earnings annually rather than quarterly. Remarkably, the earnings season between May and July, which comprises half of all announcements, coincides with the weakest disposition behavior throughout the year. This pattern is consistent with our information-based explanation of the disposition effect, since the information asymmetry between informed and uninformed investors presumably decreases most during periods in which earnings announcements are clustered.

The model further predicts that the disposition behavior of uninformed investors is concentrated primarily in stocks with weak return persistence. Intuitively, selling winners and holding on to losers is less detrimental to investors when stock returns are serially uncorrelated. The data are consistent with this prediction as well.

Our empirical results do not imply that the disposition effect is an entirely 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.

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.[4] This admittedly restrictive assumption and our focus on a finite-horizon setting allow us to characterize equilibrium demands and prices in closed form and to derive conditions for the disposition behavior of various investor groups.[5]

[4]See, e.g., Grundy and McNichols (1989), Brown and Jennings (1989), Wang (1993, 1994), 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.

[5]In the infinite-horizon setting of Wang (1994), analytical expressions for the equilibrium price functions in terms of exogenous model parameters are not available.

A.1. Assets

There are two assets available for trading in the market: a riskless bond and a risky stock.[6] The bond is in perfectly elastic supply. Its interest rate is normalized 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.[7] For simplicity, we assume that z_0 and z_1 are normally distributed with mean zero and variances $\sigma^2_{z_0}$ and $\sigma^2_{z_1}$, respectively, and are independent of each other and all other random variables.[8]

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:

$$S_t = P_2 + \epsilon_t, \qquad \text{for } t = 0, 1, \tag{1}$$

where the error terms $\{\epsilon_t\}_{t=0,1}$ are independently and normally distributed with mean zero and variance $\sigma^2_{\epsilon_t}$, 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'

[6] Although the disposition effect is usually presented as a cross-sectional phenomenon in the empirical literature, we focus on a setting with a single risky asset for expositional simplicity. We note, however, that our analysis readily extends to the case of multiple risky assets. Indeed, since wealth effects play no role in our CARA-normal setting, the results for the multi-asset case are identical to those for the single-asset case if payoffs and signals are uncorrelated across assets.

[7] The 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.

[8] Normalizing 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.

private information from market prices.

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, $U(W) = -e^{-\gamma W}$. We further assume that 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.[9]

B. Equilibrium

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.

As is customary in this literature, 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

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

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

Solving for an REE entails determining values for the price coefficients a, b, c, d, e, and f, such

[9] The 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.

that the market clearing conditions are satisfied with probability one:

$$M\, x_t + (1 - M)\, y_t = z_t, \qquad \text{for } t = 0, 1, \tag{4}$$

where x_t (y_t) denotes an informed (uninformed) investor's demand at date t. The following lemma shows that a linear rational expectations equilibrium exists and provides sufficient conditions for its uniqueness (among the class of linear REE).[10]

Lemma 1. *There exists a linear REE in which equilibrium prices are as in (2) and (3); the equilibrium price coefficients are given in Appendix B. The linear REE is unique if*

$$M\Big(3\,(2 + M)\,\sigma^2_{\epsilon_1} + 4\,\big(1 + 2M + 2\sigma^2_{\epsilon_1}\big)\,\sigma^2_{\epsilon_0}\Big) > \sigma^2_{\epsilon_1}. \tag{5}$$

Depending on the parameter values, there may be multiple linear equilibria in our economy. However, as the proof of Lemma 1 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.[11]

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.

In our empirical study, we measure the disposition effect by calculating the difference between the investors' propensity to realize winners and their propensity to realize losers. Specifically, we

[10] All proofs are contained in Appendix B.

[11] The proof of Lemma 1 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.

compare the proportion of gains realized (PGR) with the proportion of losses realized (PLR).[12] In our model, these measures correspond to the conditional probabilities with which a winning and a losing stock are sold at date 1.[13]

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.[14] 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 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

[12] For a more detailed description of our methodology, see Section III.

[13] In our single-asset setting, interpreting these conditional probabilities as cross-sectional averages can be justified by the fact that, with CARA preferences, an investor's demand for a risky asset is independent of her wealth. Indeed, if the payoffs and signals are uncorrelated across assets, the PGR and PLR measures converge to the conditional probabilities as the number of assets approaches infinity.

[14] In 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.

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 that*

$$\sigma_{\epsilon_1}\sigma_{z_1} < \frac{M\,\sigma_{\epsilon_0}\sigma_{z_0}}{\sqrt{M^2\left(1+\sigma_{\epsilon_0}^2\right)+\gamma^2\sigma_{\epsilon_0}^4\sigma_{z_0}^2}} \equiv \sigma_{crit}. \tag{6}$$

Then, informed investors are more likely to sell their winning stocks than their losing stocks, that is,

$$Pr\big(x_1 < 0 \mid x_0 > 0, \Delta P_1 > 0\big) > Pr\big(x_1 < 0 \mid x_0 > 0, \Delta P_1 < 0\big), \tag{7}$$

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

The above result is consistent with Brennan and Cao (1997) and Watanabe (2008). In these models, better-informed investors tend to be contrarians, especially when their marginal information advantage is small. Our model, however, can also generate contrarian behavior among uninformed investors, which seems to be more in line with the empirical evidence. Using a data set that documents the shareholdings of both institutional and retail investors in Finland, Grinblatt and Keloharju (2000), for example, report that the frequency of contrarian behavior is inversely related to investor sophistication. In the next section, we show that uninformed investors act as contrarians if the informational gap between investors increases over time.

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 over time.

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

$$Pr\big(y_1 < 0 \mid y_0 > 0, \Delta P_1 > 0\big) > Pr\big(y_1 < 0 \mid y_0 > 0, \Delta P_1 < 0\big), \tag{8}$$

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

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.

[15] See, 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.

[16] In 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.

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 (e.g., Odean, 1998; Brown, Chappel, da Silva Rosa, and Walter, 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.

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 return of winning stocks that uninformed investors sell exceeds that of losing stocks that they buy, that is,*

$$E\big[\Delta P_2 \mid y_0 > 0, \Delta P_1 > 0, y_1 < 0\big] > E\big[\Delta P_2 \mid y_0 > 0, \Delta P_1 < 0, y_1 > 0\big]. \tag{9}$$

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

[17]See the proof of Proposition 1.

informed. Put differently, the negative effect that 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 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.

C.4. Return Persistence

The consistent profitability of momentum strategies, that is, 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.[19]

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

[18] This 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.

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

the conditional risk premium and thus leads to return persistence.

As pointed out in the previous section, the same effect is at work in our model. 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 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*

$$\sigma_{\epsilon_1}\sigma_{z_1} < \sqrt{\frac{M\,\sigma_{\epsilon_0}^2\sigma_{z_0}^2\left(M+\gamma^2\sigma_{\epsilon_0}^2\sigma_{z_0}^2\right)}{M^2\left(1+\sigma_{\epsilon_0}^2\right)+\gamma^2\sigma_{\epsilon_0}^2\sigma_{z_0}^2\left(M+\sigma_{\epsilon_0}^2\right)}}. \tag{10}$$

It is straightforward to show that σ_{crit} satisfies the above inequality, implying that both scenarios—informed investors exhibiting the disposition effect and uninformed investors exhibiting the disposition effect—are consistent with return persistence. This result contrasts the finding in Grinblatt and Han (2005) that the higher demand of "disposition investors" for losing stocks can lead to a short-term price underreaction to public news. While Grinblatt and Han take the trading strategies of disposition investors as given and show that such a behavioral bias can cause return persistence, we demonstrate that both the disposition effect and return persistence can arise in a world with fully rational agents.

D. Empirical Implications

Our theoretical analysis shows that, depending on how the degree of information asymmetry changes over time, both informed and uninformed investors can exhibit the disposition effect.[20] Of

[20] While 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

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 public news releases that reduce information asymmetries between investors. In contrast, our analysis predicts that the disposition behavior of uninformed traders is more pronounced prior to 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).[21] This leads to the following hypothesis.

> HYPOTHESIS 1: *The difference between PGR and PLR of uninformed investors decreases after corporate announcements.*

Our analysis also predicts that the disposition behavior of uninformed investors is related to the persistence in stock returns. In particular, Proposition 4 shows 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 uninformed investors is concentrated primarily in stocks with weak return persistence. Put differently, the propensity of uninformed 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.

market, we cannot expect all investors to follow disposition strategies all the time.

[21] We will provide a more detailed description of our methodology in Section III.

Hypothesis 2: *The difference between PGR and PLR of uninformed investors is higher for stocks with weak return persistence.*

III. Empirical Results

A. The Data

The empirical analysis is based on daily transaction records for a sample of almost 50,000 clients trading more than 1,100 stocks at one of the three largest German discount brokers at some point between January 1995 and May 2000. The broker is labeled a discount broker because no investment advice is given. The transaction records allow us to reconstitute the portfolio of each client at the end of each day during the sample period.

The client sample is drawn from the entire population of active and former clients who opened their accounts sometime before June 1999. As of the end of 1999, the sample represents more than 5% of the entire German discount brokerage population, which is the largest in Europe (Van Steenis and Ossig, 2000). Dorn, Huberman, and Sengmueller (2008) report that, during the subperiod from February 1998 to May 2000, the aggregate order imbalance across a subsample of investors considered in this paper represents, on average, close to 1% of the market-wide trading volume across stock-days. Moreover, the sample is likely representative of the broader population of retail clients at German discount brokers.

The analysis includes all stocks that satisfy the following criteria: (i) they are held by at least five investors in the sample at some time during the sample period; (ii) they have a valid ticker and at least one earnings announcement in the Institutional Brokers' Estimate System (IBES) database during the sample period; and (iii) Datastream provides total return index values. Such stocks account for a sample trading volume of 10.5 billion Deutsche Mark [DEM] (roughly 6 billion U.S. dollars [USD] at the prevailing USD/DEM exchange rates during the sample period) or 71% of the total brokerage stock trading volume (which is spread across almost 8,000 stocks).

We use a measure of the disposition effect similar to that proposed by Odean (1998). For each stock-trading day combination, we 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, relative to the value-weighted average purchase price. 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. The number of realized gains, paper gains, realized losses, and paper losses are then summed across all stock-trading day observations. 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 between PGR and PLR, or a PGR/PLR ratio greater than one, is interpreted as evidence of the disposition effect. We discuss the properties of this measure and contrast it with the measure proposed by Odean (1998) in Appendix C.

Summary statistics for PGR and PLR are reported in Table I. When pooled across all stock-days, there are more than 104 million realized gains, paper gains, realized losses, and paper losses. Consistent with previous empirical work on the disposition effect, our sample investors are reluctant to realize their losses: the PGR of 0.54% exceeds the PLR of 0.41%, as reported in Column (1) of Table I. When PGRs and PLRs are first calculated for a given stock-week and then averaged across all stock-weeks, the PGR and PLR levels are higher at 0.71% and 0.57%, respectively, as reported in Column (2) of Table I. This implies that more widely held stocks tend to be traded less by their holders, on average. Column (3) of Table I reports the corresponding PGR and PLR statistics for the two-week window surrounding the 4,300 sample earnings announcements. The higher PGR and PLR levels reflect the heightened trading activity around earnings announcements.

B. Disposition Effect and Changes in Information Asymmetry

Our first hypothesis states that the difference between PGR and PLR of uninformed investors should decrease after events that reduce the informational asymmetry between informed and uninformed investors. Earnings announcements provide a suitable setting to test this hypothesis. First, earnings releases contain information that is useful in estimating future cash flows. Such information should come as a greater surprise to uninformed investors than to informed investors, that is, investors who had previously received a signal about the now-public information and positioned themselves accordingly. Second, earnings releases can be dated accurately and receive considerable media attention, which guides our empirical test specification. For example, one would expect earnings releases to have their greatest effect on trading behavior during the first few days, as opposed to weeks or months after the announcement. Indeed, 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). This evidence is consistent with earnings announcements quickly reducing the informational gap between investors and the gap gradually widening during the time between announcements.

We classify all sample investors as uninformed. This classification is simple and intuitive: individual investors typically face higher information acquisition and processing costs than professional investors and are thus better off remaining uninformed. Consistent with this intuition, Barber and Odean (2000) report that U.S. discount brokerage customers underperform the market after fees. Barber, Lee, Liu, and Odean (2009) report that individual investors in the Taiwanese stock market systematically and substantially underperform institutional investors.[22]

Alternative classifications are possible, but problematic for at least two reasons. First, the identification of informed investors is challenging and there is little consensus on observable proxies for the likelihood of being informed. Portfolio diversification is an example for an ambiguous proxy. Ivković, Sialm, and Weisbenner (2008) report that investors with more concentrated stock portfolios outperform investors with more diversified portfolios, which they interpret as "potentially reflecting concentrated investors' successful exploitation of information asymmetries" (p. 613). In contrast, Goetzmann and Kumar (2008)—using the same sample as Ivković, Sialm, and Weisbenner (2008)—report that "younger, less wealthy, and less sophisticated investors and those with stronger

[22]In apparent contrast, Kaniel, Saar, and Titman (2008) report that positive returns follow buying by retail investors and negative returns follow retail selling. However, the authors interpret this evidence as consistent with retail investors being compensated for providing liquidity to institutions rather than widespread informed trading by individuals.

behavioral biases [...] exhibit greater underdiversification." Dorn and Huberman (2005) and Feng and Seasholes (2005) also report a positive association between portfolio diversification and other proxies for investor sophistication in different samples.

Second, even if informed investors could be identified ex ante, they will likely form a small subsample, as noted by Coval, Hirshleifer, and Shumway (2005). A failure to reject the null hypothesis of no changes in disposition behavior for such a small group would not be very informative. Indeed, one might then also fail to reject the null hypothesis that the disposition behavior of informed investors does not differ from the disposition behavior of uninformed investors.

B.1. Stock-Announcement Level Analysis

Baseline Results

Our first empirical specification is a difference-in-differences test: we compare the difference between PGR and PLR before and after an earnings announcement for a given stock. This specification effectively controls for any stock fixed effects and weights each stock announcement equally. It assumes that trading behavior is independent across stock-announcement pairs, but allows individual trading behavior to be arbitrarily correlated for a given stock-announcement pair. The latter is a desirable feature given that trading decisions are unlikely to be independent across investors in a given stock, as reported by Kumar and Lee (2006) and Dorn, Huberman, and Sengmueller (2008), for example.

Table II reports PGR and PLR statistics for different sub-periods before and after the announcement. Since many announcements do not have a time stamp, the announcement day (day 0) is always excluded. To avoid the results being driven by stocks held by very few investors, which tend to generate more extreme PGR and PLR differences, stocks need to be held by an average of at least 5 investors during the pre- and post-event period. The results are robust to changing this cutoff.

Panel A of Table II contrasts the disposition behavior during days [-2, -1] and [1, 2], that is, the two days before and after the announcement. Consistent with our hypothesis, the difference between PGR and PLR decreases immediately after the announcement. Remarkably, the average difference between PGR and PLR turns negative during the first two days after the earnings announcement, that is, the disposition effect observed prior to the announcement turns into a reverse disposition effect immediately after the announcement. We can reject the null hypothesis of an unchanged disposition effect against the (two-sided) alternative hypothesis of a change in the disposition effect at the 1% significance level. The absolute levels of both PGR and PLR around earnings announcements are higher than their unconditional averages reported in Table I, which is not surprising given the increased trading activity around announcements in the sample (and also reported by Kandel and Pearson, 1995; Lamont and Frazzini, 2007).

Panel B of Table II reports PGR and PLR statistics for days [-5, -3] and days [3, 5] relative to the announcement day. The average difference between PGR and PLR during days [-5, -3] is similar to that for days [-2, -1], indicating that there is a robust disposition effect prior to the earnings announcement. During days [3, 5] after the announcement, PGR and PLR are similar, which indicates that there is neither a disposition effect nor a reverse disposition effect. Overall, the decline in disposition behavior is also significant between these two periods.

Panel C of Table II reports the corresponding PGR and PLR statistics for trading days [-10, -6] and [6, 10], that is, the weeks adjacent to the two week window centered around the earnings announcement. During both of these weeks, the average difference between PGR and PLR is positive, indicating a disposition effect during both periods. Moreover, the difference in differences is no longer distinguishable from zero.

The evidence in Table II is thus consistent with the change in disposition behavior starting immediately after the announcement and being short lived: by the second week after the earnings announcement, disposition behavior has reappeared and is indistinguishable from the disposition behavior prior to the announcement.

Despite the abrupt change of disposition behavior around earnings announcements, one might still be concerned 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. To gauge the validity of this argument, we compute the empirical distribution of changes in disposition behavior in adjacent stock-weeks without an earnings announcement. The resulting distribution is based on more than 140,000 observations. It is centered at -0.02%, indicating that disposition behavior indeed weakens over time. However, this average time effect is an order of magnitude smaller than the average decrease during the two weeks surrounding earnings announcements.

Surprises

The market's reaction to earnings announcements allows us to further refine our hypothesis. 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 due to the announcement. One would therefore expect the change in disposition behavior to be more pronounced for stocks with larger earnings surprises. Following Brandt, Kishore, Santa-Clara, and Venkatachalam (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 corresponding market index.

Table III contrasts the change in disposition behavior around earnings announcements for two subsets of observations: the subset of above-median earnings surprises and the subset of below-median earnings surprises. As hypothesized, the reduction in the disposition effect among the sample investors is only negative and significant for the subset of above-median surprises during the two week window centered on the announcement day. In particular, there is a strong reverse disposition effect during the two days after the announcement. Disposition behavior also appears to be reduced in the case of less surprising earnings announcements, but the effect is smaller and only significant at the 10% significance level when comparing days [-10, -6] and [6, 10]. The absolute levels of PGR and PLR are higher for the subset of above-median surprises, corresponding to the higher trading activity around greater earnings surprises.

Rebalancing

Rebalancing can be a rational trading strategy that generates a disposition effect. In particular, one might observe a decline in disposition behavior around earnings announcements if rebalancing activities were more prevalent before than after earnings announcements. We follow Odean (1998) and define rebalancing trades as partial sales (that is, trades that lead to a partial rather than a complete liquidation of the investor's position). Note that this is a rather generous definition of what constitutes a rebalancing trade that may include many information-motivated trades. One can decompose the decrease in disposition behavior around earnings announcements into an effect due to rebalancing trades and in an effect due to non-rebalancing trades by calculating two sets of PGRs and PLRs. The proportion of gains realized through rebalancing trades is defined as the number of gains realized through partial sales, divided by the sum of the number of gains realized through partial sales, the number of gains realized through complete sales, and the number of paper gains. The proportion of gains realized through non-rebalancing trades is defined as the number of gains realized through complete sales, divided by the sum of the number of gains realized through partial sales, the number of gains realized through complete sales, and the number of paper gains. Rebalancing and non-rebalancing PLRs are calculated accordingly.

Table IV reports the results of the decomposition into rebalancing and non-rebalancing effects. Note that, given the above definition, the aggregate PGRs and PLRs can be expressed as the sum of the underlying rebalancing and non-rebalancing PGRs and PLRs. For example, the average disposition effect of $PGR - PLR = 0.765 - 0.643 = 0.123$ (rounding error) observed during the two days before an earnings announcement (see Panel A of Table II) can be decomposed into an effect due to rebalancing of $(PGR - PLR)_{rebalancing} = 0.123 - 0.077 = 0.046$ and an effect due to non-rebalancing of $(PGR - PLR)_{non-rebalancing} = 0.642 - 0.565 = 0.077$ (see Panel A of Table IV). Also, the average change in aggregate disposition behavior is the sum of the average change in rebalancing disposition behavior and the average change in non-rebalancing disposition behavior. The levels of rebalancing PGR and PLR are much lower than those of the non-rebalancing PGR and PLR because investors typically engage in complete as opposed to partial sales. Rebalancing activity is indeed associated with disposition behavior, that is, the differences between PGR and PLR due to rebalancing are reliably positive, regardless of the event window. Changes in rebalancing intensity, however, fail to explain the abrupt decrease in disposition behavior during the two days surrounding the earnings announcement (Panel A of Table IV). When comparing periods further away from the announcement, changes in rebalancing activity do contribute to a slight decrease in disposition behavior, as can be seen from the results reported in Panels B and C of Table IV.

Limit Orders

The use of limit orders can create the appearance of contrarian trading and a disposition effect, as pointed out by Dorn, Huberman, and Sengmueller (2008) and Linnainmaa (2010). It is possible that investors rely less on limit orders immediately after earnings announcements to guard against their orders being picked off by quick traders. Such a change in order submission strategy could mechanically weaken the observed disposition behavior. Since the broker reports for most orders whether they are market or limit orders, we can examine this possibility. Similar to decomposing changes in disposition behavior into rebalancing and non-rebalancing effects, we separately estimate the effects of limit and market orders. For example, the proportion of gains realized through limit orders is defined as the number of gains realized through limit orders, divided by the sum of the number of gains realized through limit orders, the number of gains realized through market orders, the number of gains realized through unclassified orders, and the number of paper gains.

Table V reports limit and market order effects separately. Note that, by definition, the average changes in disposition behavior due to limit orders, market orders, and unclassified orders sum to the aggregate changes in disposition behavior reported in Table II. Not surprisingly, there is a strong disposition effect in limit orders as evidenced by the positive gap between PGR and PLR based on executed limit orders both before and after the announcement. Limit orders also contribute to the decrease in disposition behavior around earnings announcements, but the effect is relatively small and not statistically significant. Market orders account for most of the decrease in the disposition effect during the four-day window centered on the announcement day. In contrast to limit orders, market orders reflect a reverse disposition effect both before and after the announcement, but the reverse disposition effect is much more pronounced after the announcement. The disposition effect in limit orders and the reverse disposition effect in market orders is not surprising, given that Dorn, Huberman, and Sengmueller (2008) document a strong momentum tendency in market orders and a contrarian tendency in limit orders for a subsample of the investors considered here.

B.2. Investor-Level Regression Results

So far, we have examined the disposition effect at the stock-announcement level. One can also ask whether disposition behavior changes around information events at the investor level in a regression framework. The advantage of such a specification is that one can simultaneously control for a wide range of attributes that have been reported to affect an investor's propensity to sell, such as past returns and volatility.

For each earnings announcement, we focus on investors' holdings and trades during the ten-trading-day window centered on the earnings announcement date. As before, the announcement day is excluded from the analysis since we do not have time stamps for most announcements and can thus not identify whether announcement-day trades are made before or after the announcement. Each day an investor holds the stock during this window generates an observation. The dependent variable is one if the investor sells her position on that day and zero otherwise. Relative to the stock-announcement level analysis in the previous section, this empirical approach thus overweights (in terms of the number of observations) stocks that are widely held and investors with many positions.

Using a linear probability model, we regress the dependent variable on a capital loss dummy (which is one if the security trades below the investor's value-weighted average purchase price), a post-earnings announcement dummy (which is one if the observation is after the earnings announcement), the interaction between these two dummies, and a wide range of control variables similar to those suggested by Grinblatt and Keloharju (2001) to affect the propensity to sell stocks. According to our hypothesis, the coefficient on the interaction term should be positive: investors should be relatively more likely to sell a loser after an earnings announcement. We choose a linear probability model because the interpretation of marginal effects of interacted variables in nonlinear models is challenging, as noted by Ai and Norton (2003). Moreover, although a nonlinear specification would not generate predicted values outside the unit interval, we are interested in the determinants of the propensity to sell rather than its predicted value. We explicitly model explanatory variables that are stock-specific, such as past excess returns for different time horizons, and include investor-, stock-, and time-fixed effects to address the concern that our results may be spuriously generated by heterogeneity across one or more of these three dimensions.

Table VI reports the results of regressions with different variable specifications. The most basic specification, reported in Column (1) of Table VI, uses ordinary least squares (OLS) and only includes the explanatory variables of particular interest: the capital loss dummy, the post-earnings announcement dummy, and the interaction between these two dummies. The results show that the capital loss dummy is negative, indicating that investors are indeed reluctant to sell their losers. This reluctance appears to be economically and statistically significant: a capital loss reduces the unconditional propensity to sell on a given day during the two-week period surrounding the earnings announcement of 0.6% by 0.14%, that is, by about a quarter. Consistent with the model's prediction, however, the reluctance to sell losers is much less pronounced during the week after an earnings announcement. The coefficient on the interaction between the capital loss and the post-earnings announcement dummies is 0.07%, indicating that the effect of a capital loss on the propensity to sell is halved during the week after the announcement.

Column (2) of Table VI reports the results of a similar regression with stock-specific control variables: daily stock excess returns for the past trading week including the contemporaneous excess return, stock excess returns for the weeks [-4,-2] and [-8,-5], dummy variables indicating whether a stock is trading below its minimum price or above its maximum price during the past month, and the volatility of daily excess returns during the prior month. The inclusion of these control variables reduces the effect of capital losses by about half (the coefficient is -0.07% as opposed to -0.14%). The interaction of the capital loss and post-earnings announcement dummies remains significantly positive: the coefficient of the interaction term is 0.05%, suggesting that it reduces the reluctance to sell losers by more than two thirds. Apart from excess return volatility, which is positively correlated with the propensity to sell, the control variables have a similar effect as in Grinblatt and Keloharju (2001). In particular, excess returns are strongly positively correlated with the propensity to sell.

Column (3) of Table VI reports the results for the same regression, but with heteroskedasticity-robust standard errors that allow same-investor observations to be arbitrarily correlated. The coefficient standard errors for the variables of interest are little changed. Column (4) of Table VI reports the results for a regression that adds 40,000 investor-fixed effects as control variables; the standard errors are again estimated using OLS. Not surprisingly, these fixed effects help explain additional variation in sell propensities. The adjusted R^2 of the regression jumps from 0.2% to 1.4%. Their inclusion also affects the coefficient of the capital loss dummy and the interaction coefficient with the post-earnings announcement dummy, which are -0.18% and +0.04%, respectively. Put differently, the reluctance to sell losers is reduced by about 20% during the week after an earnings announcement. This is lower than the estimates obtained previously, but it still appears economically meaningful and is statistically significant.

The regressions reported in Columns (5) and (6) of Table VI add 1,400 day- and more than 1,000 stock-fixed effects to the kitchen sink of explanatory variables. The coefficient of the interaction between capital loss and post-earnings announcement dummies stays economically meaningful and statistically significant. Compared with investor fixed effects, however, the explanatory power of day- and stock-fixed effects is modest as suggested by the small increase in the adjusted R^2.

C. Disposition Effect and Return Persistence

Our second hypothesis predicts that the difference between the proportion of gains and losses realized by uninformed investors should be greater for stocks with weak return persistence. In the context of the model, a stock exhibits weak persistence if its period-1 price change ΔP_1 is negatively correlated with its period-2 price change ΔP_2, that is, if returns during adjacent periods are negatively correlated. The PGR-PLR difference measured during the two periods should thus be larger for such stocks.

Relative to the first hypothesis, the model offers little guidance as to the precise test specification. In light of the results in the previous section, one might want to consider a relatively short period such as a week, but this conflicts with the need to estimate return persistence, which requires a relatively long estimation period. Moreover, return persistence is not a stable stock attribute, but changes as a function of the information environment.

With these caveats in mind, we divide the sample period into 11 non-overlapping sub-periods of 26 weeks (except for the last period January-May 2000 which lasts 21 weeks) and sort stocks by their first-order autocorrelation of their weekly returns during each sub-period. To avoid stale price issues, we require stocks to have non-zero daily returns at some point during each week (as reported by Datastream).[23] For a given sub-period, stocks in the bottom half in terms of their autocorrelation are classified as having weak persistence, stocks in the top half are classified as having strong persistence.

Table VII reports the PGR and PLR statistics for the two categories. As hypothesized, the disposition behavior is more pronounced for the stocks classified as having weak return persistence, although the difference between the two groups is not statistically significant. Also, the average PGR and PLR levels are higher than for the full sample of stocks. This is due to the requirement that stocks have non-zero daily returns at some point during each week, which selects more actively traded stocks.

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

[23] In principle, we could also use daily returns to estimate persistence. Unfortunately, there is a considerable number of zero daily return observations reported by Datastream—either because the underlying stocks happen to be thinly traded and the prices are stale or because of data errors in Datastream (see Ince and Porter, 2005).

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 uninformed investors are more prone to the disposition effect prior to public news releases, whereas informed investors are more likely to exhibit such behavior immediately after public news releases. It further suggests that the disposition behavior of uninformed investors is concentrated primarily in stocks with weak return persistence. The data, trading records of 50,000 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 approach is not designed to assess the relative importance of rational and behavioral explanations for the disposition effect. Rather, it highlights 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.

Appendix A: Investors' Optimal Demand

The following lemma is a standard result on multivariate normal random variables (e.g., Marin and Rahi, 1999) and is used to calculate the investors' optimal demand.

Lemma 2. *Let $\boldsymbol{X} \in \mathbb{R}^n$ be a normally distributed random vector with mean (vector) $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. If $\boldsymbol{I} - 2\boldsymbol{\Sigma}\boldsymbol{A}$ is positive definite, then*

$$\begin{aligned} E\left[e^{\boldsymbol{X}^\top \boldsymbol{A}\boldsymbol{X} + \boldsymbol{b}^\top \boldsymbol{X} + c}\right] &= |\boldsymbol{I} - 2\boldsymbol{\Sigma}\boldsymbol{A}|^{-\frac{1}{2}} \exp\left\{c + \boldsymbol{b}^\top \boldsymbol{\mu} + \boldsymbol{\mu}^\top \boldsymbol{A}\boldsymbol{\mu}\right. \\ &\quad \left. + \frac{1}{2}(\boldsymbol{b} + 2\boldsymbol{A}\boldsymbol{\mu})^\top (\boldsymbol{\Sigma}^{-1} - 2\boldsymbol{A})^{-1}(\boldsymbol{b} + 2\boldsymbol{A}\boldsymbol{\mu})\right\}, \end{aligned} \tag{A1}$$

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

A. 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

$$W_I = x_0(P_2 - P_0) + x_1(P_2 - P_1), \tag{A2}$$

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[24]

$$x_1 = \frac{E\left[P_2 \mid \mathcal{F}_1^I\right] - P_1}{\gamma Var\left[P_2 \mid \mathcal{F}_1^I\right]} - x_0. \tag{A3}$$

The conditional expectation and variance of P_2 can be calculated from the projection theorem:[25]

$$E\left[P_2 \mid \mathcal{F}_1^I\right] = \underbrace{\frac{\sigma_{\epsilon_1}}{\sigma_{\epsilon_0} + \sigma_{\epsilon_1} + \sigma_{\epsilon_0}\sigma_{\epsilon_1}}}_{\equiv \lambda_0} S_0 + \underbrace{\frac{\sigma_{\epsilon_0}}{\sigma_{\epsilon_0} + \sigma_{\epsilon_1} + \sigma_{\epsilon_0}\sigma_{\epsilon_1}}}_{\equiv \lambda_1} S_1, \tag{A4}$$

$$Var\left[P_2 \mid \mathcal{F}_1^I\right] = \frac{\sigma_{\epsilon_0}\sigma_{\epsilon_1}}{\sigma_{\epsilon_0} + \sigma_{\epsilon_1} + \sigma_{\epsilon_0}\sigma_{\epsilon_1}} \equiv \tau_I. \tag{A5}$$

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, that is, $\mathcal{F}_0^I = \{S_0, P_0, z_0\}$. Let us define

[24] The 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.

[25] See, e.g., Anderson (1984), chapter 2.

$\mathcal{J}_I(x_0)$ 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,

$$\mathcal{J}_I(x_0) = \max_{x_1} \; E\left[-\exp\left\{-\gamma\left(x_0(P_2 - P_0) + x_1(P_2 - P_1)\right)\right\} \mid \mathcal{F}_1^I\right]. \tag{A6}$$

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

$$\max_{x_0} \; E\left[\mathcal{J}_I(x_0) \mid \mathcal{F}_0^I\right] \tag{A7}$$

Substituting the investor's optimal date 1 demand given by equation (A3) into equation (A6), we can rewrite the investor's date 1 value function as

$$\mathcal{J}_I(x_0) \;=\; -\exp\left\{-\gamma\left(x_0(P_1 - P_0) + \frac{(\lambda_0 S_0 + \lambda_1 S_1 - P_1)^2}{2\,\gamma\,\tau_I}\right)\right\} \tag{A8}$$

$$= \; -\exp\left\{\gamma P_0 x_0 - \frac{1}{2\tau_I}\lambda_0^2 S_0^2 - \underbrace{\begin{pmatrix} \gamma x_0 - \frac{1}{\tau_I}\lambda_0 S_0 \\ \frac{1}{\tau_I}\lambda_0\lambda_1 S_0 \end{pmatrix}^{\top}}_{\equiv \boldsymbol{b}_I^{\top}} \begin{pmatrix} P_1 \\ S_1 \end{pmatrix}\right.$$

$$\left. - \begin{pmatrix} P_1 \\ S_1 \end{pmatrix}^{\top} \underbrace{\frac{1}{2\tau_I}\begin{pmatrix} 1 & -\lambda_1 \\ -\lambda_1 & \lambda_1^2 \end{pmatrix}}_{\equiv \boldsymbol{A}_I} \begin{pmatrix} P_1 \\ S_1 \end{pmatrix}\right\}. \tag{A9}$$

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 2 that maximizing the expression in (A7) with respect to x_0 is equivalent to maximizing[26]

$$\boldsymbol{b}_I^{\top}\boldsymbol{\mu}_I - \frac{1}{2}(\boldsymbol{b}_I + 2\boldsymbol{A}_I\,\boldsymbol{\mu}_I)^{\top}\underbrace{(\boldsymbol{\Sigma}_I^{-1} + 2\boldsymbol{A}_I)^{-1}}_{\equiv \boldsymbol{G}_I}(\boldsymbol{b}_I + 2\boldsymbol{A}_I\,\boldsymbol{\mu}_I) - \gamma\,P_0\,x_0, \tag{A10}$$

where $\boldsymbol{\mu}_I$ denotes the expectation and $\boldsymbol{\Sigma}_I$ the variance of the random vector $(P_1, S_1)^{\top}$, conditional

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

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

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.

on $\mathcal{F}_0^I$:

$$\boldsymbol{\mu}_I \equiv E\left[\begin{pmatrix} P_1 \\ S_1 \end{pmatrix} \big| \mathcal{F}_0^I\right] = \begin{pmatrix} \left(c + \frac{d}{1+\sigma_{\epsilon_0}^2}\right) S_0 + e\, z_0 \\ \frac{1}{1+\sigma_{\epsilon_0}^2} S_0 \end{pmatrix}, \tag{A11}$$

$$\begin{aligned} \boldsymbol{\Sigma}_I &\equiv Var\left[\begin{pmatrix} P_1 \\ S_1 \end{pmatrix} \big| \mathcal{F}_0^I\right] \\ &= \begin{pmatrix} \frac{d^2(\sigma_{\epsilon_0}^2+\sigma_{\epsilon_1}^2+\sigma_{\epsilon_0}^2\sigma_{\epsilon_1}^2)}{1+\sigma_{\epsilon_0}^2} + f^2\sigma_{z_1}^2, & d\left(\frac{\sigma_{\epsilon_0}^2}{1+\sigma_{\epsilon_0}^2} + \sigma_{\epsilon_1}^2\right) \\ d\left(\frac{\sigma_{\epsilon_0}^2}{1+\sigma_{\epsilon_0}^2} + \sigma_{\epsilon_1}^2\right), & \frac{\sigma_{\epsilon_0}^2}{1+\sigma_{\epsilon_0}^2} + \sigma_{\epsilon_1}^2 \end{pmatrix}. \end{aligned} \tag{A12}$$

Substituting the expressions for $\boldsymbol{A}_I$ and $\boldsymbol{b}_I$ from (A9) into (A10), we derive the first-order condition for a maximum with respect to x_0 as

$$x_0 = \frac{E\left[P_1 \mid \mathcal{F}_0^I\right] - P_0}{\gamma\, G_{11}^I} + \frac{G_{11}^I - \lambda_1\, G_{12}^I}{G_{11}^I} \frac{\lambda_0 S_0 + \lambda_1 E\left[S_1 \mid \mathcal{F}_0^I\right] - E\left[P_1 \mid \mathcal{F}_0^I\right]}{\gamma\, \tau_I}, \tag{A13}$$

where G_{ij}^I are the elements of the matrix $\boldsymbol{G}_I$. It is easily verified that the demand defined by (A13) is the unique maximum, because (A10) is strictly concave in x_0.[27]

B. Optimal Demand of Uninformed Investors

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

$$\max_{y_1} E\left[-\exp\left\{-\gamma\left(y_0(P_2 - P_0) + y_1(P_2 - P_1)\right)\right\} \mid \mathcal{F}_1^U\right], \tag{A14}$$

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, that is, $\mathcal{F}_1^U = \{P_0, P_1\}$. 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

[27] The second derivative of (A10) 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:

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

This expression clearly shows that G_{11}^I is strictly positive and, hence, that (A10) is a concave function of x_0.

given by

$$y_1 = \frac{E\left[P_2 \mid \mathcal{F}_1^U\right] - P_1}{\gamma\, Var\left[P_2 \mid \mathcal{F}_1^U\right]} - y_0. \tag{A15}$$

The conditional moments of P_2 can again be calculated from the projection theorem:

$$E\left[P_2 \mid \mathcal{F}_1^U\right] = \underbrace{\frac{a\,\sigma_{P_1}^2 - (c+d)\,\sigma_{P_0,P_1}}{\sigma_{P_0}^2\sigma_{P_1}^2 - \sigma_{P_0,P_1}^2}}_{\equiv \kappa_0} P_0 + \underbrace{\frac{(c+d)\,\sigma_{P_0}^2 - a\,\sigma_{P_0,P_1}}{\sigma_{P_0}^2\sigma_{P_1}^2 - \sigma_{P_0,P_1}^2}}_{\equiv \kappa_1} P_1, \tag{A16}$$

$$Var\left[P_2 \mid \mathcal{F}_1^U\right] = 1 - \frac{a^2\,\sigma_{P_1}^2 + (c+d)^2\,\sigma_{P_0}^2 - 2\,a\,(c+d)\,\sigma_{P_0,P_1}}{\sigma_{P_0}^2\sigma_{P_1}^2 - \sigma_{P_0,P_1}^2} \equiv \tau_U, \tag{A17}$$

where

$$\sigma_{P_0}^2 \equiv Var[P_0] = a^2(1+\sigma_{\epsilon_0}^2) + b^2\sigma_{z_0}^2, \tag{A18}$$

$$\sigma_{P_1}^2 \equiv Var[P_1] = c^2(1+\sigma_{\epsilon_0}^2) + d^2(1+\sigma_{\epsilon_1}^2) + 2\,c\,d + e^2\sigma_{z_0}^2 + f^2\sigma_{z_1}^2, \tag{A19}$$

$$\sigma_{P_0,P_1} \equiv Cov[P_0,P_1] = a\,c(1+\sigma_{\epsilon_0}^2) + a\,d + b\,e\,\sigma_{z_0}^2. \tag{A20}$$

At date 0, uninformed investors can infer information about P_2 from the observed market price P_0, that is, $\mathcal{F}_0^U = \{P_0\}$. The optimal date 0 stock holdings of uninformed investors are found by solving the problem

$$\max_{y_0}\; E\left[\mathcal{J}_U(y_0) \mid \mathcal{F}_0^U\right], \tag{A21}$$

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

$$\begin{aligned}
\mathcal{J}_U(y_0) &= \max_{y_1}\; E\left[-\exp\left\{-\gamma\left(y_0(P_2-P_0) + y_1(P_2-P_1)\right)\right\} \mid \mathcal{F}_1^U\right] && \text{(A22)}\\
&= -\exp\left\{-\gamma\left(y_0(P_1-P_0) + \frac{(\kappa_0 P_0 + (\kappa_1-1)P_1)^2}{2\,\gamma\,\tau_U}\right)\right\}. && \text{(A23)}
\end{aligned}$$

The only random variable in (A21) is the date 1 price P_1, which is normally distributed given $\mathcal{F}_0^U$. Therefore, we can use Lemma 2 to rewrite the uninformed investors' objective as

$$\max_{y_0}\; \gamma(\mu_U - P_0)\,y_0 - \frac{1}{2}\,G_U\left(\gamma y_0 + \frac{\kappa_1 - 1}{\tau_U}(\kappa_0 P_0 + (\kappa_1-1)\mu_U)\right)^2, \tag{A24}$$

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:

$$\mu_U \equiv E\left[P_1 \mid \mathcal{F}_0^U\right] = \frac{\sigma_{P_0,P_1}}{\sigma_{P_0}^2} P_0, \tag{A25}$$

$$\Sigma_U \equiv Var\left[P_1 \mid \mathcal{F}_0^U\right] = \sigma_{P_1}^2 - \frac{\sigma_{P_0,P_1}^2}{\sigma_{P_0}^2}. \tag{A26}$$

The unique optimum of this quadratic maximization problem is given by[28]

$$y_0 = \frac{E\left[P_1 \mid \mathcal{F}_0^U\right] - P_0}{\gamma\, G_U} + \frac{1-\kappa_1}{G_U} \frac{\kappa_0 P_0 + (\kappa_1 - 1) E\left[P_1 \mid \mathcal{F}_0^U\right]}{\gamma\, \tau_U}. \tag{A27}$$

Appendix B: Proofs

The following results on normally distributed random variables have been established by David (1953) and Kamat (1953), respectively, and are used to calculate the conditional probabilities and expectations in Section II.

Lemma 3. *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,*

$$Pr(x_1 > 0, x_2 > 0) = \frac{1}{2\pi}(\pi - \arccos \rho_{12}) \tag{A28}$$

and

$$Pr(x_1 > 0, x_2 > 0, x_3 > 0) = \frac{1}{4\pi}(2\pi - \arccos \rho_{12} - \arccos \rho_{13} - \arccos \rho_{23}). \tag{A29}$$

Lemma 4. *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*

$$[m, n] = \int_0^\infty \int_0^\infty x_1^m\, x_2^n\, f(x_1, x_2)\, dx_1 dx_2, \tag{A30}$$

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

$$[1, 0] = \frac{1+\rho}{2\sqrt{2\pi}}, \tag{A31}$$

$$[2, 0] = \frac{1}{2\pi}\left(\pi - \arccos \rho + \rho\sqrt{1-\rho^2}\right), \tag{A32}$$

$$[1, 1] = \frac{1}{2\pi}\left(\rho(\pi - \arccos \rho) + \sqrt{1-\rho^2}\right). \tag{A33}$$

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

Proof of Lemma 1. First, we demonstrate that the following price coefficients constitute a rational expectations equilibrium:

$$
\begin{aligned}
a &= \frac{M}{D_0}\,(M+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2), && \text{(A34)}\\
b &= -\frac{\gamma\,\sigma_{\epsilon_0}^2}{M}\,a, && \text{(A35)}\\
c &= \frac{M\,\sigma_{\epsilon_1}^2}{D_1}\,(M+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2)(M^2+\gamma^2\,\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2), && \text{(A36)}\\
d &= \frac{M\,\sigma_{\epsilon_0}^2}{D_1}\,(M^2+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2)(M+\gamma^2\,\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2), && \text{(A37)}\\
e &= -\frac{\gamma\,\sigma_{\epsilon_0}^2}{M}\,c, && \text{(A38)}\\
f &= -\frac{\gamma\,\sigma_{\epsilon_1}^2}{M}\,d, && \text{(A39)}
\end{aligned}
$$

where

$$
\begin{aligned}
D_0 &= M^2(1+\sigma_{\epsilon_0}^2)+\gamma^2(M+\sigma_{\epsilon_0}^2)\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2, && \text{(A40)}\\
D_1 &= \sigma_{\epsilon_0}^2\sigma_{\epsilon_1}^2\delta_0\,\delta_1+M(\sigma_{\epsilon_0}^2+\sigma_{\epsilon_1}^2)\,\delta_0\,\delta_1+M^2\big(\sigma_{\epsilon_0}^2(1+\sigma_{\epsilon_1}^2)\,\delta_0+\sigma_{\epsilon_1}^2(1+\sigma_{\epsilon_0}^2)\,\delta_1\big)\\
&\quad +M^3(\sigma_{\epsilon_1}^2\delta_0+\sigma_{\epsilon_0}^2\delta_1)+M^4(\sigma_{\epsilon_0}^2+\sigma_{\epsilon_1}^2+\sigma_{\epsilon_0}^2\sigma_{\epsilon_1}^2), && \text{(A41)}
\end{aligned}
$$

and $\delta_0=\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2$ 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

$$M\,x_0+(1-M)\,y_0=z_0. \tag{A42}$$

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 equations (A11), (A12), (A25), and (A26), respectively, we can rewrite the investors' date 0 demand functions derived in Appendix A as follows:

$$
\begin{aligned}
x_0 &= \frac{1}{\gamma}\left(\frac{1}{\sigma_{\epsilon_0}^2}\,S_0-\left(1+\frac{1}{\sigma_{\epsilon_0}^2}\right)\,P_0\right), && \text{(A43)}\\
y_0 &= -\left(\frac{1}{\gamma}+\frac{\gamma\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2}{M}\right)P_0. && \text{(A44)}
\end{aligned}
$$

Thus, the stock market clears at date 0 if

$$\frac{M}{\gamma\,\sigma_{\epsilon_0}^2}\Big(S_0 - \big(1+\sigma_{\epsilon_0}^2\big)\;P_0\Big) - \frac{(1-M)\,\gamma\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2}{M+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2}\,P_0 = z_0, \tag{A45}$$

or, equivalently, if

$$P_0 = \frac{M\,\big(M+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2\big)}{M^2\,\big(1+\sigma_{\epsilon_0}^2\big)+\gamma^2\,\big(M+\sigma_{\epsilon_0}^2\big)\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2}\;\left(S_0 - \frac{\gamma\,\sigma_{\epsilon_0}^2}{M}\,z_0\right). \tag{A46}$$

This expression is identical to the price function defined above.

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

$$M\,x_1 + (1-M)\,y_1 = z_1, \tag{A47}$$

or, in terms of total stock holdings, by

$$M\,(x_0+x_1) + (1-M)\,(y_0+y_1) = z_0 + z_1. \tag{A48}$$

From equations (A3), (A4), and (A5) in Appendix A, it follows that an informed investor's optimal stock holdings are given by

$$x_0 + x_1 = \frac{1}{\gamma}\left(\frac{1}{\sigma_{\epsilon_0}^2}\,S_0 + \frac{1}{\sigma_{\epsilon_1}^2}\,S_1 - \left(1+\frac{1}{\sigma_{\epsilon_0}^2}+\frac{1}{\sigma_{\epsilon_1}^2}\right)\,P_1\right). \tag{A49}$$

The optimal date 1 stock holdings of an uninformed investor are given by equation (A15). 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 equations (A16) and (A17), we have

$$\begin{aligned} y_0 + y_1 \quad = \quad & \frac{\gamma M^2\big((1+\sigma_{\epsilon_0}^2)\,\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2 - \sigma_{\epsilon_0}^2\,\sigma_{z_0}^2\big) + \gamma^3\,\sigma_{\epsilon_0}^4\,\sigma_{\epsilon_1}^2\,\sigma_{z_0}^2\,\sigma_{z_1}^2}{\big(M^2+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2\big)\,\big(M+\gamma^2\,\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2\big)\,\sigma_{\epsilon_0}^2}\;\big(P_0 - P_1\big) \\ & -\left(\frac{1}{\gamma}+\frac{\gamma\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2}{M}\right)\,P_0. \end{aligned} \tag{A50}$$

Substituting the demand functions in (A49) and (A50) into the market clearing condition in (A48), replacing P_0 by $a\,S_0 + b\,z_0$, and solving for P_1, we get

$$\begin{aligned} P_1 \quad = \quad & \frac{M\,\sigma_{\epsilon_1}^2}{D_1}\,(M+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2)(M^2+\gamma^2\,\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2)\;\left(S_0 - \frac{\gamma\,\sigma_{\epsilon_0}^2}{M}\,z_0\right) \\ & + \frac{M\,\sigma_{\epsilon_0}^2}{D_1}\,(M^2+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2)(M+\gamma^2\,\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2)\;\left(S_1 - \frac{\gamma\,\sigma_{\epsilon_1}^2}{M}\,z_1\right), \end{aligned} \tag{A51}$$

where D_1 is defined in (A41). 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 Appendix A, 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:

$$\theta_0 \equiv \frac{1}{a} \, P_0, \tag{A52}$$

$$\theta_1 \equiv \frac{\gamma \, \tau_I}{M \, \lambda_0} \left(\left(\frac{M}{\gamma \, \tau_I} - (1 - M) \, \beta_1 \right) P_1 - (1 - M) \, \beta_0 \, P_0 \right) - \frac{1}{a} \, P_0. \tag{A53}$$

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

$$\frac{\gamma \, \tau_I}{M \, \lambda_0} \left(\left(\frac{M}{\gamma \, \tau_I} - (1 - M) \, \beta_1 \right) P_1 - (1 - M) \, \beta_0 \, P_0 \right) = S_0 + \frac{\lambda_1}{\lambda_0} \, S_1 - \frac{\gamma \, \tau_I}{M \, \lambda_0} \, (z_0 + z_1). \tag{A54}$$

Thus,

$$\theta_1 = S_0 + \frac{\lambda_1}{\lambda_0} \, S_1 - \frac{\gamma \, \tau_I}{M \, \lambda_0} \, (z_0 + z_1) - (S_0 + \phi \, z_0) \tag{A55}$$

$$= \frac{\sigma_{\epsilon_0}^2}{\sigma_{\epsilon_1}^2} \, S_1 - \left(\frac{\gamma \, \sigma_{\epsilon_0}^2}{M} + \phi \right) z_0 - \frac{\gamma \, \sigma_{\epsilon_0}^2}{M} \, z_1. \tag{A56}$$

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

$$y_0 + y_1 = \frac{E \left[P_2 \mid \theta_0, \theta_1 \right] - P_1}{\gamma \, Var \left[P_2 \mid \theta_0, \theta_1 \right]}. \tag{A57}$$

Applying the projection theorem, we get

$$y_0 + y_1 = \frac{\hat{\kappa}_0 \, \theta_0 + \hat{\kappa}_1 \, \theta_1 - P_1}{\gamma \, \hat{\tau}_U}, \tag{A58}$$

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 equation (A49) into the market clearing condition and solving for P_1 yields

$$P_1 = c \, S_0 + d \, S_1 + e \, z_0 + f \, z_1, \tag{A59}$$

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 equation (A13) 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:

$$x_0 = \alpha_S\, S_0 + \alpha_P\, P_0. \tag{A60}$$

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

$$M\,(\alpha_S\, S_0 + \alpha_P\, P_0) + (1-M)\,\psi\, P_0 = z_0, \tag{A61}$$

implies that

$$a = -\frac{M\,\alpha_S}{M\,\alpha_P + (1-M)\,\psi}, \tag{A62}$$

$$b = \frac{1}{M\,\alpha_P + (1-M)\,\psi}. \tag{A63}$$

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

$$\phi = -\frac{1}{M\,\alpha_S}. \tag{A64}$$

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

$$\left(\gamma\,\sigma^2_{\epsilon_0} + M\,\phi\right)\left(h_0 + h_1\,\phi + h_2\,\phi^2\right) = 0, \tag{A65}$$

where

$$\begin{aligned} h_0 &= \sigma^4_{\epsilon_0}\Big(M^3(\sigma^2_{\epsilon_0} + \sigma^2_{\epsilon_1} + \sigma^2_{\epsilon_0}\,\sigma^2_{\epsilon_1}) + \gamma^4\,\sigma^2_{\epsilon_0}\,\sigma^4_{\epsilon_1}\,\sigma^2_{z_1}(\sigma^2_{z_0} + \sigma^2_{z_1}) \\ &\quad + \gamma^2\,M\,\sigma^2_{\epsilon_1}\left(\sigma^2_{\epsilon_0}\,\sigma^2_{z_1} + (M\,\sigma^2_{\epsilon_0} + (1+\sigma^2_{\epsilon_0})\,\sigma^2_{\epsilon_1})(\sigma^2_{z_0} + \sigma^2_{z_1})\right)\Big), & \text{(A66)} \\ h_1 &= \gamma\,\sigma^2_{\epsilon_0}\,\sigma^2_{\epsilon_1}\,\sigma^2_{z_0}\left(2\,M^2(\sigma^2_{\epsilon_0} + \sigma^2_{\epsilon_1} + \sigma^2_{\epsilon_0}\,\sigma^2_{\epsilon_1}) + \gamma^2(1+M)\,\sigma^2_{\epsilon_0}\,\sigma^2_{\epsilon_1}\,\sigma^2_{z_1}\right), & \text{(A67)} \\ h_2 &= \sigma^2_{z_0}\left(M^2(\sigma^2_{\epsilon_0} + \sigma^2_{\epsilon_1}) + \gamma^2\,\sigma^2_{\epsilon_0}\,\sigma^2_{\epsilon_1}\,\sigma^2_{z_1}\right) \\ &\quad \times\left(M(\sigma^2_{\epsilon_0} + \sigma^2_{\epsilon_1} + \sigma^2_{\epsilon_0}\,\sigma^2_{\epsilon_1}) + \gamma^2\,\sigma^2_{\epsilon_0}\,\sigma^2_{\epsilon_1}\,\sigma^2_{z_1}\right). & \text{(A68)} \end{aligned}$$

This shows that $\phi = -\gamma\,\sigma^2_{\epsilon_0}/M$ is indeed an equilibrium.

Moreover, if $M\Big(3\,(2+M)\,\sigma^2_{\epsilon_1} + 4\left(1 + 2M + 2\sigma^2_{\epsilon_1}\right)\sigma^2_{\epsilon_0}\Big) > \sigma^2_{\epsilon_1}$, then $h_1^2 < 4\,h_0\,h_2$ 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 (A65) has three real roots, they other two roots result in a negative price coefficient d and a positive price coefficient f:

$$d = -\frac{M^2}{\gamma^2\, \sigma_{\epsilon_1}^2\, \sigma_{z_1}^2} \tag{A69}$$

$$f = \frac{M}{\gamma\, \sigma_{z_1}^2} \tag{A70}$$

Thus, for these other solutions of equation (A65), 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 (A54) imply that $\beta_1 > 0$, that is, 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 equations (A44) and (A50), it follows that an uninformed investor's stock demand at date 1 can be written as

$$y_1 = -\frac{\gamma M^2\Big(\left(1+\sigma_{\epsilon_0}^2\right)\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2 - \sigma_{\epsilon_0}^2\,\sigma_{z_0}^2\Big) + \gamma^3\,\sigma_{\epsilon_0}^4\,\sigma_{\epsilon_1}^2\,\sigma_{z_0}^2\,\sigma_{z_1}^2}{\left(M^2+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2\right)\left(M+\gamma^2\,\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2\right)\sigma_{\epsilon_0}^2}\;\Delta P_1. \tag{A71}$$

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

$$\sigma_{crit} = \frac{M\,\sigma_{\epsilon_0}\sigma_{z_0}}{\sqrt{M^2(1+\sigma_{\epsilon_0}^2)+\gamma^2\sigma_{\epsilon_0}^4\sigma_{z_0}^2}}. \tag{A72}$$

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

$$\begin{aligned} Pr\big(x_1 < 0 \mid x_0 > 0, \Delta P_1 > 0\big) &= Pr\big(z_1 < (1-M)\,y_1 \mid x_0 > 0, \Delta P_1 > 0\big) && \text{(A73)}\\ &> Pr\big(z_1 < 0 \mid x_0 > 0, \Delta P_1 > 0\big), && \text{(A74)} \end{aligned}$$

where the inequality follows from the fact that a price increase implies an increase in the uninformed investors' stock holdings (that is, $y_1 > 0$), 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 3 allows us to rewrite the conditional probability as

$$
\begin{aligned}
Pr\big(z_1 < 0 \mid x_0 > 0, \Delta P_1 > 0\big) \\
&= \frac{2\pi - \arccos \rho_{x_0,\Delta P_1} - \arccos(-\rho_{x_0,z_1}) - \arccos(-\rho_{z_1,\Delta P_1})}{2\,(\pi - \arccos \rho_{x_0,\Delta P_1})} && \text{(A75)}\\
&= \frac{1}{2} - \frac{\arcsin \rho_{z_1,\Delta P_1}}{\pi + 2 \arcsin \rho_{x_0,\Delta P_1}}, && \text{(A76)}
\end{aligned}
$$

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 (that is, $\arccos(-\rho_{x_0,z_1}) = \frac{\pi}{2}$), 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 $Cov[z_1, \Delta P_1] = f\,\sigma^2_{z_1} < 0$. This inequality obviously holds, because a positive supply shock increases the required risk premium and thus reduces the date 1 price (that is, the coefficient f is negative).

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

$$
\begin{aligned}
Pr\big(x_1 < 0 \mid x_0 > 0, \Delta P_1 < 0\big) &= Pr\big(z_1 < (1-M)\,y_1 \mid x_0 > 0, \Delta P_1 < 0\big) && \text{(A77)}\\
&< Pr\big(z_1 < 0 \mid x_0 > 0, \Delta P_1 < 0\big) && \text{(A78)}\\
&= \frac{1}{2} + \frac{\arcsin \rho_{z_1,\Delta P_1}}{\pi - 2\arcsin \rho_{x_0,\Delta P_1}} && \text{(A79)}
\end{aligned}
$$

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

$$
Pr\big(y_0 > 0, \Delta P_1 < 0, y_1 < 0\big) = 0, \tag{A80}
$$

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

$$
Pr\big(y_0 > 0, \Delta P_1 > 0, y_1 < 0\big) = 0. \tag{A81}
$$

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 $E[P_2 - P_1 \mid \mathcal{F}_1^U]$, where $\mathcal{F}_1^U$ contains y_0 and ΔP_1. Thus,

$$
\begin{aligned}
E\big[\Delta P_2 \mid y_0, \Delta P_1, y_1\big] &= E\big[P_2 - P_1 \mid y_0 + y_1, \Delta P_1, y_1\big] && \text{(A82)}\\
&= E\big[P_2 - P_1 \mid y_0 + y_1\big] && \text{(A83)}\\
&= \alpha\,(y_0 + y_1), && \text{(A84)}
\end{aligned}
$$

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 $E[y_0 + y_1 \mid y_0 > 0, \Delta P_1 > 0, y_1 < 0]$ and $E[y_0 + y_1 \mid y_0 > 0, \Delta P_1 < 0, y_1 > 0]$ 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,

$$
\lim_{\sigma_{z_1} \downarrow \underline{\sigma}_{z_1}} E\big[y_0 + y_1 \mid y_0 > 0, \Delta P_1 \underset{(<)}{>} 0, y_1 \underset{(>)}{<} 0\big] = \lim_{\sigma_{z_1} \downarrow \underline{\sigma}_{z_1}} E\big[y_0 \mid y_0 > 0, \Delta P_1 \underset{(<)}{>} 0\big]. \tag{A85}
$$

We are therefore left to show that

$$
\lim_{\sigma_{z_1} \downarrow \underline{\sigma}_{z_1}} E\big[y_0 \mid y_0 > 0, \Delta P_1 > 0\big] > \lim_{\sigma_{z_1} \downarrow \underline{\sigma}_{z_1}} E\big[y_0 \mid y_0 > 0, \Delta P_1 < 0\big]. \tag{A86}
$$

From Lemmas 3 and 4, 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 $\underline{\sigma}_{z_1} \leq \sigma_{z_1} < \overline{\sigma}_{z_1}$, where

$$
\overline{\sigma}_{z_1} = \frac{1}{\sigma_{\epsilon_1}} \sqrt{\frac{M\, \sigma_{\epsilon_0}^2\, \sigma_{z_0}^2 \left(M + \gamma^2\, \sigma_{\epsilon_0}^2\, \sigma_{z_0}^2\right)}{M^2 \left(1 + \sigma_{\epsilon_0}^2\right) + \gamma^2\, \sigma_{\epsilon_0}^2\, \sigma_{z_0}^2 \left(M + \sigma_{\epsilon_0}^2\right)}}. \tag{A87}
$$

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

$$
Cov[y_0 + y_1, \Delta P_1] = \beta\, E\big[E[\Delta P_2 \mid \mathcal{F}_1^U]\, \Delta P_1\big] = \beta\, Cov[\Delta P_1, \Delta P_2], \tag{A88}
$$

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

$$
Cov[y_0, \Delta P_1] = Cov[y_0 + y_1, \Delta P_1] - Cov[y_1, \Delta P_1], \tag{A89}
$$

that $Cov[y_0, \Delta P_1] > 0$ for all $\underline{\sigma}_{z_1} \leq \sigma_{z_1} < \overline{\sigma}_{z_1}$ (recall that, for these parameter values, y_1 is linearly decreasing in ΔP_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

$$\begin{aligned} Cov[\Delta P_1, \Delta P_2] &= Cov[(c-a)\,S_0 + d\,S_1 + (e-b)\,z_0 + f\,z_1, \\ &\qquad P_2 - c\,S_0 - d\,S_1 - e\,z_0 - f\,z_1] \qquad \text{(A90)} \\ &= (c-a)\left(1 - c\left(1+\sigma_{\epsilon_0}^2\right) - d\right) + d\left(1 - c - d\left(1+\sigma_{\epsilon_1}^2\right)\right) \\ &\quad -e(e-b)\,\sigma_{z_0}^2 - f^2\,\sigma_{z_1}^2 \qquad \text{(A91)} \\ &= K\Big(M^2\left(\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2 - \left(1+\sigma_{\epsilon_0}^2\right)\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2\right) \\ &\quad + \gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2\left(M\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2 - \left(M+\sigma_{\epsilon_0}^2\right)\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2\right)\Big), \qquad \text{(A92)} \end{aligned}$$

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

$$\sigma_{\epsilon_1}^2\,\sigma_{z_1}^2 < \frac{M\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2\left(M+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2\right)}{M^2\left(1+\sigma_{\epsilon_0}^2\right)+\gamma^2\,\sigma_{\epsilon_0}^2\,\sigma_{z_0}^2\left(M+\sigma_{\epsilon_0}^2\right)}. \qquad \text{(A93)}$$

■

Appendix C: Properties of the Disposition Effect Measure

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, a realized loss, a paper gain, or a paper loss (depending on whether the stock is sold and on whether the current price exceeds the share-weighted average purchase price). Realized gains, paper gains, realized losses, and paper losses are then summed across investors and sale dates. The proportion of gains realized (PGR) is calculated as the number of realized gains divided by the sum of realized gains and paper gains, and the proportion of losses realized (PLR) as the number of realized losses divided by the sum of realized losses and paper losses.

The main difference between the measure just described and the measure used in the paper lies in the conditioning on trading. The Odean (1998) measure answers the question "Conditional on selling, is an investor more likely to sell a winner?" and thus controls for the trading needs of the investor. In contrast, the paper's measure 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.[29]

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. This translates into a difference between PGR and PLR for stock A, as defined in our paper, of $2/10 - 1/10 = 1/10$. The difference between PGR and PLR defined as in Odean (1998) 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 $2/(2+3) - 1/(1+1) = -1/10$.

In the context of the model developed in the paper, our measure of the disposition effect offers three advantages over the measure pioneered by Odean (1998). First, whether a stock position is counted as a paper gain or loss does not depend on the trading of other stocks. Under the alternative measure, 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, the paper's measure of the disposition effect is not dominated by active investors. Under the alternative measure, 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; hence, active investors generate a disproportionate number of observations. Moreover, the methodology proposed by Odean (1998) discards all trades in portfolios consisting of a single stock, a substantial portion of our (and his) sample.

Third, when paper gains and losses are recognized only on dates when the investor trades some other stock, 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).

[29] One could also aggregate realized gains, paper gains, realized losses, and paper losses defined as in Odean (1998) for each stock-day (e.g., Kumar, 2009).

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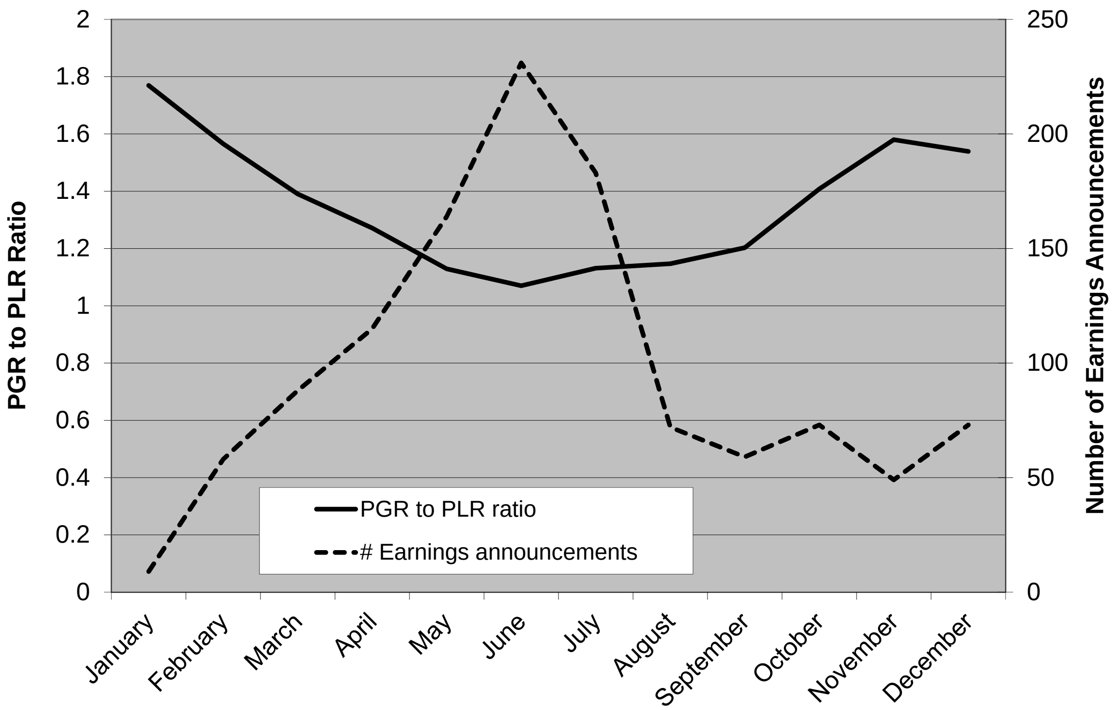

Figure 1: Calendar distribution of the disposition effect and earnings announcements. The solid line represents the ratio of the proportion of gains realized (PGR) to the proportion of losses realized (PLR) as a function of the calendar month for a sample of trades and holdings of German stocks by 50,000 retail clients at a German discount broker between January 1995 and December 1999. The dotted line represents the number of earnings announcements for each calendar month for these stocks, as reported by I/B/E/S, for the same period.

Table I: Summary Statistics on the Disposition Effect

The sample consists of all German stocks held and traded by almost 50,000 clients at a German discount broker between January 1995 and May 2000 that are held by at least 5 sample investors at some time during the sample period, have a valid ticker and at least one earnings announcement in the Institutional Brokers' Estimate System (IBES) database during the sample period, and are covered by Datastream. Each day on which such a stock is held, the position of each holder of that stock can be classified as either a realized gain, a paper gain, a realized loss, or a paper loss, based on whether the investor holds or sells (part of) her position and based on the closing price that day with the holder's value-weighted average purchase price. Realized gains, paper gains, realized losses, and paper losses are then summed across all stock-days. In Column (1), the proportion of gains realized (PGR) and the proportion of losses realized (PLR) are calculated by pooling all observations. In Column (2), PGR and PLR are calculated for each stock-week and then averaged across all stock-weeks. In Column (3), PGR and PLR are separately calculated for the week before and the week after each sample earnings announcement and then averaged.

Sample	(1) Pooled	(2) Stock-week	(3) Stock-EA week
Number of observations	104,828,892	156,842	8,714
PGR	0.54%	0.71%	0.81%
PLR	0.41%	0.57%	0.74%
PGR-PLR	0.13%	0.14%	0.07%
PGR/PLR	1.31	1.25	1.10

Table II: Changes in disposition behavior around earnings announcement – baseline results

Realized gains, paper gains, realized losses, and paper losses are computed for each stock-day during the two-week window surrounding each sample earnings announcement; the announcement day (day 0) is omitted. The sample includes all stocks, provided they are held by an average of at least 5 investors during the two-week window. PGR and PLR statistics are reported for different sub-periods: days [-2, -1] and [1, 2] relative to the earnings announcement in Panel A, days [-5, -3] and [3, 5] in Panel B, and days [-10, -6] and [6, 10] in Panel C. $t-1$ 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 $(PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1}) \neq 0$ at the 1%/5%/10% level, assuming that the observations are independent across stocks and over time. All PGR and PLR statistics are in percent.

Panel A: Days [-2, -1] vs Days [1, 2]	Before Earnings	After Announcement
PGR [%]	0.765	0.829
PLR [%]	0.643	0.930
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**-0.223*** **	
σ_D [%]	4.785	
T-stat	-3.020	
Nobs	4,190	
Panel B: Days [-5, -3] vs Days [3, 5]		
PGR [%]	0.728	0.702
PLR [%]	0.600	0.703
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**-0.128** **	
σ_D [%]	4.022	
T-stat	-2.078	
Nobs	4,234	
Panel C: Days [-10, -6] vs Days [6, 10]		
PGR [%]	0.773	0.684
PLR [%]	0.663	0.636
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**-0.062**	
σ_D [%]	4.447	
T-stat	-0.903	
Nobs	4,145	

Table III: Changes in disposition behavior around earnings announcement – surprises

Realized gains, paper gains, realized losses, and paper losses are computed for each stock-day during the two-week window surrounding each sample earnings announcement; the announcement day (day 0) is omitted. The sample includes all stocks, provided they are held by an average of at least 5 investors during the two-week window. Earnings announcements are classified as large or small surprises based on the absolute value of the stock's cumulative return in excess of the local market's return from the trading day before the announcement day until the first trading day after the announcement day. Above-median announcement returns are classified as large surprises and below-median returns are classified as small surprises. PGR and PLR statistics are reported for different sub-periods: days [-2, -1] and [1, 2] relative to the earnings announcement in Panel A, days [-5, -3] and [3, 5] in Panel B, and days [-10, -6] and [6, 10] in Panel C. $t-1$ 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 $(PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1}) \neq 0$ at the 1%/5%/10% level, assuming that the observations are independent across stocks and over time. All PGR and PLR statistics are in percent.

	Large surprise EA		Small surprise EA	
Panel A: Days [-2, -1] vs Days [1, 2]	Before EA	After EA	Before EA	After EA
PGR [%]	0.936	1.069	0.595	0.598
PLR [%]	0.817	1.334	0.473	0.537
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**-0.383*** **		**-0.062**	
σ_D [%]	5.829		3.466	
T-stat	-2.996		-0.824	
Nobs	2,074		2,106	
Panel B: Days [-5, -3] vs Days [3, 5]				
PGR [%]	0.899	0.798	0.560	0.602
PLR [%]	0.787	0.870	0.416	0.538
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**-0.185***		**-0.081**	
σ_D [%]	4.388		3.623	
T-stat	-1.932		-1.024	
Nobs	2,106		2,119	
Panel C: Days [-10, -6] vs Days [6, 10]				
PGR [%]	0.910	0.849	0.639	0.520
PLR [%]	0.827	0.752	0.500	0.522
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**0.015**		**-0.141***	
σ_D [%]	5.241		3.489	
T-stat	0.128		-1.837	
Nobs	2,064		2,074	

Table IV: Changes in disposition behavior around earnings announcement – rebalancing

Realized rebalancing gains, realized non-rebalancing gains, paper gains, realized rebalancing losses, realized non-rebalancing losses, and paper losses are computed for each stock-day during the two-week window surrounding each sample earnings announcement; the announcement day (day 0) is omitted. A rebalancing trade is the partial sale of a position; a non-rebalancing trade is the complete sale of a position. The rebalancing PGR is estimated as the number of realized rebalancing gains divided by the sum of realized rebalancing gains, realized non-rebalancing gains, and paper gains, the non-rebalancing PGR is estimated as the number of realized non-rebalancing gains divided by the sum of realized rebalancing gains, realized non-rebalancing gains, and paper gains, and so on. The sample includes all stocks, provided they are held by an average of at least 5 investors during the two-week window. PGR and PLR statistics are reported for different sub-periods: days [-2, -1] and [1, 2] relative to the earnings announcement in Panel A, days [-5, -3] and [3, 5] in Panel B, and days [-10, -6] and [6, 10] in Panel C. $t-1$ 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 $(PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1}) \neq 0$ at the 1%/5%/10% level, assuming that the observations are independent across stocks and over time. All PGR and PLR statistics are in percent.

	Rebalancing		Non-rebalancing	
Panel A: Days [-2, -1] vs Days [1, 2]	Before EA	After EA	Before EA	After EA
PGR [%]	0.123	0.133	0.642	0.697
PLR [%]	0.077	0.087	0.565	0.843
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**0.000**		**-0.22*****	
σ_D [%]	1.576		4.567	
T-stat	-0.011		-3.160	
Nobs	4,190		4,190	
Panel B: Days [-5, -3] vs Days [3, 5]				
PGR [%]	0.118	0.109	0.610	0.593
PLR [%]	0.064	0.091	0.536	0.611
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**-0.036***		**-0.093***	
σ_D [%]	1.293		3.772	
T-stat	-1.806		-1.597	
Nobs	4,234		4,234	
Panel C: Days [-10, -6] vs Days [6, 10]				
PGR [%]	0.134	0.110	0.639	0.574
PLR [%]	0.067	0.078	0.596	0.558
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**-0.036**		**-0.027**	
σ_D [%]	1.918		3.988	
T-stat	-1.193		-0.433	
Nobs	4,145		4,145	

Table V: Changes in disposition behavior around earnings announcement – limit orders

Realized limit order gains, realized market order gains, realized other order gains, paper gains, realized limit order losses, realized market order losses, realized other order losses, and paper losses are computed for each stock-day during the two-week window surrounding each sample earnings announcement; the announcement day (day 0) is omitted. The limit order PGR is estimated as the number of realized limit order gains divided by the sum of realized limit order gains, realized market order gains, realized other order gains, and paper gains; the market order PGR is estimated as the number of realized market order gains divided by the sum of realized limit order gains, realized market order gains, realized other order gains, and paper gains, and so on. The sample includes all stocks, provided they are held by an average of at least 5 investors during the two-week window. PGR and PLR statistics are reported for different sub-periods: days [-2, -1] and [1, 2] relative to the earnings announcement in Panel A, days [-5, -3] and [3, 5] in Panel B, and days [-10, -6] and [6, 10] in Panel C. $t-1$ 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 $(PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1}) \neq 0$ at the 1%/5%/10% level, assuming that the observations are independent across stocks and over time. All PGR and PLR statistics are in percent.

	Limit orders		Market orders		Unclassified orders	
Panel A: Days [-2, -1] vs Days [1, 2]	Before	After	Before	After	Before	After
PGR [%]	0.404	0.445	0.286	0.285	0.076	0.099
PLR [%]	0.256	0.349	0.331	0.529	0.056	0.052
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**-0.053**		**-0.198*****		**0.028**	
σ_D [%]	3.10		3.68		1.39	
T-stat	-1.11		-3.48		1.31	
Nobs	4,190		4,190		4,190	
Panel B: Days [-5, -3] vs Days [3, 5]						
PGR [%]	0.362	0.348	0.286	0.282	0.080	0.072
PLR [%]	0.230	0.240	0.317	0.368	0.053	0.095
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**-0.024**		**-0.054**		**-0.050**	
σ_D [%]	2.248		2.535		2.041	
T-stat	-0.698		-1.386		-1.604	
Nobs	4,234		4,234		4,234	
Panel C: Days [-10, -6] vs Days [6, 10]						
PGR [%]	0.385	0.338	0.301	0.289	0.088	0.057
PLR [%]	0.236	0.233	0.356	0.351	0.071	0.052
$D \equiv (PGR_t - PLR_t) - (PGR_{t-1} - PLR_{t-1})$ [%]	**-0.044**		**-0.007**		**-0.011**	
σ_D [%]	2.939		3.103		1.059	
T-stat	-0.961		-0.147		-0.695	
Nobs	4,145		4,145		4,145	

Table VI: Linear Probability Model of the Propensity to Sell

The dependent variable is one if the investor sells her position on a given day during a two-week window centered at the earnings announcement date and zero otherwise (excepting the day of the announcement which is omitted). The independent variables are defined as follows. The "capital loss" dummy is one if the current stock price is equal to or below the value-weighted average purchase price and zero otherwise; the "Post EA" dummy is one if the observation is after the earnings announcement and zero otherwise; r_0^e is the stock's return on the observation day in excess of the local market index, r_1^e is the stock's excess return on the trading day before the observation day, and so on; the "sell below prior month minimum" dummy is one if on the day of observation the stock sells below its minimum during the past month; "prior month stock volatility" is the standard deviation of daily stock returns during the past month. Standard errors are OLS, except for those in Column (3) which are robust to heteroskedasticity and allow for clustering of errors across same-investor observations (see White, 1980; Williams, 2000). All values are in percent. ***/**/* indicate that the coefficient estimates are significantly different from zero at the 1%/5%/10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable			Sell indicator			
Constant	0.607***	0.354***	0.354***	0.442***	0.088	0.558
	(0.005)	(0.005)	(0.007)	(0.006)	(1.774)	(1.788)
Capital loss X Post EA	0.069***	0.049***	0.049***	0.036***	0.043***	0.034***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)
Capital loss indicator	-0.136***	-0.068***	-0.068***	-0.176***	-0.175***	-0.188***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Post EA indicator	-0.012*	0.018**	0.018**	0.041***	0.049***	0.051***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
r_0^e		1.231***	1.231***	0.990***	1.078***	1.109***
		(0.122)	(0.152)	(0.120)	(0.087)	(0.088)
r_1^e		1.213***	1.213***	0.988***	0.779***	0.808***
		(0.103)	(0.123)	(0.102)	(0.079)	(0.081)
r_2^e		1.309***	1.309***	1.027***	1.052***	1.018***
		(0.099)	(0.107)	(0.097)	(0.076)	(0.077)
r_3^e		1.100***	1.100***	0.769***	0.734***	0.723***
		(0.090)	(0.103)	(0.089)	(0.076)	(0.077)
r_4^e		1.175***	1.175***	0.848***	0.726***	0.664***
		(0.089)	(0.096)	(0.088)	(0.075)	(0.077)
r_{5-19}^e		0.832***	0.832***	0.496***	0.399***	0.290***
		(0.029)	(0.036)	(0.030)	(0.022)	(0.025)
r_{20-39}^e		0.406***	0.406***	0.243***	0.172***	0.104***
		(0.022)	(0.025)	(0.022)	(0.015)	(0.018)
Sell below prior month min		0.392***	0.392***	0.368***	0.292***	0.263***
		(0.012)	(0.013)	(0.012)	(0.012)	(0.012)
Sell above prior month max		0.255***	0.255***	0.254***	0.253***	0.261***
		(0.010)	(0.012)	(0.010)	(0.010)	(0.010)
Prior month stock volatility		70.023***	70.023***	37.230***	30.588***	40.434***
		(1.533)	(2.516)	(1.693)	(1.416)	(2.677)
Ancillary statistics						
Number of observations	7,397,143	7,022,854	7,022,854	7,022,854	7,022,854	7,022,854
Investor fixed effects	No	No	No	Yes	Yes	Yes
Day fixed effects	No	No	No	No	Yes	Yes
Stock fixed effects	No	No	No	No	No	Yes
Adjusted R^2	0.0%	0.2%	0.2%	1.4%	1.5%	1.6%

Table VII: Disposition Effect and Return Persistence

The sample period is divided into 11 non-overlapping sub-periods of 26 weeks, except for the last period January-May 2000 which has 21 weeks. Each sub-period, stocks are sorted by the first-order autocorrelation of their weekly returns. Stocks in the bottom half are classified as having weak return persistence, stocks in the top half are classified as having strong return persistence. ***/**/* 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. All values are in percent.

	Return persistence		
	Weak	Strong	Weak - Strong
PGR	0.90	0.91	
PLR	0.59	0.62	
Average PGR-PLR	0.31	0.29	0.02
Std PGR-PLR	0.92	0.79	
Nobs	1,425	1,443	