

# When do Investors Exhibit Stronger Behavioral Biases?\*

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# When do Investors Exhibit Stronger Behavioral Biases?

## ABSTRACT

This paper examines whether individual investors exhibit stronger behavioral biases when value ambiguity or information uncertainty is higher. Using a six year (1991 to 1996) panel of retail stock holdings and trades, I find that investors are more overconfident and exhibit stronger disposition effect when stocks are more difficult to value. Furthermore, using trading correlation as a proxy for other behavioral biases such as limited attention and representativeness, I find that those biases also get amplified when valuation is more difficult. Additionally, behavioral biases are stronger when there is greater market-wide uncertainty, as reflected by higher mean stock-level volatility and higher unemployment rate. Collectively, the results indicate that both stock-specific and market-wide uncertainty exacerbates investors' behavioral biases.

INVESTOR OVERCONFIDENCE AND THE DISPOSITION EFFECT are perhaps two of the most widely documented biases in the recent behavioral finance literature.<sup>1</sup> In the context of the stock market, the extant evidence indicates that people are overconfident in their stock investment choices, where overconfidence is a function of their personal characteristics. For instance, Odean (1999) finds that individual investors either overestimate the quality of their private information or their ability to interpret that private information. Consequently, following the trade date, the stocks these investors purchase underperform the stocks they sell. Additionally, Barber and Odean (2001) show that men exhibit greater overconfidence than women, where men trade more aggressively than women but earn lower net returns. More recently, Christoffersen and Sarkissian (2004) show that managers located

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<sup>1</sup>See Odean (1998b), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hirshleifer (2001) for a review of the literature on investor overconfidence. Odean (1998a) and Feng and Seasholes (2005) review the literature on the disposition effect.

in large metropolitan areas (financial centers) exhibit greater overconfidence, even though those managers are relatively more sophisticated.

Previous studies (e.g., Shefrin and Statman (1985), Odean (1998a), Grinblatt and Keloharju (2001b), Feng and Seasholes (2005)) also document that individual investors exhibit the disposition effect, i.e., investors exhibit greater reluctance to sell their “losers” (investments where they have suffered a loss) relative to their propensity to sell “winners” (stock investments where investors have experienced a gain). Additionally, there is considerable evidence (e.g., Shapira and Venezia (2001), Frazzini (2005), Jin and Scherbina (2005)) that even relatively more sophisticated institutional investors exhibit the disposition effect, though the magnitude of their bias is weaker than individual investors. Echoing similar views, Dhar and Zhu (2002) show that, within the individual investor category, investors who are more sophisticated exhibit weaker disposition effect.<sup>2</sup>

Overall, the extant evidence suggests that overconfidence and the disposition effect biases vary with investor type and characteristics in an expected manner. But how do behavioral biases vary in the cross-section of stocks? In particular, how does value ambiguity (or information uncertainty) influence the strength of investors’ behavioral biases? Are investors more likely to make mistakes in settings with greater uncertainty?

It is conceivable that investors would be able to sustain their “erroneous” beliefs relatively more easily when there is greater ambiguity and more disagreement about the true value of a security. They may be able to “stretch their beliefs” more when the feedback is noisy or ambiguous. In contrast, when the true value of an asset is “transparent” and there is little doubt or disagreement about its valuation, investors would find it difficult to hold on to their biased beliefs. Consequently, behavioral biases which are at least partially induced by investors erroneous beliefs may vary with stock characteristics. Additionally, when uncertainty is higher, reasoning may be more difficult and investors may resort to intuitive decisions (Kahneman (2003)) which may be associated with stronger behavioral biases.

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<sup>2</sup>See Grinblatt and Han (2005), Goetzmann and Massa (2003), Frazzini (2005), and Shumway and Wu (2005) for return implications of the disposition effect bias.

More formally, theoretical studies (Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Hirshleifer (2001)) conjecture that behavioral biases are likely to be stronger among stocks which operate in informationally sparse environments and have greater ambiguity about their valuations.<sup>3</sup> In other words, value ambiguity or information uncertainty may exacerbate investors' behavioral biases. Specifically, Hirshleifer (2001, Page 1537) conjecture that:

*... people are likely to be more prone to bias in valuing securities for which information is sparse. This suggests that misperceptions are strongest in the dusty, idiosyncratic corners of the market place.*

Furthermore, building on the theoretical literature on overconfidence (e.g., Odean (1998b), Daniel, Hirshleifer, and Subrahmanyam (1998, 2001)), Jiang, Lee, and Zhang (2005) argue that investor overconfidence is likely to be stronger when there is greater ambiguity about the true value of a stock. Additionally, Baker and Wurgler (2005) argue that investor sentiment is likely to be stronger among stocks which are more difficult to value. If behavioral biases such as investor overconfidence and the disposition effect are important determinants of investor sentiment, those biases would vary in the cross-section of stocks with value ambiguity.<sup>4</sup> Overall, it is commonly believed that behavioral biases are likely to be stronger in certain specific segments of the market.

In this paper, I examine the validity of these widely held beliefs using an extensive database of individual investors. The data contain all trades and end-of-month portfolio positions of individual investors at a major U.S. discount brokerage house for the January 1991 to November 1996 time period. This database has been used in several studies including Odean (1998a, 1999) and Barber and Odean (2000, 2001).

First, I focus on the overconfidence bias and examine whether individual investors exhibit

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<sup>3</sup>These predictions are inspired by evidence in the cognitive psychology literature (e.g., Lichtenstein and Fischhoff (1975), Einhorn (1980), Griffin and Tversky (1992)) where people exhibit greater overconfidence in more difficult settings (e.g., when they face difficult questions, engage in non-mechanical tasks, etc.) and when feedback is delayed and noisy.

<sup>4</sup>Barber, Odean, and Zhu (2003) show that psychological biases (limited attention, representativeness, and the disposition effect) induce correlated trading among individual investors. For instance, investors who follow the representative heuristic would condition their trades on past returns and may exhibit correlated trading behavior.

greater degree of overconfidence among stocks which have greater value ambiguity. Motivated by Zhang (2005) and Jiang, Lee, and Zhang (2005), I employ multiple measures of value ambiguity (idiosyncratic volatility, volume turnover, and firm age), and inspired by Odean (1999), I use  $k$ -day post-trade sell-buy return differential (*PTSBD*) as a measure of investor overconfidence. Consistent with the theoretical predictions, I find that investor overconfidence is higher for stocks which are more difficult to value. Additionally, I find that higher market-wide (or economy-wide) uncertainty (higher mean stock volatility, higher unemployment rate, etc.) induces greater overconfidence among individual investors.

Next, I consider another robust and widely documented behavioral bias, namely, the disposition effect. Specifically, I examine whether greater value ambiguity also induces stronger disposition effect among individual investors. Additionally, because the disposition effect is likely to be at least partially induced by a more fundamental bias of narrow framing (Kumar and Lim (2005)), I also examine whether the degree of narrow framing is higher among stocks which are more difficult to value accurately.<sup>5</sup> For this set of tests, I primarily follow the Odean (1998a) methodology and measure stock-level disposition effect (*DE*) as the difference between investors' propensity to realize gains (*PGR*) and their propensity to realize losses (*PLR*). For robustness, I also employ other related measures of *DE*.

My results indicate that, like investor overconfidence, the stock-level disposition effect increases as value ambiguity increases. I also find that the degree of trade clustering (a narrow framing proxy) is lower among stocks which are hard-to-value, which indicates that investors are more likely to frame their decisions narrowly when value ambiguity is higher. Additionally, I find that the aggregate disposition effect is stronger when the market-wide uncertainty is higher. Lastly, I find that market uncertainty also exacerbates investors' local bias (e.g., Huberman (2001), Grinblatt and Keloharju (2001a), Zhu (2002), Ivković and Weisbenner (2005)). During times of greater uncertainty, investors gravitate toward local and familiar stocks while they shun non-local stocks. Collectively, these results indicate that

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<sup>5</sup>*Narrow framing* refers to the observation that people often tend to consider each decision as unique, often isolating the current choice from their past and future choices (Kahneman and Lovallo (1993), Kahneman (2003)). Typically, interactions among multiple decisions are ignored which often leads to inefficient choices.

both stock-specific and market-wide uncertainty exacerbates investors' behavioral biases.

For robustness, I examine whether other types of behavioral biases are stronger among hard-to-value stocks. For these tests, motivated by the findings in Barber, Odean, and Zhu (2003), I use trading correlation as a proxy for other behavioral biases such as limited attention and representativeness.<sup>6</sup> I find that trading correlations are higher within the subset of stocks which are more difficult to value. This indicates that, in addition to overconfidence and the disposition effect, other behavioral biases also get amplified when environmental uncertainty is higher.

Overall, my results provide direct and strong empirical support for theoretical studies (Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Hirshleifer (2001)) which posit that behavioral biases are stronger when there is greater ambiguity about firm's value. Zhang (2005) and Jiang, Lee, and Zhang (2005) also provide results which are consistent with the theoretical predictions. However, those studies do not directly measure investor overconfidence and, as a result, their findings are open to alternative interpretations. In contrast, because I measure investors' behavioral biases directly using their portfolio holdings and trades, my findings are relatively less susceptible to such criticisms. Furthermore, unlike these related studies, I also investigate how other behavioral biases respond to uncertainty, where I examine the influences of both stock-specific and market-wide uncertainty levels.

Additionally, my results highlight the importance of the information environment (in addition to investors' preferences) as one of the main determinants of investors' ability to make appropriate investment decisions. The extant evidence indicates that investor characteristics (e.g., age, income, gender, etc.), which reflect investors' preferences, would influence investors' behavioral biases. Building on this evidence, my results provide a different perspective and indicate that stock characteristics, which reflect firm's information environment, are likely to be important determinants of investors' behavioral biases. Of course, biases would be strongest for hard-to-value stocks which are held by investors who exhibit stronger behavioral biases.

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<sup>6</sup>In Section III (footnote 22), I discuss other interpretations of the trading correlation measure.

Understanding whether behavioral biases vary in the cross-section of stocks is also important because it may allow us to precisely identify the segments of the market where the pricing effects of those biases (e.g., under-reaction, momentum) would be stronger and thus easier to detect. Additionally, the link between uncertainty and behavioral biases may help us better understand the mechanisms through which uncertainty may influence returns. While market-wide uncertainty may act as an additional source of risk (e.g., Veronesi (1999), Ozoguz (2004)), higher returns for stocks with higher uncertainty may at least partially reflect mispricing due to investors' amplified behavioral biases.

The rest of the paper is organized as follows. In the next section, I examine the relation between value ambiguity and investor overconfidence. In Section II, I examine the relation between value ambiguity and the disposition effect. The impact of value ambiguity on other behavioral biases is examined in Section III. In Section IV, I examine whether market-wide uncertainty is an important determinant of investors' behavioral biases, including their local bias. I conclude in Section V with a brief summary of the paper and few pointers for future research.

## **I. Value Ambiguity and Investor Overconfidence**

### *A. Background and Motivation*

Recent studies on overconfidence (Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Jiang, Lee, and Zhang (2005)) argue that investor overconfidence is likely to be stronger when there is greater ambiguity about the true value of a stock. Perhaps, it is easier for investors to hold on to their erroneous beliefs when there is greater value ambiguity. This may be true especially when investment decisions yield negative outcomes. When there is greater value ambiguity, the feedback is likely to be noisy, and investors may be able to attribute negative outcomes to chance (or to random events). Such severely biased attribution may differentially exacerbate overconfidence and generate cross-sectional variation in the degree of stock-level overconfidence.

Prior studies have empirically examined whether greater task difficulty indeed increases the degree of overconfidence among individual investors. For instance, Odean (1999) and Barber and Odean (2001) show that investors, especially men, exhibit greater overconfidence in their overall stock selection decisions. Extending this analysis, I examine whether investor overconfidence increases as task difficulty (as captured by the value ambiguity measure) increases in the cross-section of stocks.

### *B. Data*

There are a total of 77,995 households in the database of which 62,387 have traded in stocks. Investors hold and trade a variety of other securities including mutual funds, options, ADRs, etc. An average investor holds a four-stock portfolio (median is three) with an average size of \$35,629 (median is \$13,869). For a subset of households, demographic information such as age, income, location (zipcode), total net worth (i.e., wealth), occupation, marital status, family size, gender, etc. is available. Further details on the investor database are available in Barber and Odean (2000).

My empirical analysis focuses primarily on investors' trades. Investors in the sample execute 26,000 trades in a typical month and 1,244 trades on a typical day. The number of buy trades is greater than the number of sell trades, and in a typical year, approximately 6000-7000 stocks are traded. This indicates that investors' trades span a large set of stocks. Additional statistics on the trading activities of investors in the sample are available in Kumar and Lee (2004).

Several other common datasets are used in this study. I obtain quarterly institutional holdings from Thomson Financial which contain the end of quarter stock holdings of all institutions that file form 13F with the Securities and Exchange Commission.<sup>7</sup> I obtain prices, returns, volume, dividends, and market capitalization data from the Center for Research on Security Prices (CRSP), quarterly book value of common equity data from COMPUSTAT,

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<sup>7</sup>See Gompers and Metrick (2001) for details on the institutional investor database.



and monthly macro-economic data from Datastream. The unemployment data are obtained from the Bureau of Labor Statistics website ([www.bls.gov](http://www.bls.gov)). Lastly, the time-series of the three Fama-French factors, the momentum factor, the NYSE size break-points, and the B/M break-points are obtained from Ken French’s data library.<sup>8</sup>

### C. Stock-Level Overconfidence Measures

Investors may be overconfident about the quality of their private information or they may overestimate their ability to process their private information. In either case, an overconfident investor is likely to make systematic errors when she formulates her trading decisions. Consequently, the stocks an overconfident investor sells is likely to systematically outperform the stocks she purchases. With this motivation, I follow Odean (1999) and use the mean  $k$ -day post-trade sell-buy return differential (*PTSBD*) to measure investor overconfidence. A positive value of *PTSBD* for a stock indicates that investors holding the stock are systematically making mistakes, where they either systematically misinterpret their private information or overestimate their investment ability.<sup>9</sup> Additionally, motivated by Zhang (2005) and Jiang, Lee, and Zhang (2005), I employ three measures of value ambiguity: (i) idiosyncratic volatility, (ii) volume turnover, and (iii) firm age.<sup>10</sup> Among these three measures, I focus primarily on the idiosyncratic volatility measure as it has been shown to be a robust measure of valuation uncertainty (e.g., Pástor and Veronesi (2003), Gaspar and Massa (2005)).

Table I, Panel A reports the summary statistics for the various stock-level overconfidence measures (*PTSBD*( $k$ ),  $k = 5, 10, 21, 42, 63, 84, 126,$  and  $252$  days). The mean overconfidence measures are significantly positive for higher values of  $k$  and statistically insignificant

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<sup>8</sup>Ken French’s data library is available at <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/>.

<sup>9</sup>If investors do not exhibit overconfidence and simply trade in a random fashion, the stocks an investor sells will perform similar to the stocks she purchases. Consequently, the post-trade sell-buy return differential would be close to zero. See Odean (1999) for additional discussion.

<sup>10</sup>Among various measures of value ambiguity suggested in previous studies, I selected three measures which are easiest to compute and allow me to measure the value ambiguity for the largest number of stocks. Specifically, I do not use dispersion in analysts’ forecasts of future earnings as a value ambiguity proxy because a large number of firms with high uncertainty (as measured by other proxies) are not in the IBES sample. See Pástor and Veronesi (2003) for a critique.

for lower values of  $k$ . More importantly, the results indicate that there is considerable heterogeneity in the stock-level overconfidence measures. Specifically, irrespective of the value of  $k$ , at least one-fourth of the stocks have positive overconfidence measures and another one-fourth of them have negative overconfidence measures. In the following sections, I examine whether the stock-level heterogeneity in overconfidence is induced by uncertainty about stock valuation.

#### *D. Univariate Results*

To examine the uncertainty-overconfidence relation, as a first cut, I measure the mean 252-day *PTSBD* for stocks with different levels of idiosyncratic volatility. I sort all CRSP stocks into idiosyncratic volatility deciles, where the idiosyncratic volatility measure is the variance of the residual obtained by fitting a four-factor model to the stock returns time-series. The idiosyncratic volatility for each stock is estimated each month using daily returns data, where stocks with fewer than 17 daily observations are excluded.<sup>11</sup> The sample period mean of monthly volatility measures is used to measure the value ambiguity of a stock.<sup>12</sup>

The 252-day (one-year) *PTSBD* measures for the ten idiosyncratic volatility (value ambiguity) decile portfolios are presented in Figure 1. In lower idiosyncratic volatility deciles, I find that the stocks investors sell underperform the stocks they buy. This indicates that investors are making appropriate investment choices among stocks in lower ambiguity deciles. However, when idiosyncratic volatility is higher, the stocks investors sell outperform the stocks they buy. For instance, the highest idiosyncratic volatility decile portfolio has a mean one-year *PTSBD* of 8.598%. This evidence suggests that investors are making larger systematic errors and exhibit greater overconfidence among stocks with higher value ambiguity.<sup>13</sup>

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<sup>11</sup>The approach is identical to the methodology followed in Ang, Hodrick, Xing, and Zhang (2005).

<sup>12</sup>These results (and other results in the paper) are very similar when I use total volatility or variance of the residuals from the CAPM or the three-factor model to measure value ambiguity. Also, the results are similar when I use monthly returns during the sample period to estimate idiosyncratic volatility. Overall, echoing the observation in Jiang, Lee, and Zhang (2005), I find that the results are insensitive to the choice of the specific volatility measure.

<sup>13</sup>One might argue that learning would mitigate the effects of overconfidence (Odean and Gervais (2001)) and consequently, the effect of value ambiguity on overconfidence may weaken over time. However, as Odean and Gervais (2001) also indicate, while overconfidence may decline over time for an existing investor or a

The results are quite similar when I examine the *PTSBD* for other values of  $k$  (see Table II). The  $k$ -day *PTSBD* is positive (negative) for lower (higher) idiosyncratic volatility stock portfolios. Overall, the univariate test results indicate that investors make larger mistakes and exhibit stronger overconfidence when there is greater uncertainty about stock valuation.

### *E. Multivariate Regression Estimates*

The results from univariate tests are obviously encouraging because they indicate a strong positive relation between investor overconfidence and value ambiguity. This evidence supports the theoretical predictions of Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) and Hirshleifer (2001). However, prior studies have assigned other interpretations to the idiosyncratic volatility measure. For instance, idiosyncratic volatility has been used as a proxy for arbitrage costs (e.g., Wurgler and Zhuravskaya (2002), Mendenhall (2004), Kumar and Lee (2004)) and firm-specific information (e.g., Roll (1988), Durnev, Morck, Yeung, and Zarowin (2003)). To better examine the uncertainty-overconfidence relation, I adopt a multiple regression framework, where I employ three different (but related) measures of value ambiguity and various stock-specific control variables as independent variables. The dependent variable is the mean  $k$ -day *PTSBD* measure.

The regression estimates are presented in Table III. In the first regression specification, I use the mean 252-day *PTSBD* as the dependent variable and three value ambiguity measures (idiosyncratic volatility, monthly volume turnover, and firm age) as independent variables. Monthly volume turnover for a stock is the ratio of the number of shares traded in a month and the number of shares outstanding. The sample period average of this measure is employed in the regression. Firm age is the number of years since the stock first appears in the CRSP database and December 1996. Consistent with the results from univariate tests, I find that individual investors exhibit greater overconfidence when value ambiguity is higher (see column (1)). The coefficient estimates of idiosyncratic volatility and firm age variables

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subgroup of investors, the stock-level or market-level overconfidence may not decline due to the arrival of new investors.

support this assertion while the estimate of the monthly turnover variable is statistically insignificant.<sup>14</sup>

In the second regression specification, I use the same dependent variable but employ various firm-specific variables as independent variables. Specifically, the following independent variables are considered: (i) market beta, which is estimated using past 60 months of returns data, (ii) firm size, (iii) the book-to-market ratio, (iv) past twelve-month stock returns, and (v) dividend paying stock dummy, which is set to one if the stock pays dividend at least once during the sample period. The sample period averages of variables (i)-(iv) are employed in the regression specifications.<sup>15</sup> The results (see column (2)) indicate that investor overconfidence is relatively higher among stocks which have lower market capitalization, have lower book-to-market ratio, and do not pay dividends. These small-cap, non-dividend-paying, growth stocks are generally perceived as being more difficult to value, so the evidence supports the key assertion that behavioral biases are stronger when value ambiguity is higher.

When I estimate the regression model with both value ambiguity measures and stock-specific control variables, the results change only slightly. Most importantly, the monthly turnover coefficient estimate becomes positive and significant (see column (3)) and all three value ambiguity measures paint a consistent picture. Additionally, the estimate of dividend paying dummy becomes insignificant but retains the expected negative sign. Overall, the results indicate that investor overconfidence is higher among stocks which are hard-to-value. These stocks are relatively younger and have higher idiosyncratic volatility, higher turnover, lower market capitalization, and lower B/M.

As a robustness check, I re-estimate the regression model with the mean 126-day *PTSBD* measure as the dependent variable. These estimates are also reported in Table III (column (4)). The coefficient estimates with the mean 126-day *PTSBD* measure are very similar to

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<sup>14</sup>To ensure that extreme values are not affecting my results, I Winsorize all variables at their 0.5 and 99.5 percentile levels. Additionally, to ensure that my results are robust to concerns about multi-collinearity, I compute the variance inflation factor (*VIF*) for each of the independent variables. *VIF* measures the degree to which an explanatory variable can be explained by other explanatory variables in a regression model. As a rule of thumb, multi-collinearity is not of concern if  $VIF < 2$ . I find that the *VIF* is less than two for all independent variables, which suggests that multi-collinearity is not a major concern.

<sup>15</sup>The coefficient estimates are similar when the variables are measured at the beginning, middle, or the end of the sample period.

those obtained with the mean 252-day *PTSBD* measure. Most importantly, the estimates of the three value ambiguity measures have the expected signs and are statistically significant. Collectively, the regression estimates provide strong empirical support to studies (Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Hirshleifer (2001), Jiang, Lee, and Zhang (2005)) which posit that investor overconfidence would be stronger among hard-to-value stocks.

#### *F. Additional Robustness Checks*

For further robustness, I carry out three additional tests. The robustness test results are summarized in Table VII, Panel A. First, I examine whether the *PTSBD* measure is indeed capturing investor overconfidence. Prior studies (e.g., Odean (1999)) show that overconfident investors are likely to trade more frequently and exhibit poor portfolio . To capture this characterization of overconfidence, previous studies (e.g., Bailey, Kumar, and Ng (2005)) have also measured investor-level overconfidence using a combination of realized portfolio performance and portfolio turnover measures. Specifically, an overconfidence proxy is defined, which is set to one for investors who belong to the highest portfolio turnover quintile and the lowest risk-adjusted portfolio performance (Sharpe ratio) quintile.

Given this alternate measure of overconfidence, I examine whether the  $k$ -day *PTSBD* overconfidence measure is positively related to the performance and turnover based overconfidence dummy. Specifically, I regress the investor-level 252-day *PTSBD* measure on the over-confidence dummy. In untabulated results, I find that the coefficient estimate of the overconfidence dummy is positive (0.049) and significant ( $t$ -stat = 6.771). The coefficient estimate remains positive and significant even when other investor and portfolio characteristics such as age, income, wealth, portfolio diversification level, etc. are used as control variables. This indicates that *PTSBD* and overconfidence dummy measures capture common aspects of investors' overconfidence bias.

Next, to address the concern that the uncertainty-overconfidence relation may be sensitive

to the rising market during the sample period, I re-estimate the overconfidence regression for the 1991-93 and 1994-96 sub periods. I find that the subsample coefficient estimates of value ambiguity measures are similar to the full-sample results (see Table VII, Panel A). Most notably, the coefficient estimates of idiosyncratic volatility are positive and significant during both sub periods.

Lastly, I examine the impact of a potential bias in the overconfidence measure due to its reliance on realized stock returns. The overconfidence bias measure depends upon realized stock returns but stock returns are also likely to be influenced by individual investors' behavioral biases or sentiment, especially when the stock has higher retail concentration and higher arbitrage costs (e.g., Kumar and Lee (2004), Kumar (2004), Baker and Wurgler (2005)).

To minimize the potential bias introduced in the overconfidence measure (and consequently, in the regression coefficient estimates) due to the causality running from sentiment to returns, I re-estimate the overconfidence regression for the subsample of stocks with high (top quintile) institutional ownership. This test is based on the assumption that individual investors are unlikely to influence stock returns when institutional ownership is higher. I find that coefficient estimates of value ambiguity measures for high institutional ownership subsample have the same signs as the full sample estimates (see Table VII, Panel A). Particularly, the idiosyncratic volatility variable has a weaker (but still highly significant) coefficient estimate while the firm age variable has a stronger coefficient estimate.

Overall, the results from these additional tests provide robust evidence of a positive relation between value ambiguity and the overconfidence bias.

## **II. Value Ambiguity and the Disposition Effect**

### *A. Background and Motivation*

Is the positive relation between value ambiguity and overconfidence specific to the overconfidence bias or does the relation generalize to other types of biases? To answer this question, I

investigate the relation between value ambiguity and another widely documented and robust behavioral bias, namely, the disposition effect.

The typical explanation for the disposition effect (Shefrin and Statman (1985)) relies on the combination of loss aversion (Kahneman and Tversky (1979)) and stock-level mental accounting (Thaler (1980)). Under this prospect-theoretic framework, ambiguity about the valuation of a stock is unlikely to influence investors' relatively lower propensity to realize losses. However, as discussed in Odean (1998a), the disposition effect can also arise through an alternate mechanism, namely, a belief in mean reversion. Additionally, experimental results (Andreassen (1988)) indicate that people exhibit stronger "tracking" behavior ("buy low, sell high") when price volatility is higher. In other words, investors believe that price reversals are more likely when a stock has higher volatility and it is believed to "bounce around". Taken together, these findings suggest that investors would exhibit stronger disposition effect when there is more uncertainty in the environment.

In addition to a belief in mean reversion, gambling behavior may motivate some investors to hold on to their losers for a longer period when idiosyncratic volatility is higher. Those investors would take speculative positions in stocks with higher volatility and higher skewness (Kumar (2005)) and they may wait for their stock gambles to yield extreme payoffs. Consequently, those investors would exhibit stronger disposition effect when uncertainty is higher. Furthermore, certain investors may be more sensitive to individual gains and losses when stock volatility is higher, i.e., they may engage in stock-level mental accounting (Barberis and Huang (2001)) for stocks which may be the salient stocks in the portfolio due to their higher idiosyncratic volatility.

Lastly, and most importantly, when idiosyncratic volatility is higher, investors would receive very noisy feedback about their stock selection decisions. If the stock is believed to "bounce around", investors may get a positive reinforcement when the returns are positive and they would discount the negative return events due to their self-attribution bias (Daniel, Hirshleifer, and Subrahmanyam (1998)). Consequently, biased self-attribution would exacerbate investors' propensity to exhibit the disposition effect.

Overall, multiple mechanisms can potentially induce stronger disposition effect when there is greater environmental uncertainty. I examine the uncertainty-disposition effect relation but do not identify the precise mechanism through which uncertainty influences and amplifies the disposition effect.

### B. Stock-Level Disposition Effect Measure

To examine the uncertainty-disposition effect relation, I use a slightly modified form of the PGR-PLR methodology (Odean (1998a)) and obtain stock-level measures of the disposition effect. First, I define the following variables:

- $N_{gr}^i$  = number of trades in stock  $i$  where a gain is realized,
- $N_{lr}^i$  = number of trades in stock  $i$  where a loss is realized,
- $N_{gp}^i$  = number of potential (or paper) trades in stock  $i$  where there is a gain,
- $N_{lp}^i$  = number of potential (or paper) trades in stock  $i$  where there is a loss,
- $N_g^i = N_{gr}^i + N_{gp}^i$  = total number of trades in stock  $i$  where there is a gain,
- $N_l^i = N_{lr}^i + N_{lp}^i$  = total number of trades in stock  $i$  where there is a loss,
- $N_{atrades}^i = N_{gr}^i + N_{lr}^i$  = total number of actual trades executed in stock  $i$ ,
- $N_{ptrades}^i = N_{gp}^i + N_{lp}^i$  = total number of potential (or paper) trades in stock  $i$ ,
- $PGR_i$  = proportion of gains realized in stock  $i$ ,
- $PLR_i$  = proportion of losses realized in stock  $i$ , and
- $DE_i$  = the disposition effect measure for stock  $i$ .

Next, considering the actual trades and potential trades in stock  $i$  during the sample period, I compute

$$PGR_i = \frac{N_{gr}^i}{N_{gr}^i + N_{gp}^i} \times 100, \quad PLR_i = \frac{N_{lr}^i}{N_{lr}^i + N_{lp}^i} \times 100. \quad (1)$$

Finally, I measure the disposition effect for ( $DE$ ) stock  $i$  as

$$DE_i = PGR_i - PLR_i. \quad (2)$$

A value of  $DE_i > 0$  indicates that a smaller proportion of losers are sold compared to the



proportion of winners in the stock.<sup>16</sup> Consequently, investors exhibit the disposition effect in stock  $i$ . Alternatively, the disposition effect can also be measured using the ratio of  $PGR$  and  $PLR$ , i.e.,  $DE_i = PGR_i/PLR_i$ .

Table I, Panel B reports the summary statistics for the two disposition effect measures. The mean  $PGR-PLR$  measure is positive and significant and the mean  $PGR/PLR$  measure is greater than one. This indicates that, on average, investors exhibit disposition effect at the stock-level. The mean stock-level  $DE$  of 7.347% is comparable to the investor-level  $DE$  of 5-8% reported in Odean (1998a). Furthermore, like overconfidence measures, there is considerable heterogeneity in stock-level disposition effect measures. For instance, about 20% of stocks do not exhibit the disposition effect (i.e., investors are not reluctant to sell these stocks at a loss) while about 38% of stocks have the  $PGR/PLR$  measure above two (i.e., investors exhibit very strong  $DE$ ). Again, in the following sections, I examine whether this heterogeneity in stock-level disposition effect is induced by uncertainty in stock valuation.

### C. Univariate Results

To examine the uncertainty-disposition effect relation, first, I follow the sorting procedure employed in the overconfidence univariate analysis (see Section I.D) and measure the mean disposition effect for stocks in ten idiosyncratic volatility decile portfolios. The results are reported in Figure II. I find that investors exhibit stronger disposition effect among stocks with higher value ambiguity. The pattern is strongly monotonic with the  $PGR - PLR$  measure (see Panel A) and with the  $PGR/PLR$  measure, the pattern is similar but somewhat weaker (see Panel B). Collectively, the results support Hirshleifer's (2001) conjecture, who posits that behavioral biases would be stronger in informationally sparse environments.<sup>17</sup>

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<sup>16</sup>The potential trades or paper trades refer to those trades which an investor could have executed at the time she executes an actual trade. They are defined by examining the portfolio composition of the investor at the time of the trade.

<sup>17</sup>Using the same individual investor data and a similar methodology, Rangelova (2001) shows that the disposition effect is non-existent for small-cap stocks and it increases with firm size. Small-cap stocks have relatively higher value ambiguity and hence those results are inconsistent with the findings in my paper. However, in a personal communication, Terrance Odean indicated that he was unable to replicate Rangelova's (2001) findings either. This suggests that there was perhaps an error in her empirical analysis.

#### *D. Multivariate Regression Estimates*

Next, to better understand the uncertainty-disposition effect relation, I estimate a multiple regression model, where I employ three different (but related) measures of value ambiguity and various stock-specific control variables as independent variables. The independent variables are identical to those used in the overconfidence regression model (see Section I.E) and the dependent variable is one of the two stock-level disposition effect measures ( $PGR - PLR$  or  $PGR/PLR$ ).

The regression estimates are presented in Table IV. In the first regression specification, I use the  $PGR - PLR$  measure as the dependent variable and the three value ambiguity measures as independent variables. Similar to the results from the overconfidence regression, I find that individual investors exhibit stronger disposition effect when value ambiguity is higher (see column (1)). The coefficient estimates of idiosyncratic volatility and monthly turnover variables support this assertion while the estimate of the firm age variable is statistically insignificant. Overall, I find that the uncertainty-disposition effect relation is very similar to the uncertainty-overconfidence relation estimated earlier.

When I employ various firm-specific variables as independent variables and use the same dependent variable, I find that the disposition effect is relatively stronger among stocks which have higher market beta, lower market capitalization, weaker price momentum, and do not pay dividends (see column (2)). Again, stocks with these characteristics are generally perceived as being more difficult to value, so the evidence further indicates that the disposition effect is stronger when value ambiguity is higher.

When I estimate the regression model with both value ambiguity measures and stock-specific control variables (see column (3)), the coefficient estimates of the value ambiguity measures maintain their signs and statistical significance levels. Additionally, the estimate of the book-to-market variable becomes insignificant but retains the expected negative sign.

Lastly, for robustness, I re-estimate the regression model with the  $PGR/PLR$  disposition effect measure as the dependent variable. These estimates are also reported in Table IV

(column (4)). The coefficient estimates of the value ambiguity measures with the *PGR/PLR* measure are similar to those obtained with the *PGR – PLR* disposition effect measure. However, the estimates of some of the control variables lose their statistical significance.

Overall, the regression estimates indicate that, similar to the overconfidence bias, the disposition effect bias is higher among stocks which are harder-to-value. These stocks are relatively younger and have higher idiosyncratic volatility, higher turnover, lower market capitalization, weaker momentum, and do not pay dividends. Collectively, the regression estimates provide strong empirical support to Hirshleifer’s (2001) conjecture, who posits that behavioral biases are likely to be stronger for stocks which operate in informationally sparse environments and are more difficult to value.

#### *E. Value Ambiguity and Narrow Framing*

In this section, I examine the relation between value ambiguity and narrow framing, a behavioral bias which has been identified as a fundamental determinants of the disposition effect bias (Kumar and Lim (2005)). Narrow framing refers to the observation that people often people tend to consider each decision as unique, often isolating the current choice from their past and future choices (Kahneman and Lovallo (1993), Kahneman (2003)). Typically, interactions among multiple decisions are ignored which often leads to inefficient choices. Using trade clustering as a narrow framing proxy, Kumar and Lim (2005) show that the disposition effect bias is at least partially induced by a more fundamental bias of narrow framing.<sup>18</sup> This suggests that stock-level narrow framing bias may also be stronger among stocks which are more difficult to value.

To examine the uncertainty-narrow framing relation, I compute the mean trade clustering measure for stocks with different levels of idiosyncratic volatility. To measure stock-level

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<sup>18</sup>The choice of trade clustering as a narrow framing proxy is motivated by experimental research which finds that the decision frames people adopt are affected by the manner in which different alternatives are presented to them (e.g., Tversky and Kahneman (1981), Tversky and Kahneman (1986), Redelmeier and Tversky (1992)). In particular, the time interval between two consecutive decisions influences the perception of a given decision problem and plays an important role in the overall decision-making process. Consequently, simultaneous decisions are more likely to be framed broadly than decisions which are temporally separated (e.g., Read and Loewenstein (1995), Read, Loewenstein, and Rabin (1999)).

trade clustering, I assume that trades which are executed simultaneously with other trades by the same investor on the same day are likely to be broadly framed. In contrast, trades which are executed separately are likely to be narrowly framed. The stock-level trade clustering measure is the proportion of trades which are executed simultaneously in a given month.

The results (see Figure 3) indicate that the degree of trade clustering is lower among stocks which are harder-to-value. Consequently, investors are more likely to frame their decisions narrowly when value ambiguity is higher. In untabulated results, I find that the uncertainty-narrow framing relation is positive and significant even in a multivariate setting, where several value ambiguity measures and stock-specific control variables are used as independent variables. Specifically, the coefficient estimate of the idiosyncratic volatility and monthly turnover variables are positive and significant – the estimates ( $t$ -values) are 0.125 (7.378) and 0.064 (8.183), respectively. The firm age variable has an insignificant coefficient estimate. Taken together, these results indicate that investors are also more likely to adopt narrower decision frames in uncertain environments. Again, the evidence supports Hirshleifer’s (2001) fundamental conjecture.

#### *F. Additional Robustness Checks*

For further robustness, I carry out three additional tests. The robustness test results are summarized in Table VII, Panel B. First, as before (see Section I.F), to address the concern that my results may be sensitive to the rising market during the sample period, I re-estimate the disposition effect regression for the 1991-93 and 1994-96 sub periods. I find that the subsample coefficient estimates of the value ambiguity measures are similar to the full-sample results. Most notably, the idiosyncratic volatility coefficient estimates are positive and significant during both sub periods.

For the second robustness test, I define a modified measure of the disposition effect. Odean (1998a) indicates that the investor-level  $PLR$  and  $PGR$  measures are sensitive to portfolio size and investors’ trading frequency. In a similar manner, the stock-level  $PLR$

and *PGR* measures would be sensitive to trading frequency and the number of investors holding the stock. Consequently, a cross-sectional analysis using the original stock-level *DE* measure may yield inaccurate estimates (Feng and Seasholes (2005)).<sup>19</sup>

To eliminate the mechanically induced biases in the disposition effect measure, I employ a measure of stock-level disposition effect which is insensitive to trading frequency and the number of investors holding the stock. I follow the Kumar and Lim (2005) methodology and define an “adjusted” measure of the disposition effect (*ADE*) at the stock-level, where

$$APRG_i = \frac{N_{gr}^i}{N_{gr}^i + N_{lr}^i}, \quad EPRG_i = \frac{N_{gp}^i}{N_{gp}^i + N_{lp}^i}, \quad \text{and finally,} \quad (3)$$

$$ADE_i = APRG_i - EPRG_i. \quad (4)$$

Here,  $EPRG_i$  is the proportion of winners among all paper trades in stock  $i$  and indicates investors’ expected propensity to realize gains.  $APRG_i$  is the proportion of winners among all actual trades in stock  $i$  and indicates investors’ actual propensity to realize gains.<sup>20</sup> A value of  $ADE_i > 0$  indicates that a greater than expected proportion of winners are sold (or a smaller than expected proportion of losers are sold) and thus the group of investors who hold stock  $i$  exhibit the disposition effect.<sup>21</sup>

I re-estimate the disposition effect regression using the adjusted disposition effect measure. Again, I find that the coefficient estimates of value ambiguity measures are similar to the estimates obtained using the original disposition effect measure (see Table VII, Panel B).

Lastly, because realized returns are likely to be influenced by investors’ disposition effect

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<sup>19</sup>Feng and Seasholes (2005) provide an excellent discussion of the weaknesses of the original *DE* measure when employed in cross-sectional studies (see Appendix D). The adjusted disposition effect measure used in the robustness test is free from those weaknesses and hence appropriate for a cross-sectional analysis. The adjusted disposition effect calculations for the examples provided in Appendix D of their study are available upon request.

<sup>20</sup>The adjustment is based on the simple observation that if a benchmark that varies with trading frequency and the number of investors holding the stock is used to measure investors’ excess propensity to realize gains (or their reluctance to realize losses), the sensitivity of the *DE* measure to trading frequency and the number of investors holding the stock can be eliminated (or at least minimized). See Kumar and Lim (2005) for details.

<sup>21</sup>Note that the original and the “adjusted” stock-level disposition effect measures are related in the following manner:  $ADE_i = \frac{N_g^i \times N_l^i}{N_{atrades}^i \times N_{ptrades}^i} \times DE_i = f_i \times DE_i$ , where  $f_i$  is a stock-specific adjustment factor which depends upon trading frequency and the number of investors holding the stock.

(see footnote (2)), I examine the sensitivity of the disposition effect regression estimates to the presence of potential bias in the disposition effect measure. I re-estimate the disposition effect regression for the subsample of stocks with high (top quintile) institutional ownership, where the impact individual investors' biases on returns would be minimal. My results indicate that coefficient estimates of value ambiguity measures for the subsample have the same signs as the full sample estimates (see Table VII, Panel B). In fact, both the idiosyncratic volatility and the firm age variables have stronger coefficient estimates.

Overall, the results from these additional tests provide robust evidence of a positive relation between value ambiguity and the disposition effect bias.

### III. Value Ambiguity and Other Behavioral Biases

#### A. Motivation

My analysis so far has focused on two behavioral biases, namely, overconfidence and the disposition effect. However, investors are also known to exhibit other types of biases such as limited attention (Barber and Odean (2005)) and representativeness (e.g., Kahneman and Tversky (1973), Barberis, Shleifer, and Vishny (1998)). Do these biases also get amplified in an uncertain environment? Evidence in favor of this would further reinforce the positive relation between value ambiguity and the magnitude of behavioral biases established earlier.

To investigate whether other behavioral biases vary with value ambiguity, I exploit the findings in Barber, Odean, and Zhu (2003) who show that behavioral biases such as limited attention and representativeness induce correlated trading among individual investors. Motivated by their findings, I use trading correlation as a proxy for the magnitude of investors' other behavioral biases and examine whether the average trading correlations are higher among stocks which are more difficult to value.<sup>22</sup>

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<sup>22</sup>Investors may also exhibit correlated trading for informational (i.e., non-behavioral) reasons. For instance, Feng and Seasholes (2004) show that correlated trading among investors in a geographical region may result from information asymmetry between local and non-local investors. However, for the investors in my sample, Kumar and Lee (2004) show that strong trading correlations are unlikely to reflect correlated trading induced by common information signals about certain subset of stocks. Additionally, in the

### B. Randomization Tests

I follow the Kumar and Lee (2004) methodology to measure trading correlations. Specifically, I proceed as follows: First, I identify low (quintiles 1-2) and high (quintiles 4-5) value ambiguity stock categories. As before, the sample period mean idiosyncratic volatility of a stock is used to measure its value ambiguity. Next, within each of the low and high value ambiguity stock categories, I carry out a series of randomization tests. I identify 1,000 non-overlapping  $k$ -stock portfolio pairs ( $k = 25, 50, 75,$  and  $100$ ) and compute the buy-sell balance for each portfolio at the end of each month ( $BSI_{pt}$ ) using the following relation:

$$BSI_{pt} = \frac{100}{N_{pt}} \sum_{i=1}^{N_{pt}} BSI_{it}, \quad (5)$$

where the  $BSI$  for stock  $i$  in month  $t$  is defined as:

$$BSI_{it} = \frac{\sum_{j=1}^{D_t} (VB_{ijt} - VS_{ijt})}{\sum_{j=1}^{D_t} (VB_{ijt} + VS_{ijt})}. \quad (6)$$

In this definition,  $D_t$  is the number of days in month  $t$ ,  $VB_{ijt}$  is the buy volume (measured in dollars) for stock  $i$  on day  $j$  in month  $t$ ,  $VS_{ijt}$  is the sell volume (measured in dollars) for stock  $i$  on day  $j$  in month  $t$ , and  $N_{pt}$  is the number of stocks in portfolio  $p$  formed in month  $t$ . Finally, the  $BSI$  time-series for each stock portfolio pair is obtained and portfolio  $BSI$  correlation is computed. I also measure the correlations between residual portfolio  $BSI$  measures, where the residual portfolio  $BSI$  is obtained by removing the common dependence of portfolio  $BSI$  on the market. Specifically, the following regression model is estimated:

$$BSI_{pt} = b_0 + b_1 RMRF_t + \varepsilon_{pt}. \quad (7)$$

Here,  $BSI_{pt}$  is the buy-sell imbalance index for portfolio  $p$  in month  $t$ ,  $RMRF_t$  is the market return in excess of the riskfree rate in month  $t$ , and  $\varepsilon_{pt}$  is the residual  $BSI$  for portfolio  $p$  in month  $t$ .

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asymmetric information model of Feng and Seasholes (2004), the trades of local and non-local investors are negatively correlated. In contrast, I find that buy-sell imbalance time-series of local and non-local investors are positively correlated. This evidence indicates that trading correlations are more likely to be induced by behavioral biases.

The correlation results are reported in Table V. Consistent with the results for overconfidence and disposition effect biases, I find that trading correlations are higher among stocks which are more difficult to value. For instance, when 50-stock portfolios are randomly chosen, the mean *BSI* correlation is 0.272 for high ambiguity stocks and significantly lower (0.173) for low ambiguity stocks (see Panel A). The mean correlation difference of 0.099 is statistically significant ( $p$ -value  $< 0.001$ ) and the mean residual *BSI* correlations paint a similar picture (see Panel B). Overall, the results from the randomization tests indicate that, like overconfidence and disposition effect biases, other biases such as limited attention and representativeness, get amplified in uncertain environments. Taken together, my evidence provides strong support to theoretical studies (Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Hirshleifer (2001)) which posit that value ambiguity amplifies behavioral biases.

#### IV. Market-wide Uncertainty and Behavioral Biases

##### A. Motivation

The evidence using stock-level uncertainty measures indicates that many behavioral biases get exacerbated when stock-level ambiguity or uncertainty is higher. In other words, investor and stock characteristics jointly shape investors' behavioral biases,. Overall, the evidence provides strong support for Hirshleifer's (2001) fundamental conjecture.

For additional robustness, I also examine a direct extension of Hirshleifer's (2001) conjecture. If stock-level uncertainty exacerbates investors' behavioral biases, it is natural to ask whether uncertainty at an aggregate level, i.e., market-wide (or economy-wide) uncertainty, induces stronger behavioral biases as well. If investors are sensitive to uncertainty in stock valuation, it is very likely that during times when the valuation of *all* stocks becomes more difficult and market-wide uncertainty is higher, investors would be more prone to stronger behavioral biases.<sup>23</sup>

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<sup>23</sup>In a related study, Kumar (2005) finds that gambling tendencies are stronger during bad and uncertain economic times.



### B. Time-Series Regression Estimates

To examine the relation between market-wide uncertainty and investors' behavioral biases, I estimate the following time-series model:

$$\begin{aligned} BIAS_t = & b_0 + b_1 IDIOVOL_{t-1} + b_2 UNEMP_{t-1} \\ & + b_3 UEI_{t-1} + b_4 MP_{t-1} + b_5 \Delta RP_{t-1} + b_6 \Delta TS_{t-1} + b_7 BIAS_{t-1} + \epsilon_t. \end{aligned} \quad (8)$$

In this specification,  $BIAS_t$  is the aggregate behavioral bias in a given month. Furthermore,  $IDIOVOL_t$  is the mean idiosyncratic volatility of all stocks in month  $t$ ,  $UNEMP_t$  is the national unemployment rate in month  $t$ ,  $UEI_t$  is the unexpected inflation in month  $t$ , where the average of twelve most recent inflation realizations is used to estimate the expected level of inflation,  $MP_t$  is the monthly growth in industrial production,  $RP_t$  is the monthly risk premium, measured as the difference between the yields of Moody's BAA-rated corporate bond and AAA-rated corporate bond, and  $TS_t$  is the term spread, measured as the difference between the yield of a constant-maturity ten-year Treasury bond and the yield of a three-month Treasury bill). As before, the idiosyncratic volatility for each stock is estimated each month using daily returns data, where stocks with fewer than 17 daily observations are excluded.

In the regression specification, the key explanatory variable is the market-wide uncertainty measure. It is the cross-sectional mean idiosyncratic stock volatility during a given month, where all CRSP common stocks are used to compute the measure.<sup>24</sup> Additionally, among the macro-economic variables, the unexpected inflation rate and the unemployment rate are likely to indicate the level of aggregate uncertainty in the economy.

The estimation results are reported in Table VI. Consistent with the results on stock-level uncertainty, I find that periods of high mean idiosyncratic volatility are associated with stronger behavioral biases. Both the disposition effect and overconfidence biases are

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<sup>24</sup>I checked the robustness of my results using two other measures of market-wide uncertainty: (i) the mean monthly turnover and (ii) Michigan consumer sentiment index. The sentiment index captures people's opinions about both current and future economic conditions. The results (available upon request) with these alternative measures are similar to the reported results.

stronger when mean idiosyncratic volatility is higher. Furthermore, investors’ biases are stronger during times when the U.S. unemployment levels are higher. Additionally, in the overconfidence regression, the unexpected inflation variable has a positive coefficient estimate. Collectively, the time-series regression estimates indicate that behavioral biases are stronger when market-wide uncertainty is higher.

### *C. Do Investors Seek Familiar Stocks During Uncertain Times?*

Does the preference for local stocks also increase when market-wide uncertainty is higher? Previous studies (e.g., Huberman (2001), Grinblatt and Keloharju (2001a), Zhu (2002), Ivković and Weisbenner (2005)) have shown that individual investors prefer local stocks. This preference may at least be partially induced by investors’ familiarity bias, where they may perceive local stocks as being less risky or may have a perception of superior information (“they think they know more”). During times of greater uncertainty, investors may gravitate more toward local and familiar stocks, and additionally, they may shun non-local stocks.

To examine the relation between market-wide uncertainty and local bias, I again estimate the time-series model (see equation (6)), where the dependent variable ( $BIAS_t$ ) is the aggregate local bias of investors in the sample.<sup>25</sup> The aggregate local bias in month  $t$  is the cross-sectional mean local bias of all investors in the sample. In untabulated results, I find that, similar to the results for overconfidence and the disposition effect biases, local bias is stronger when there is greater market-wide uncertainty.<sup>26</sup> Specifically, the lagged idiosyncratic volatility variable has a significantly positive coefficient estimate (= 0.103 with a  $t$ -stat of 2.310) while lagged unemployment rate has a positive but insignificant coefficient

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<sup>25</sup>The local bias ( $LB$ ) measure is defined as,  $LB = D_{act} - D_{mkt}$ , where  $D_{act}$  is the distance between an investor’s location and her stock portfolio and  $D_{mkt}$  is the distance between an investor’s location and the market portfolio. The distance between an investor’s location and her portfolio is defined as,  $D_{act} = \sum_{i=1}^N w_i D_i$ , where  $N$  is the number of stocks in the portfolio,  $w_i$  is the weight of stock  $i$  in the portfolio, and  $D_i$  is the distance between an investor’s zipcode and the zipcode of a firm’s headquarters. The distance between an investor’s location and the market portfolio is defined in an analogous manner. See Coval and Moskowitz (2001) and Zhu (2002) for details of this measure. Note that my results are very similar when I use other related measures of local bias (e.g., the proportion of portfolio that is invested in firms located within a 100 or 250 mile radius from an investor’s location).

<sup>26</sup>For brevity I do not report these results but they are available upon request.

estimate. Additionally, all macro-economic variables have insignificant estimates.

Overall, the time-series results indicate that even market-wide uncertainty exacerbates investors' behavioral biases. This evidence supports the extended form of Hirshleifer's (2001) conjecture and indicates that investors' misperceptions are stronger not only in the "dusty corners of the market place" but also during "dark and uncertain times".

## V. Summary and Conclusion

This paper examines whether individual investors exhibit stronger behavioral biases when value ambiguity or information uncertainty is higher. I primarily focus on two behavioral biases, namely, investor overconfidence and the disposition effect, which are perhaps two of the most widely documented biases in the recent behavioral finance literature. Using a six year (1991 to 1996) panel of retail stock holdings and trades, I find that investors are more overconfident and exhibit stronger disposition effect when stocks are more difficult to value. Additionally, because narrow framing induces disposition effect among investors (Kumar and Lim (2005)), I also find that investors are more likely to frame their decisions narrowly when value ambiguity is higher. Furthermore, motivated by the findings in Barber, Odean, and Zhu (2003), I use trading correlation as a proxy for other behavioral biases such as limited attention and representativeness. Using this proxy, I find that other behavioral biases also get amplified when stock valuation is more difficult. Taken together, these results provide strong empirical support to theoretical studies (Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Hirshleifer (2001)) which posit that behavioral biases would be stronger among stocks which operate in informationally sparse environments and are more difficult to value.

For additional robustness, I also examine a direct extension of Hirshleifer's (2001) fundamental conjecture. If stock-level uncertainty exacerbates investors' behavioral biases, it is very likely that uncertainty at an aggregate level, i.e., market-wide (or economy-wide) uncertainty, would induce stronger behavioral biases. Consistent with this expectation, I find that overconfidence and the disposition effect biases are stronger when there is greater

market-wide uncertainty, as reflected by higher mean stock-level volatility and higher unemployment rate. Market uncertainty also exacerbates investors' local bias. During times of greater uncertainty, investors gravitate more toward local and familiar stocks while they shun non-local stocks. Taken together, these results support the extended form of Hirshleifer's (2001) conjecture and indicate that investors' misperceptions are stronger not only in the "dusty corners of the market place" but also during "dark and uncertain times". Collectively, my results indicate that both stock-specific and market-wide uncertainty exacerbates behavioral biases among individual investors.

These results also provide several pointers for future research. For instance, the results in the paper may be used to better identify the main determinants of idiosyncratic volatility. Does higher idiosyncratic volatility reflect more informed trading or more severe behavioral biases? While higher idiosyncratic volatility exacerbates investors' behavioral biases, those biases, in turn, may increase idiosyncratic volatility.<sup>27</sup> Additionally, given that both overconfidence and the disposition effect exhibit similar variations across stock characteristics, there may be a common and a more fundamental determinant of the two behavioral biases. It would also be interesting to examine whether value ambiguity or information uncertainty has similar influence on institutional investors. Institutions may exhibit similar behavior as individuals in the cross-section of stocks or they may take advantage of individual investors' biases using their private information and thus may exhibit relatively weaker behavioral biases when individual biases are stronger. I investigate these issues in my ongoing research.

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<sup>27</sup>For instance, Roll (1988) suggests that lower  $R^2$  (i.e., higher idiosyncratic volatility) in asset pricing models reflects "either private information or else occasional frenzy unrelated to concrete information".

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**Table I**  
**Overconfidence and the Disposition Effect Measures: Summary Statistics**

This table reports the summary statistics for stock-level overconfidence and disposition effect measures. Investor overconfidence is defined as the  $k$ -day post-trade sell-buy return differential (*PTSBD*) and the disposition effect measure is defined as the difference between investors' propensity to realize gains (*PGR*) and their propensity to realize losses (*PLR*). *PGR* is the proportion of gains realized and it is defined as the ratio of the number of "winners" (stock positions where an investor experiences a gain) realized and the total number of winners (realized + paper). *PLR* is the proportion of losses realized and is defined in an analogous manner. The *PGR* and *PLR* ratio is an alternative measure of the disposition effect. The overconfidence and disposition effect measures are defined for each stock using all executed trades during the six year sample period. The individual investor data are from a large U.S. discount brokerage house for the period spanning 1991 to 1996.

*Panel A: Stock-Level Overconfidence (k-day PTSBD in Percent)*

Measure	Mean	Median	Std Dev	10th Pctl	25th Pctl	75th Pctl	90th Pctl
<i>PTSBD</i> (5)	0.027	-0.039	2.747	-2.467	-1.028	0.999	2.636
<i>PTSBD</i> (10)	0.076	-0.028	3.472	-3.313	-1.365	1.481	3.485
<i>PTSBD</i> (21)	-0.081	-0.150	4.961	-4.816	-2.111	1.923	4.665
<i>PTSBD</i> (42)	-0.093	-0.308	7.047	-6.921	-3.030	2.768	7.055
<i>PTSBD</i> (63)	0.086*	-0.291	8.774	-8.483	-3.810	3.588	9.225
<i>PTSBD</i> (84)	0.216**	-0.295	10.236	-9.666	-4.064	4.258	10.472
<i>PTSBD</i> (126)	0.466**	-0.224	12.767	-11.621	-5.097	5.282	13.124
<i>PTSBD</i> (252)	1.132***	-0.284	18.116	-16.247	-7.147	7.517	19.096

*Panel B: Stock-Level Disposition Effect*

Measure	Mean	Median	Std Dev	10th Pctl	25th Pctl	75th Pctl	90th Pctl
<i>PGR-PLR</i>	7.347***	5.831	10.441	-3.077	0.975	12.097	19.965
<i>PGR/PLR</i>	2.307***	1.688	2.327	0.709	1.120	2.465	4.035

**Table II**  
**Value Ambiguity and Investor Overconfidence**

This table reports the mean overconfidence measures for value ambiguity sorted stock portfolios. Investor overconfidence is defined as the  $k$ -day post-trade sell-buy return differential (*PTSBD*). The overconfidence measures are defined for each stock using all executed trades during the six year sample period. The value ambiguity is measured using idiosyncratic volatility. The idiosyncratic volatility for each stock is estimated each month using daily returns data, where stocks with fewer than 17 daily observations are excluded. The sample period mean of monthly volatility measures is used to measure the value ambiguity of a stock. The individual investor data are from a large U.S. discount brokerage house for the period spanning 1991 to 1996.

Days	Idiosyncratic Volatility Quintiles				
	Q1	Q2	Q3	Q4	Q5
5	-0.162***	-0.190***	0.029	0.060*	0.438***
10	-0.240***	-0.300***	-0.009	0.057**	0.570***
21	-0.405***	-0.445***	-0.072	0.065	0.491*
42	-0.504***	-0.538***	0.014	0.155	0.840**
63	-0.563***	-0.532***	0.247	0.171**	1.478***
84	-0.522***	-0.461**	0.405	0.237*	1.593***
126	-0.861***	-0.485**	0.446	0.764***	2.669***
252	-1.232***	-0.550	0.616	1.647**	4.673***

**Table III**  
**Stock Characteristics and Investor Overconfidence:**  
**Cross-Sectional Regression Estimates**

This table reports the cross-sectional regression estimates, where the level of investor overconfidence in a given stock, measured over the six year sample period, is the dependent variable. Investor overconfidence is defined as the  $k$ -day post-trade sell-buy return differential (*PTSBD*). Three measures of value ambiguity, namely, idiosyncratic volatility, monthly volume turnover, and firm age are used as primary independent variables. The idiosyncratic volatility measure is the variance of the residual obtained by fitting a four-factor model to the stock returns time-series. The idiosyncratic volatility for each stock is estimated each month using daily returns data, where stocks with fewer than 17 daily observations are excluded. Monthly volume turnover is the ratio of the number of shares traded in a month and the number of shares outstanding. The sample period averages of these two measures are employed in the regressions. Firm age is the number of years since the stock first appears in the CRSP database and December 1996. Additionally, the following control variables are employed: (i) market beta, which is estimated using past 60 months of data, (ii) firm size, (iii) book-to-market ratio, (iv) past twelve-month stock returns, and (v) dividend paying stock dummy which is set to one if the stock pays dividend at least once during the sample period. The sample period averages of variables (i)-(iv) are employed in the regressions. The estimates in columns (1)-(3) are for  $k = 252$  days and for robustness, in column (4), I report the estimates for  $k = 126$  days. The  $t$ -statistic for the coefficient estimate is reported in parenthesis below the estimate. The individual investor data are from a large U.S. discount brokerage house for the period spanning 1991 to 1996.

Dependent variable: Mean PTSBD for stock $i$ during the 1991 to 1996 sample period.				
Variable	(1)	(2)	(3)	(4)
<i>Intercept</i>	0.010 (0.714)	0.009 (0.665)	0.012 (0.862)	0.020 (1.411)
<i>Idiosyncratic Volatility</i>	0.113 (5.450)		0.078 (2.716)	0.065 (2.837)
<i>Monthly Turnover</i>	-0.008 (-0.850)		0.057 (4.334)	0.042 (3.752)
<i>Firm Age</i>	-0.040 (-2.769)		-0.061 (-3.988)	-0.031 (-1.985)
<i>Market Beta</i>		-0.016 (-0.850)	-0.022 (-1.157)	-0.013 (-0.730)
<i>Log(Firm Size)</i>		-0.122 (-6.520)	-0.127 (-5.378)	-0.142 (-5.857)
<i>Book-To-Market Ratio</i>		-0.037 (-1.905)	-0.031 (-2.557)	-0.049 (-1.956)
<i>Past 12-month Stock Returns</i>		0.022 (0.959)	-0.024 (-0.939)	-0.060 (-2.183)
<i>Dividend Paying Dummy</i>		-0.037 (-3.289)	-0.015 (-1.342)	-0.020 (-1.855)
<i>Number of Stocks</i>	4,957	4,813	4,785	4,785
<i>Adjusted R<sup>2</sup></i>	1.29%	1.56%	2.33%	2.64%

**Table IV**  
**Stock Characteristics and the Disposition Effect:**  
**Cross-Sectional Regression Estimates**

This table reports the cross-sectional regression estimates, where the level of disposition effect ( $DE$ ) in a given stock, measured over the six year sample period, is the dependent variable. Three measures of value ambiguity, namely, idiosyncratic volatility, monthly volume turnover, and firm age are used as primary independent variables. The idiosyncratic volatility measure is the variance of the residual obtained by fitting a four-factor model to the stock returns time-series. The idiosyncratic volatility for each stock is estimated each month using daily returns data, where stocks with fewer than 17 daily observations are excluded. Monthly volume turnover is the ratio of the number of shares traded in a month and the number of shares outstanding. The sample period averages of these two measures are employed in the regressions. Firm age is the number of years since the stock first appears in the CRSP database and December 1996. Additionally, the following control variables are employed: (i) market beta, which is estimated using past 60 months of data, (ii) firm size, (iii) book-to-market ratio, (iv) past twelve-month stock returns, and (v) dividend paying stock dummy which is set to one if the stock pays dividend at least once during the sample period. The sample period averages of variables (i)-(iv) are employed in the regressions. The estimates in columns (1)-(3) are for the first  $DE$  measure ( $PGR - PLR$ ) and for robustness, in column (4), I report the estimates for the second  $DE$  measure ( $PGR/PLR$ ).  $PGR$  is the proportion of gains realized and it is defined as the ratio of the number of “winners” (stock positions where an investor experiences a gain) realized and the total number of winners (realized + paper).  $PLR$  is the proportion of losses realized and is defined in an analogous manner. The  $t$ -statistic for the coefficient estimate is reported in parenthesis below the estimate. The individual investor data are from a large U.S. discount brokerage house for the period spanning 1991 to 1996.

Dependent variable: Disposition effect in stock $i$ during the 1991 to 1996 sample period.				
Variable	(1)	(2)	(3)	(4)
<i>Intercept</i>	-0.023 (-1.742)	-0.021 (-1.748)	-0.019 (-1.452)	-0.035 (-2.669)
<i>Idiosyncratic Volatility</i>	0.237 (12.392)		0.148 (6.264)	0.124 (5.546)
<i>Monthly Turnover</i>	0.037 (4.246)		0.127 (11.106)	0.043 (3.084)
<i>Firm Age</i>	-0.002 (-0.196)		-0.004 (-0.988)	-0.003 (-0.589)
<i>Market Beta</i>		0.104 (6.923)	0.085 (5.634)	0.013 (0.862)
<i>Log(Firm Size)</i>		-0.224 (-12.418)	-0.207 (-9.094)	-0.123 (-4.859)
<i>Book-To-Market Ratio</i>		-0.022 (-1.949)	-0.025 (-1.107)	-0.003 (-0.181)
<i>Past 12-month Stock Returns</i>		0.028 (1.228)	-0.075 (-2.781)	-0.064 (-3.583)
<i>Dividend Paying Dummy</i>		-0.056 (-4.814)	-0.054 (-4.725)	-0.005 (-0.410)
<i>Number of Stocks</i>	5,129	4,790	4,759	4,759
<i>Adjusted R<sup>2</sup></i>	5.89%	5.44%	8.65%	5.03%

**Table V**  
**Value Ambiguity and Mean Trading Correlations**

This table reports the mean trading correlations for low (quintiles 1-2) and high (quintiles 4-5) value ambiguity stock portfolios. Value ambiguity of a stock is measured using its idiosyncratic volatility. The idiosyncratic volatility for each stock is estimated each month using daily returns data, where stocks with fewer than 17 daily observations are excluded. The sample period mean of monthly volatility measures is used to measure the value ambiguity of a stock. Trading activities are measured using the buy-sell imbalance (*BSI*) measure, where *BSI* for portfolio *p* in month *t* is defined as,  $BSI_{pt} = \frac{100}{N_{pt}} \sum_{i=1}^{N_{pt}} BSI_{it}$  where the *BSI* for stock *i* in month *t* is defined as  $BSI_{it} = [\sum_{j=1}^{D_t} (VB_{ijt} - VS_{ijt})] / [(\sum_{j=1}^{D_t} (VB_{ijt} + VS_{ijt}))]$ . Here,  $D_t$  is the number of days in month *t*,  $VB_{ijt}$  is the buy volume (measured in dollars) for stock *i* on day *j* in month *t*,  $VS_{ijt}$  is the sell volume (measured in dollars) for stock *i* on day *j* in month *t*, and  $N_{pt}$  is the number of stocks in portfolio *p* formed in month *t*. For each set of randomization tests, 1,000 pairs of non-overlapping *k*-stock portfolios are formed, where *k* = 25, 50, 75, and 100. The *BSI* time-series for each stock portfolio pair is obtained and the *BSI* correlation is computed. The means of those *BSI* correlations are reported in the table. In Panel A (Panel B), the results for raw (residual) *BSI* measures are reported. The residual *BSI* is obtained by removing the common dependence of *BSI* on the market using the following regression:

$$BSI_{pt} = b_0 + b_1 RMRF_t + \epsilon_{pt}.$$

Here,  $BSI_{pt}$  is the buy-sell imbalance index for portfolio *p* in month *t*,  $RMRF_t$  is the market return in excess of the riskfree rate in month *t*, and  $\epsilon_{pt}$  is the residual *BSI* for portfolio *p* in month *t*. The individual investor data are from a large U.S. discount brokerage house for the period spanning 1991 to 1996.

*Panel A: Raw Buy-Sell Imbalance Correlations*

Portfolio Size	Low VA	High VA	High-Low	<i>t</i> -stat
25	0.092	0.151	0.059	7.848
50	0.173	0.272	0.099	13.045
75	0.349	0.472	0.123	20.024
100	0.419	0.547	0.128	27.454

*Panel B: Residual Buy-Sell Imbalance Correlations*

Portfolio Size	Low VA	High VA	High-Low	<i>t</i> -stat
25	0.086	0.144	0.058	7.765
50	0.162	0.266	0.104	13.551
75	0.330	0.463	0.133	21.359
100	0.398	0.538	0.140	28.731

**Table VI**  
**Macro-Economic Conditions and Behavioral Biases:**  
**Time-Series Regression Estimates**

This table reports the estimation results for the following time-series regression model:

$$BIAS_t = b_0 + b_1 IDIOVOL_{t-1} + b_2 UNEMP_{t-1} + b_3 UEI_{t-1} + b_4 MP_{t-1} + b_5 \Delta RP_{t-1} + b_6 \Delta TS_{t-1} + b_7 BIAS_{t-1} + \epsilon_t.$$

The *BIAS* variable is the aggregate behavioral bias (overconfidence or the disposition effect) in a given month. *IDIOVOL<sub>t</sub>* is the mean idiosyncratic volatility of all stocks in month *t*, *UNEMP<sub>t</sub>* is the national unemployment rate in month *t*, *UEI<sub>t</sub>* is the unexpected inflation in month *t*, where the average of twelve most recent inflation realizations is used to estimate the expected level of inflation, *MP<sub>t</sub>* is the monthly growth in industrial production, *RP<sub>t</sub>* is the monthly *risk premium*, measured as the difference between the yields of Moody's BAA-rated corporate bond and AAA-rated corporate bond, and *TS<sub>t</sub>* is the *term spread*, measured as the difference between the yield of a constant-maturity 10-year Treasury bond and the yield of a 3-month Treasury bill). The idiosyncratic volatility for each stock is estimated each month using daily returns data, where stocks with fewer than 17 daily observations are excluded. To allow for direct comparison among the coefficient estimates, variables are standardized so that each variable has a mean of 0 and a standard deviation of 1. The Newey-West adjusted *t*-values (with three lags) of the coefficient estimates are reported. The individual investor data are from a large U.S. discount brokerage house for the period spanning 1991 to 1996.

Dependent variable: Aggregate behavioral bias (overconfidence or the disposition effect) in month *t*.

Variable	Overconfidence				Disposition Effect			
	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat	Coeff	<i>t</i> -stat
<i>Intercept</i>	-0.050	-0.401	-0.043	-0.347	0.001	0.110	-0.053	-0.618
<i>Lagged IDIOVOL</i>	0.283	2.451	0.303	2.308	0.404	2.756	0.207	2.043
<i>Lagged UNEMP</i>			0.082	2.504			0.329	2.710
<i>Lagged UEI</i>			0.257	1.858			-0.005	-0.049
<i>Lagged MP</i>			0.204	1.488			-0.071	-0.682
<i>Lagged ΔRP</i>			0.102	0.991			0.057	1.150
<i>Lagged ΔTS</i>			-0.106	-2.075			-0.073	-0.923
<i>Lagged BIAS</i>			-0.121	-0.952			0.286	2.331
<i>Number of Months</i>		71		70		71		70
<i>Adjusted R<sup>2</sup></i>		7.37%		18.15%		15.11%		32.57%



**Table VII**  
**Robustness Tests: Overconfidence and Disposition Effect Regression Estimates**

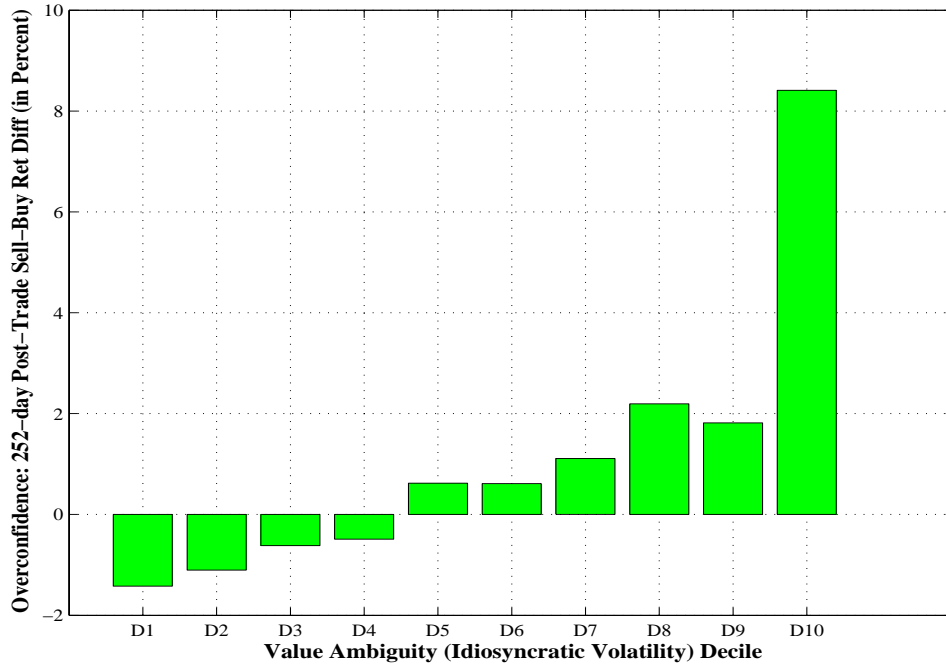
This table reports the uncertainty variable estimates for overconfidence and disposition effect regression models. In the overconfidence regression, the 252-day post-trade sell-buy return differential (*PTSBD*) is the dependent variable and three measures of value ambiguity (idiosyncratic volatility (Idio Vol), monthly volume turnover (Mon Turn), and firm age) along with the following firm-level control variables are employed: (i) market beta, which is estimated using past 60 months of data, (ii) firm size, (iii) book-to-market ratio, (iv) past twelve-month stock returns, and (v) dividend paying stock dummy which is set to one if the stock pays dividend at least once during the sample period. The sample period averages of variables (i)-(iv) are employed in the regressions. For brevity, only the estimates for the value ambiguity variables are shown. In the disposition effect regression, the level of disposition effect (*DE*) in a given stock, measured over the six year sample period, is the dependent variable. *DE* is defined as  $PGR - PLR$ , where *PGR* is the proportion of gains realized and it is defined as the ratio of the number of “winners” (stock positions where an investor experiences a gain) realized and the total number of winners (realized + paper) and *PLR* is the proportion of losses realized and is defined in an analogous manner. The “adjusted” disposition effect (*ADE*) measure is defined as  $APRG - EPRG$ . Here, *EPRG* is the proportion of winners among all paper trades and indicates investors’ expected propensity to realize gains. *APRG* is the proportion of winners among all actual trades and indicates investors’ actual propensity to realize gains. The subsample of high institutional ownership (IO) consists of stocks with institutional ownership in the highest quintile. The *t*-statistic for the coefficient estimate is reported in parenthesis below the estimate. The individual investor data are from a large U.S. discount brokerage house for the period spanning 1991 to 1996. The institutional investor data are from Thomson Financial.

*Panel A: Overconfidence Regression Estimates*

Robustness Test	Idio Vol	Mon Turn	Firm Age	Adj $R^2$
<i>Overconfidence Regression: 1991-93 Subsample</i>	0.071 (2.828)	0.061 (2.201)	0.004 (1.209)	1.74%
<i>Overconfidence Regression: 1994-96 Subsample</i>	0.151 (3.527)	0.036 (2.705)	-0.076 (-3.534)	2.20%
<i>Overconfidence Regression: High IO Subsample</i>	0.104 (2.279)	0.074 (3.293)	-0.093 (-4.073)	1.82%

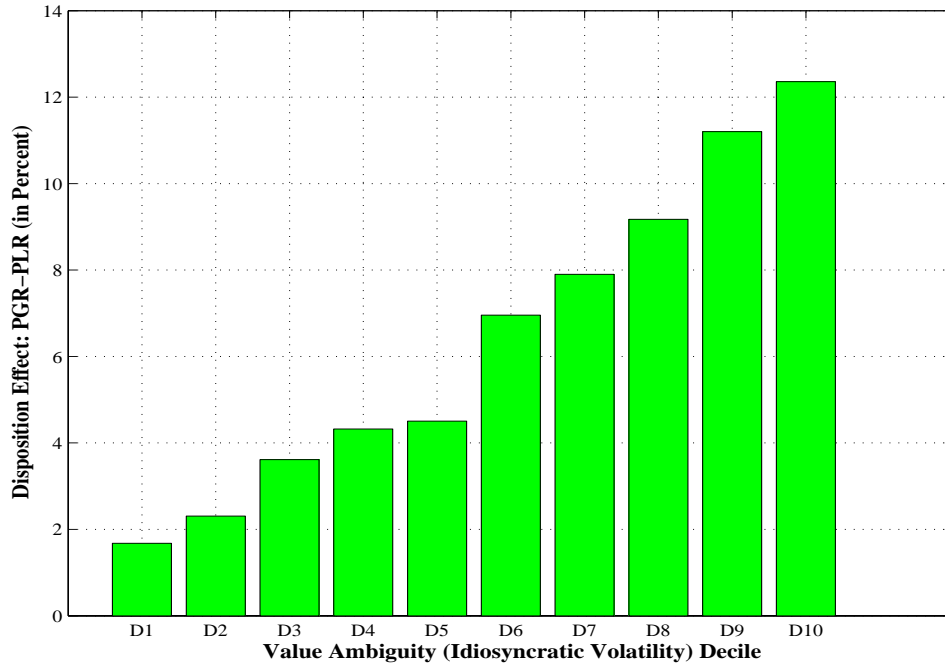
*Panel B: Disposition Effect Regression Estimates*

Robustness Test	Idio Vol	Mon Turn	Firm Age	Adj $R^2$
<i>Disposition Effect Regression: 1991-93 Subsample</i>	0.145 (7.922)	0.097 (6.396)	-0.033 (-0.254)	7.26%
<i>Disposition Effect Regression: 1994-96 Subsample</i>	0.115 (3.249)	0.133 (11.479)	0.021 (1.382)	6.44%
<i>Adjusted Disposition Effect Measure</i>	0.089 (4.523)	0.122 (10.468)	-0.026 (-1.126)	6.02%
<i>Disposition Effect Regression: High IO Subsample</i>	0.198 (4.799)	0.162 (7.045)	-0.028 (-0.945)	11.56%

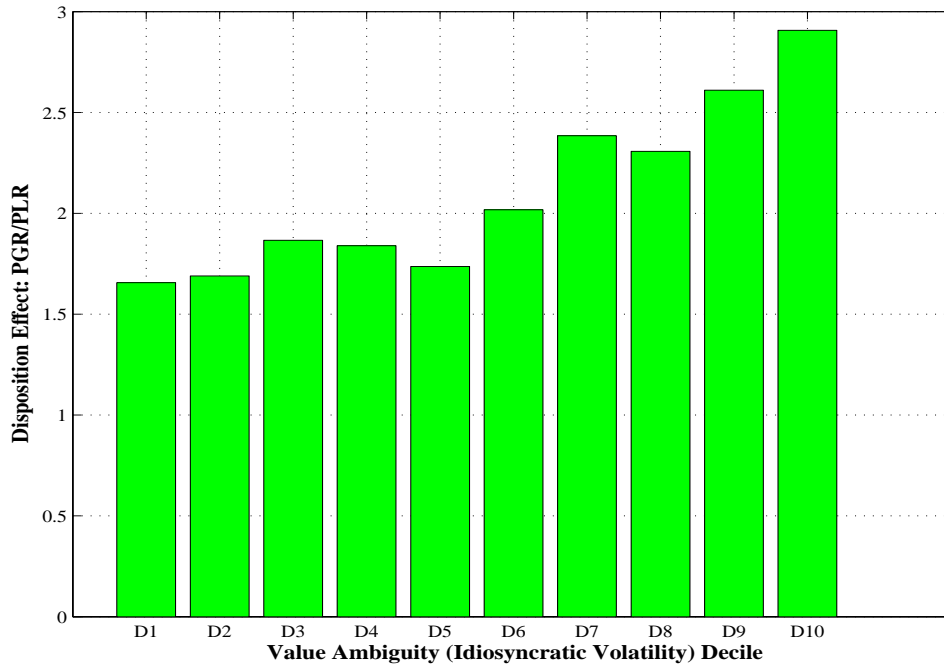


**Figure 1. Value ambiguity and investor overconfidence.** This figure shows the 252-day post-trade sell-buy return differential (a measure of investor overconfidence) for idiosyncratic volatility (a measure of a stock's value ambiguity) deciles. The idiosyncratic volatility for each stock is estimated each month using daily returns data, where stocks with fewer than 17 daily observations are excluded. The sample period mean of monthly volatility measures is used to measure the value ambiguity of a stock. The individual investor data are from a large U.S. discount brokerage house for the period spanning 1991 to 1996.

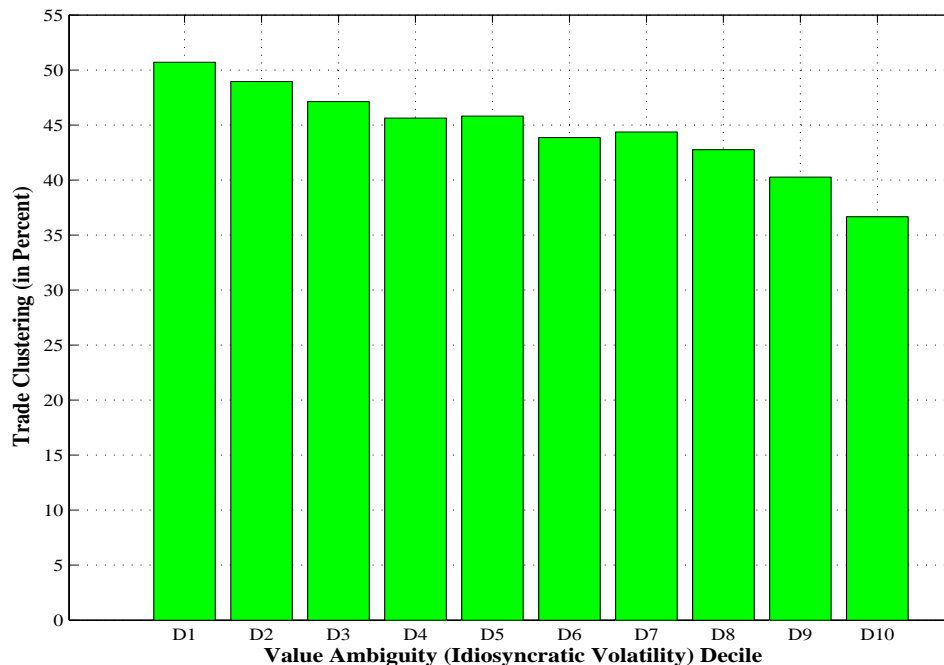
Panel A:  $PGR - PLR$  Measure



Panel B:  $PGR/PLR$  Measure



**Figure 2. Value ambiguity and the disposition effect.** This figure shows the mean disposition effect measure ( $PGR - PLR$ ) for idiosyncratic volatility (a measure of a stock’s value ambiguity) deciles.  $PGR$  is the proportion of gains realized and it is defined as the ratio of the number of “winners” (stock positions where an investor experiences a gain) realized and the total number of winners (realized + paper).  $PLR$  is the proportion of losses realized and is defined in an analogous manner. The idiosyncratic volatility for each stock is estimated each month using daily returns data, where stocks with fewer than 17 daily observations are excluded. The sample period mean of monthly volatility measures is used to measure the value ambiguity of a stock. The individual investor data are from a large U.S. discount brokerage house for the period spanning 1991 to 1996.



**Figure 3. Value ambiguity and narrow framing.** This figure shows the trade clustering (a measure of narrow framing) for idiosyncratic volatility (a measure of a stock’s value ambiguity) deciles. The stock-level trade clustering measure is the proportion of trades which are executed simultaneously in a given month. I assume that trades which are executed simultaneously with other trades by the same investor on the same day are likely to be broadly framed. In contrast, trades which are executed separately are likely to be narrowly framed. The idiosyncratic volatility for each stock is estimated each month using daily returns data, where stocks with fewer than 17 daily observations are excluded. The sample period mean of monthly volatility measures is used to measure the value ambiguity of a stock. The individual investor data are from a large U.S. discount brokerage house for the period spanning 1991 to 1996.