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# Hard-to-Value Stocks, Behavioral Biases, and Informed Trading

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## Abstract

This paper uses investor-level data to provide direct evidence for an intuitive but surprisingly untested proposition that investors make larger investment mistakes when valuation uncertainty is higher and stocks are more difficult to value. Using multiple measures of valuation uncertainty and multiple behavioral bias proxies, I show that individual investors exhibit stronger behavioral biases when stocks are harder to value and when market-level uncertainty is higher. I also find that informed trading intensity is higher among stocks where individual investors exhibit stronger behavioral biases. Collectively, these results indicate that uncertainty at both stock and market levels amplifies individual investors' behavioral biases and that relatively better informed investors attempt to exploit those biases.

## I. Introduction

Experimental evidence from research in psychology indicates that people are more likely to use heuristics and "rules of thumb" when they encounter more difficult problems, especially if the feedback is delayed or noisy. Such intuitive decisions are often associated with stronger behavioral biases (e.g., Kahneman and Tversky (1973), Kahneman (2003)). For instance, people exhibit higher levels of overconfidence when they engage in nonmechanical tasks and make decisions in relatively more difficult environments (e.g., Lichtenstein and Fischhoff (1977), Einhorn (1980), and Griffin and Tversky (1992)).

Recent theoretical behavioral finance models (Daniel, Hirshleifer, and Subrahmanyam (1998), (2001), Hirshleifer (2001)) formalize this intuition in the context of investment decisions and posit that investors' behavioral biases will

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be stronger when they trade hard-to-value stocks that operate in informationally sparse environments. In particular, Hirshleifer ((2001), p. 1537) conjectures 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." Due to the intuitive appeal of this conjecture, the empirical literature in behavioral finance either implicitly or explicitly *assumes* that investors' behavioral biases will be stronger when stocks are more difficult to value. Surprisingly, there is very little direct empirical support for the theoretical predictions.

In this study, I use investor-level portfolio holdings and trading data to provide *direct* evidence for this intuitive conjecture. Using multiple measures of valuation uncertainty (VU) and multiple proxies for behavioral biases, I examine whether individual investors' biases are amplified when stocks are more difficult to value. Using a proxy for informed trading, I also examine whether relatively better informed investors attempt to exploit individual investors' behavioral biases.

In the baseline analysis, I conduct cross-sectional tests and examine whether individual investors are more reluctant to realize their losses (i.e., exhibit greater disposition effect) and appear more overconfident when stocks are more difficult to value. Motivated by Jiang, Lee, and Zhang (2005) and Zhang (2006), I employ three distinct but related measures of VU: idiosyncratic volatility, volume turnover, and firm age.[1] To measure the disposition effect, I follow the Odean (1998) methodology, and to measure investor overconfidence, inspired by Odean (1999), I use the $k$-day post-trade sell-buy return differential (PTSBD) as an overconfidence proxy.

The empirical results indicate that individual investors make larger investment mistakes and exhibit stronger behavioral biases when stocks are more difficult to value. Both the disposition and the overconfidence biases are stronger among those stocks. The cross-sectional tests also indicate that informed investors attempt to exploit individual investors' behavioral biases. Using the probability of informed trading (PIN) measure developed in Easley, Hvidkjaer, and O'Hara (2002), I find that informed trading intensity is higher among stocks where individual investors exhibit stronger behavioral biases.

For robustness, I examine whether the positive bias-uncertainty relation generalizes to other uncertainty measures and other types of behavioral biases. I consider three alternative measures that attempt to capture the level of uncertainty in fundamentals: cash flow volatility, earnings volatility, and the level of intangible firm assets. Motivated by the findings in Barber, Odean, and Zhu (2009), I use trading correlation as a proxy for other biases such as limited attention and representativeness.[2] Furthermore, following Kumar and Lim (2008), I use trade

[1] Unlike some previous researchers, I do not use dispersion in analysts' forecasts of future earnings as a VU proxy because a large number of firms with high uncertainty (as measured by other proxies) do not have analyst coverage and must be excluded from the analysis. See Pástor and Veronesi (2003) for an additional discussion.

[2] Barber et al. (2009) show that psychological biases such as limited attention, representativeness, and the disposition effect induce correlated trading among individual investors.

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clustering (TC) as a proxy for the degree of narrow framing in investment decisions (e.g., Kahneman and Lovallo (1993), Kahneman (2003), and Barberis and Huang (2009)).[3]

The robustness test results indicate that the bias-uncertainty relation generalizes to other uncertainty measures and other types of biases. The fundamentals-based uncertainty measures indicate that behavioral biases are stronger when cash flow or earnings are more volatile or when a greater proportion of firms' assets are intangible. I also find that trading correlations are stronger and the degree of TC is lower (i.e., narrower decision frames are used) among stocks that are more difficult to value. This evidence indicates that different types of biases can get amplified when stocks are harder to value.

To gather additional support for the main conjecture, I estimate time-series regressions to examine whether the disposition and the overconfidence biases get exacerbated when market-level uncertainty is higher. I also examine whether the market-level uncertainty exacerbates investors' local bias (LB) (e.g., Huberman (2001), Grinblatt and Keloharju (2001), Zhu (2002), and Ivković and Weisbenner (2005)) and home bias (e.g., French and Poterba (1991), Bohn and Tesar (1996)).[4] The local and home bias measures offer a distinct advantage over other bias proxies that are computed using returns. Unlike those bias proxies, the local and home bias measures do not use realized returns and are less sensitive to potential concerns about endogeneity.

I consider four proxies for market-level uncertainty: i) the mean firm-level volatility, ii) the Chicago Board Options Exchange volatility index (VIX), iii) the Michigan consumer sentiment index, and iv) the national unemployment rate. Using these aggregate uncertainty proxies, I find that investors are more reluctant to realize their losses and exhibit greater overconfidence when aggregate uncertainty is higher. I also find that during times of greater market-level uncertainty, investors exhibit a stronger preference for familiar stocks and tilt their portfolios more toward domestic and local stocks.

Taken together, the empirical evidence indicates that individual investors commit larger investment mistakes and exhibit stronger behavioral biases in more uncertain environments. Both stock-level and market-wide uncertainty adversely influence their decisions. These results are consistent with the experimental evidence and provide direct empirical support for recent behavioral models, which posit that biases are stronger when stocks are more difficult to value (Daniel et al. (1998), (2001), Hirshleifer (2001)). While the results from individual tests could have alternative interpretations, the strikingly consistent results from multiple uncertainty proxies, multiple bias proxies, and both cross-sectional and time-series tests appear most aligned with the hypothesis that greater uncertainty induces stronger behavioral biases.

[3]Investors who engage in *narrow framing* are more likely to consider each decision as unique, often isolating the current choice from their past and future choices (Kahneman and Lovallo (1993), Kahneman (2003)). Typically, they ignore the interactions among multiple decisions, which could lead to inefficient choices.

[4]Investors who exhibit "LB" disproportionately tilt their portfolios toward familiar stocks in their neighborhood (e.g., their zip code), and "home biased" investors exhibit greater aversion to foreign securities.

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The rest of the paper is organized as follows. In Section II, I examine the relation between VU and the disposition effect. In Section III, I focus on the overconfidence bias. In Section IV, I examine whether market-level uncertainty influences investors' behavioral biases. In Section V, I conduct additional robustness tests. In Section VI, I examine whether better informed investors attempt to exploit individual investors' biases. I conclude in Section VII with a brief summary of the paper.

## II. Valuation Uncertainty and the Disposition Effect

To begin, I examine whether investors are more reluctant to realize losses when stocks are more difficult to value. When VU is high, several mechanisms can induce a stronger disposition effect. First, the prospect-theoretic explanation for the disposition effect (Shefrin and Statman (1985)) relies on a combination of regret aversion, loss aversion (Kahneman and Tversky (1979)), and stock-level mental accounting (Thaler (1980)). When idiosyncratic volatility is high, high price levels are more likely to be observed and investors are more likely to establish higher reference points for evaluating their individual stock positions. Higher reference points could also induce a greater feeling of regret. In both instances, the disposition effect is likely to get amplified.

Second, VU can exacerbate the disposition effect even when it is induced through other channels, such as a belief in mean reversion (e.g., Odean (1998)). The experimental evidence (Andreassen (1988)) indicates that people exhibit stronger "tracking" behavior (i.e., "buy low, sell high") when price volatility is higher because investors believe that price reversals are more likely. Thus, if the disposition effect is partially induced by a belief in mean reversion, investors would exhibit a stronger disposition effect when there is greater uncertainty about the true valuation of a stock.

Third, gambling tendencies could motivate some investors to hold on to their losses longer when idiosyncratic volatility is high. Investors with a gambling mind-set might wait for their stock gambles to yield the desired extreme payoff. Therefore, when uncertainty is high, those investors would be more reluctant to realize their losses and exhibit a strong disposition effect.

Last, the disposition effect could be amplified in uncertain environments through the overconfidence channel. If VU amplifies overconfidence by exacerbating biased self-attribution, overconfident investors would be less willing to accept their investment positions with losses as mistakes. Those investors would be more reluctant to realize their losses and could exhibit stronger disposition effect.

### A. Data

The main ingredient for the empirical analysis is the set of 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.[5] In addition, I obtain quarterly institutional holdings from Thomson Financial, including

[5]Further details on the individual investor database are available in Barber and Odean (2000).

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the end-of-quarter stock holdings of all institutions that file a form 13(F) with the Securities and Exchange Commission (Gompers and Metrick (2001)). I obtain prices, returns, volume, dividends, and market capitalization data from the Center for Research on Security Prices (CRSP) and monthly macroeconomic data from Datastream. Data on the quarterly book value of common equity, earnings, cash flow, PPE (property, plant, and equipment), and total assets are from Compustat.

I obtain a few data sets from several Web sites. The monthly U.S. unemployment data come from the Bureau of Labor Statistics (www.bls.gov). The daily Chicago Board Options Exchange VIX is at http://www.cboe.com/. I obtain the Michigan consumer sentiment index from http://www.sca.isr.umich.edu/. The monthly time series of the three Fama and French (1992), (1993) factors, the momentum factor, the New York Stock Exchange (NYSE) size break-points, and the book-to-market (BM) break-points come from Kenneth French's data library, available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

## B. Valuation Uncertainty Measures

To measure VU, I employ three distinct measures: i) idiosyncratic volatility, ii) volume turnover, and iii) firm age. The idiosyncratic volatility measure is the variance of the residual obtained by fitting a four-factor model to the stock return time series. I estimate the monthly idiosyncratic volatility for each stock using the daily returns data, excluding stocks with fewer than 17 daily observations.[6] The monthly volume turnover for a stock is the ratio of the number of shares traded in a month and the number of shares outstanding.[7] Firm age is defined as the number of years since the stock first appeared in the CRSP database.[8]

During the sample period, the correlations among the three uncertainty measures vary between $-0.066$ and 0.132. The moderate correlation estimates indicate that while the three uncertainty measures are related, they capture different aspects of VU.

## C. Stock-Level Disposition Effect Measures

To measure the disposition effect, I adapt Odean's (1998) PGR − PLR methodology and obtain stock-level measures of the disposition effect. Under this methodology, the disposition effect (DE) for stock $i$ is defined as

$$\text{(1)} \qquad \text{DE}_i = \text{PGR}_i - \text{PLR}_i, \qquad \text{where}$$

$$\text{(2)} \qquad \text{PGR}_i = \frac{N^i_{gr}}{N^i_{gr} + N^i_{gp}} \times 100, \qquad \text{PLR}_i = \frac{N^i_{lr}}{N^i_{lr} + N^i_{lp}} \times 100.$$

[6]The main results in the paper are very similar when I use other related idiosyncratic volatility measures computed using daily or monthly returns data.

[7]The turnover measure is adjusted for double-counting of NASDAQ trading volume.

[8]Firm age measured in this manner is obviously not very accurate, especially for NASDAQ stocks that were added to the CRSP database in December 1972. Thus, I use other proxies to measure VU.

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Here, $PGR_i$ ($PLR_i$) is the proportion of gains (losses) realized in stock $i$, $N^i_{gr}$ ($N^i_{lr}$) is the number of trades in stock $i$ where a gain (loss) is realized, and $N^i_{gp}$ ($N^i_{lp}$) is the number of potential or paper trades in stock $i$ associated with a gain (loss).[9]

I compute these measures by considering the actual and potential trades of all brokerage investors who hold and trade stock $i$ during a certain time period. A positive value of $DE_i$ indicates that a smaller proportion of losers are sold compared to the proportion of winners in the stock and, thus, the sample investors exhibit the disposition effect in stock $i$. The stock-level disposition effect can also be measured using the ratio of PGR and PLR (i.e., $DE_i = PGR_i/PLR_i$). In this case, investors exhibit the disposition effect if $DE_i > 1$.

To get reasonably accurate DE estimates, I only consider stocks with a minimum of 25 investor trades during the 6-year period, although the results are not sensitive to this choice. I find that the mean PGR − PLR measure is positive and significant, and the mean PGR/PLR measure is greater than 1. This evidence indicates that, on average, investors exhibit the disposition effect at the stock level. The mean stock-level DE of 7.35% is comparable to the mean investor-level DE of 5%–8% reported in Odean (1998). Furthermore, investors do not exhibit the disposition effect (i.e., $DE < 0$) in about 20% of stocks, while about 38% of stocks have PGR/PLR measures above 2 (i.e., investors exhibit very strong DE).

## D. Uncertainty and the Disposition Effect: Sorting Results

To examine whether the heterogeneity in the stock-level disposition effect is related to the uncertainty in stock valuation, I sort all CRSP stocks based on their mean monthly idiosyncratic volatility at the beginning of the sample period (year 1990). Then I measure the mean DE for stocks in the 10 idiosyncratic volatility decile portfolios. The sorting results are reported in Graph A of Figure 1. These univariate results indicate that investors exhibit a stronger disposition effect among stocks that are more difficult to value. The pattern is monotonic with the PGR − PLR measure, and in unreported results, I find that the pattern is similar but somewhat weaker with the PGR/PLR measure.

The results are similar even when I estimate the idiosyncratic volatility and the disposition effect measures year by year. Graph B of Figure 1 presents the year-by-year average disposition effect estimates for the top three (harder-to-value) and the bottom three (easier-to-value) idiosyncratic volatility deciles. To obtain this plot, I use the mean monthly idiosyncratic volatility measures in year $t$ to form the deciles and then compute the average disposition effect measures for those deciles in year $t + 1$. I find that each year, investors exhibit a stronger disposition effect when stocks have higher idiosyncratic volatility. Moreover, the disposition effect declines over time, but only for the subset of stocks that are easier to value.

[9]The potential trades or paper trades refer to trades that an investor could have executed at the time she executes an actual trade. The paper trades are identified by examining the composition of the investor portfolio at the time of an actual trade.

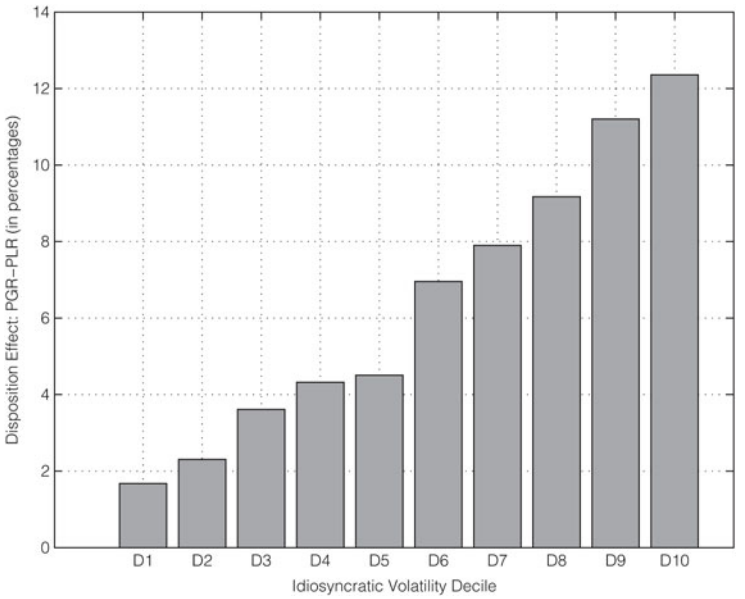
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FIGURE 1

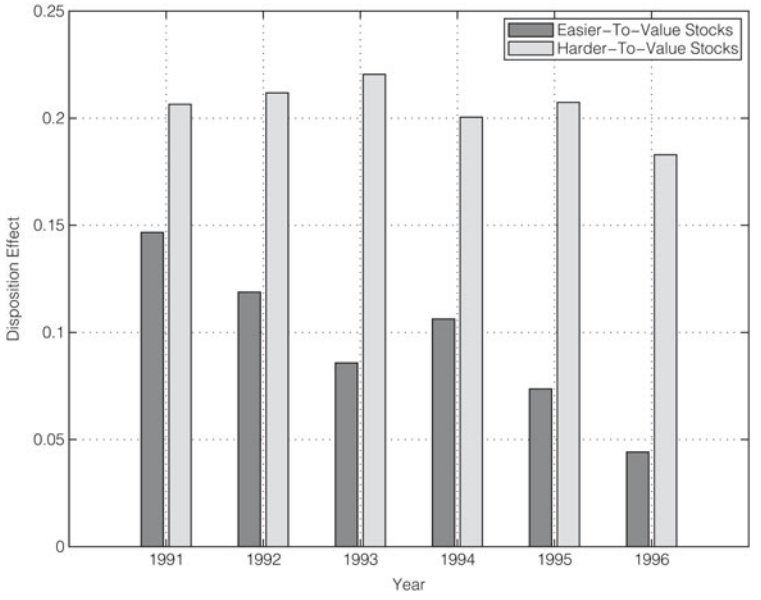
## Valuation Uncertainty and the Disposition Effect

Graph A of Figure 1 shows the mean disposition effect (PGR − PLR) for idiosyncratic volatility deciles. Panel B shows the average annual disposition effect for low (bottom three deciles) and high (top three deciles) idiosyncratic volatility stocks. PGR is the proportion of gains realized, and it is defined as the ratio of the number of realized "winners" (stock positions where an investor experiences a gain) and the total number of winners (realized + paper). PLR is the proportion of losses realized and is defined in an analogous manner. All investor trades executed during the sample period are used to estimate stock-level DE. To ensure that DE estimates are less noisy, stocks with fewer than 25 trades during the sample period are excluded. The idiosyncratic volatility for each stock is estimated each month using daily returns data.

*Graph A. Sorting Results*




*Graph B. Annual Disposition Effect Estimates*




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## E. Disposition Effect Regression Estimates

For greater accuracy, I estimate panel regressions with year fixed effects. In these specifications, the three measures of VU and several stock characteristics are the independent variables. The dependent variable is one of the two stock-level disposition effect measures (PGR − PLR or PGR/PLR) computed using the trades in year $t$. To account for potential serial and cross correlations in errors, I compute firm- and year-clustered standard errors (Petersen (2009)).[10]

The panel regression estimates are presented in Table 1. In the first regression specification, I use the annual PGR − PLR disposition effect measure in year $t$ as the dependent variable. The three VU measures for year $t-1$ are the independent variables. The estimates indicate that individual investors exhibit a stronger disposition effect when VU is higher (see column (1)). The coefficient estimates of idiosyncratic volatility and monthly volume turnover variables support this assertion, while the estimate of the firm age variable is statistically insignificant.

In the second regression specification, I use the same dependent variable but consider several firm-specific variables measured in year $t-1$ as control variables. Those variables are summarized in the caption of Table 1. In particular, the market beta and firm characteristics, such as size and BM, control for the effects of systematic risk on investors' behavioral biases. The bid-ask spread controls for the potential mechanical relation between uncertainty and overconfidence measures, induced by microstructure effects (i.e., the bid-ask bounce). The analyst coverage measure provides a control for the availability of public information. When there is greater publicly available information, investors might exhibit weaker behavioral biases, but investors could also use analysts' opinions to sustain their biased beliefs. It is also possible that analysts are biased and adversely influence investors' trading decisions.

The panel regression estimates indicate that the disposition effect is stronger among stocks that have higher market beta, lower market capitalization, weaker price momentum, and lower prices, and that do not pay dividends (see column (2)). Stocks with these characteristics are generally perceived as being more difficult to value. Thus, the evidence indicates that investors do indeed exhibit greater reluctance to realize their losses in more uncertain environments. The evidence is also consistent with Odean (1998), who finds that the disposition effect is stronger among lower priced stocks. The coefficient estimate of analyst coverage is significantly positive, which suggests that greater availability of public information does not mitigate investors' behavioral biases.

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

[10]The results are qualitatively very similar when I use the nonparametric approach of Driscoll and Kraay (1998) to simultaneously correct the standard errors for potential serial, cross, and cross-serial correlations.

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Because both dependent and independent variables have been standardized, the full specification regression estimates are easy to interpret in economic terms. For instance, the PGR − PLR measure has a mean of 7.46% and a standard deviation of 11.51%, and in column (3), idiosyncratic volatility has a coefficient estimate of 0.148. This estimate implies that, all else being equal, a one-standard-deviation increase in the idiosyncratic volatility level of a stock would induce a

TABLE 1

Valuation Uncertainty and the Disposition Effect: Regression Estimates

Table 1 reports panel regression estimates where the annual disposition effect (DE) in a given stock in year $t$ is the dependent variable. To ensure that DE measures are less noisy, stocks with fewer than 10 trades during a year are excluded. Three measures of valuation uncertainty—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 return 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 previous year 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. Additionally, the following control variables are employed: i) market beta, which is estimated using the past 60 months of returns data; ii) firm size; iii) book-to-market (BM) ratio; iv) past 12-month stock return; v) a dividend-paying dummy variable, which is set to 1 if the stock pays a dividend at least once during the previous one year; vi) institutional ownership of the stock; vii) a NASDAQ dummy variable; viii) stock price; ix) bid-ask spread; and x) analyst coverage, which is defined as the number of analysts covering the stock during the past year. All independent variables are measured during the year $t-1$. 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 is defined as the ratio of the number of realized "winners" (stock positions where an investor experiences a gain) and the total number of winners (realized + paper). PLR is the proportion of losses realized and is defined in an analogous manner. Panel A reports the baseline estimates, and Panel B reports the results from several robustness tests where only the estimates of the three uncertainty measures are reported. To ensure that extreme values are not affecting the results, I winsorize all variables at their 0.5 and 99.5 percentile levels. Both the dependent and the independent variables have been standardized (mean is set to 0, and standard deviation is 1) so that the coefficient estimates can be directly compared within and across specifications. To account for potential serial and cross correlations in errors, I compute firm- and year-clustered standard errors. The $t$-statistics, obtained using the corrected standard errors, are reported in parentheses.

*Panel A. Baseline Estimates*

| Variable | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Idiosyncratic volatility | 0.237 | | 0.148 | 0.124 |
| | (14.10) | | (7.01) | (6.11) |
| Monthly volume turnover | 0.037 | | 0.127 | 0.043 |
| | (5.02) | | (12.05) | (3.96) |
| Firm age | –0.002 | | –0.004 | –0.003 |
| | (–0.87) | | (–1.34) | (–1.10) |
| Market beta | | 0.104 | 0.085 | 0.013 |
| | | (7.32) | (6.42) | (1.61) |
| log(firm size) | | –0.224 | –0.207 | –0.123 |
| | | (–13.88) | (–9.97) | (–5.12) |
| BM ratio | | –0.022 | –0.025 | –0.003 |
| | | (–2.25) | (–1.77) | (–0.34) |
| Past 12-month stock returns | | 0.028 | –0.075 | –0.064 |
| | | (1.85) | (–3.13) | (–4.01) |
| Dividend-paying dummy | | –0.056 | –0.054 | –0.005 |
| | | (–5.33) | (–5.57) | (–0.74) |
| NASDAQ dummy | | 0.057 | –0.017 | –0.020 |
| | | (3.97) | (–1.66) | (–1.57) |
| Institutional ownership | | –0.052 | –0.027 | –0.027 |
| | | (–4.10) | (–3.12) | (–2.67) |
| Stock price | | –0.164 | –0.146 | –0.024 |
| | | (–7.08) | (–5.68) | (–2.02) |
| Bid-ask spread | | 0.038 | 0.039 | 0.086 |
| | | (2.08) | (2.15) | (4.07) |
| log(1 + analyst coverage) | | 0.134 | 0.067 | 0.038 |
| | | (5.07) | (2.76) | (1.78) |
| Number of observations | 13,856 | 13,077 | 13,077 | 13,077 |
| Adjusted $R^2$ | 0.061 | 0.086 | 0.131 | 0.063 |

*(continued on next page)*

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TABLE 1 (continued)
Valuation Uncertainty and the Disposition Effect: Regression Estimates

*Panel B. Robustness Test Results*

| Robustness Test | Idiosyncratic Volatility | Monthly Volume Turnover | Firm Age | Adj. $R^2$ |
|---|---|---|---|---|
| *Estimates with Other Estimation Methods* | | | | |
| Panel with year fixed effects | 0.095<br>(6.69) | 0.080<br>(5.82) | –0.019<br>(–2.16) | 0.131 |
| Panel with year and industry fixed effects | 0.097<br>(5.51) | 0.077<br>(4.82) | –0.021<br>(–2.29) | 0.160 |
| Idiosyncratic volatility using industry-adjusted returns | 0.082<br>(5.65) | 0.082<br>(4.74) | –0.026<br>(–2.45) | 0.157 |
| Fama-MacBeth regression | 0.079<br>(5.26) | 0.058<br>(5.73) | –0.036<br>(–3.50) | 0.055 |
| Single cross-sectional regression | 0.104<br>(6.96) | 0.084<br>(9.59) | –0.069<br>(–4.56) | 0.113 |
| *Subsample Estimates* | | | | |
| Minimum $5 stocks | 0.166<br>(8.01) | 0.176<br>(9.09) | –0.021<br>(–4.05) | 0.130 |
| Low measurement error | 0.214<br>(7.75) | 0.230<br>(8.11) | –0.022<br>(–6.01) | 0.177 |
| 1991–1993 period | 0.145<br>(8.82) | 0.097<br>(7.56) | –0.033<br>(–0.55) | 0.079 |
| 1994–1996 period | 0.115<br>(4.41) | 0.133<br>(12.70) | 0.021<br>(1.50) | 0.070 |
| No entry or exit | 0.105<br>(5.88) | 0.096<br>(6.22) | –0.017<br>(–1.86) | 0.101 |

$0.148 \times 11.51 = 1.70\%$ increase in the PGR − PLR measure for that stock. In percentage terms, relative to the mean of PGR − PLR, this corresponds to a 22.78% increase in PGR − PLR, which is economically significant.

For robustness, I reestimate the regression model with the PGR/PLR disposition effect measure as the dependent variable. These estimates are also reported in column (4) of Table 1. The coefficient estimates of the VU measures with the PGR/PLR measure are similar to those obtained with the PGR − PLR measure. However, the estimates of some of the control variables (e.g., analyst coverage) lose their statistical significance.

## F. Robustness of the Disposition Effect Regression Estimates

To further examine the robustness of the disposition effect regression estimates, I conduct additional tests. The results from these tests are summarized in Panel B of Table 1.

First, I employ different methods to estimate the disposition effect regression. Specifically, to understand whether market, industry, or firm-level uncertainty drives the key results, I estimate the panel regression with time and industry fixed effects. To remove the effects of industry-level uncertainty, I also compute the idiosyncratic volatility measure using industry-adjusted returns. The results indicate that the alternative idiosyncratic volatility measure and alternative estimation methods do not qualitatively change the disposition effect regression estimates. In all three instances, the uncertainty measures have significant and

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somewhat stronger coefficient estimates. This evidence indicates that firm-level uncertainty is a significant and more important determinant of the bias-uncertainty relation.

In the next test, I estimate one cross-sectional regression, where the dependent variable is the stock-level disposition effect measure obtained using all executed and paper trades during the sample period. In this specification, all independent variables are measured at the beginning of the sample period. I find that the cross-sectional regression estimates are very similar to the panel regression estimates. Even when I estimate monthly Fama-MacBeth (1973) regressions, the results are similar to the baseline panel estimates. All three uncertainty measures have statistically significant coefficient estimates with the expected signs.

In the third set of tests, I examine whether potential measurement errors induced by microstructure effects significantly influence the regression estimates. I estimate the disposition effect panel regression for two subsamples in which measurement errors are likely to be lower: i) stocks with prices above \$5 and ii) stocks with low (bottom three deciles) bid-ask spreads.[11] I find that the two sets of subsample estimates are somewhat stronger (especially the estimates for firm age) than the full-sample estimates. Thus, the disposition effect-uncertainty relation is robust to potential concerns about measurement errors.

To address the concern that the disposition effect regression estimates might be sensitive to the rising market during the second half of the sample period, I reestimate the disposition effect regression for the 1991–1993 and 1994–1996 subperiods. I find that the subperiod coefficient estimates of the uncertainty measures are reasonably similar to the full-sample results. Firm age has insignificant coefficient estimates, but idiosyncratic volatility and turnover coefficient estimates are positive and significant during both subperiods.

The mixed and insignificant subperiod estimates of firm age raise the possibility that changing the composition of the brokerage sample due to entry and exit of investors influences the main results. When I estimate the disposition effect regression by considering only the decisions of investors who are present throughout the sample period, I find that the results are similar to the baseline estimates. This evidence indicates that entry and exit of investors from the sample do not bias the disposition effect regression estimates.

Overall, the disposition effect regression estimates are consistent with the main conjecture. Both the evidence from the baseline tests and the robustness tests indicate that the disposition effect is stronger among stocks that are harder to value. Those stocks are relatively younger and have higher idiosyncratic volatility, higher turnover, lower market capitalization, weaker momentum, and lower prices, and they do not pay dividends.

## III. Valuation Uncertainty and Investor Overconfidence

In this section, I examine whether the positive uncertainty-disposition effect relation generalizes to the overconfidence bias. Investors who overestimate either

[11] Although I consider stock price and bid-ask spread as control variables in the regression specification, the subsample estimates would be more robust to concerns about measurement errors.

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the quality of their private information or their ability to process their private information exhibit overconfidence. Previous studies have investigated whether individual investors exhibit overconfidence in their stock investment decisions. For instance, Odean (1999) and Barber and Odean (2001) show that individual investors exhibit overconfidence in their trading decisions, where men exhibit greater overconfidence than women.

I extend this analysis by examining whether investor overconfidence increases when task difficulty, as captured by the VU proxies, increases in the cross section of stocks. Specifically, I examine whether investors are more likely to attribute negative outcomes to chance or to random events (i.e., exhibit greater biased self-attribution) when VU is higher and performance feedback is noisier.

## A. Stock-Level Overconfidence Proxies

Investors can be overconfident about the quality of their private information or they might overestimate their ability to process their private information (Odean (1999)). In either case, overconfident investors will make systematic errors in their trading decisions. Particularly, the stocks an overconfident investor sells are likely to systematically outperform the stocks she purchases by a significant margin. With this motivation, I use the mean $k$-day PTSBD as a proxy for investor overconfidence. I estimate the $k$-day PTSBD for each stock at the end of each year. Specifically, PTSBD$(i, k, t)$ is the difference between the mean $k$-day return following all sell trades in stock $i$ in year $t$ and the mean $k$-day return following all purchases in stock $i$ in year $t$.

If investors do not exhibit overconfidence and trade in an uncorrelated fashion, on average, the stocks they sell will perform similarly to the stocks they purchase, and the PTSBD will be close to 0. In contrast, a large positive value of PTSBD for a stock would indicate that investors holding the stock are systematically making mistakes, where they either systematically misinterpret their private information or overestimate their investment ability. Consequently, a large positive return differential would serve as a reasonable proxy for investor overconfidence.

## B. Uncertainty and Overconfidence: Sorting Results

To examine the uncertainty-overconfidence relation, I first compute the mean 252-day (one year) PTSBD for stocks with different levels of idiosyncratic volatility. Only buy and sell trades executed by brokerage investors are used to compute the PTSBD measures. I sort all CRSP stocks using their mean monthly idiosyncratic volatility at the beginning of the sample period. To get reasonably accurate PTSBD estimates, I exclude from the analysis stocks with fewer than 5 buy and 5 sell trades during the 6-year sample period. The mean 252-day PTSBD measures for the 10 idiosyncratic volatility decile portfolios are presented in Graph A of Figure 2.

I find that in the lower idiosyncratic volatility deciles, the stocks investors sell slightly underperform the stocks they buy. This evidence indicates that investors make relatively better investment choices when there is relatively less ambiguity

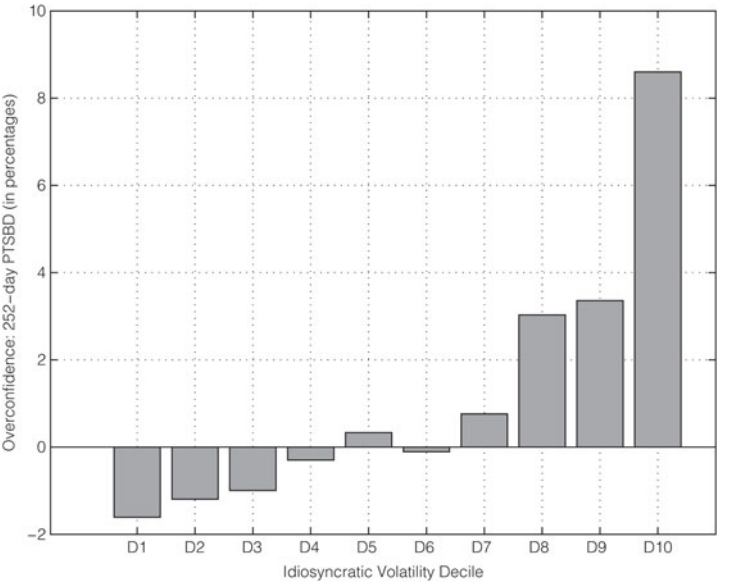
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FIGURE 2

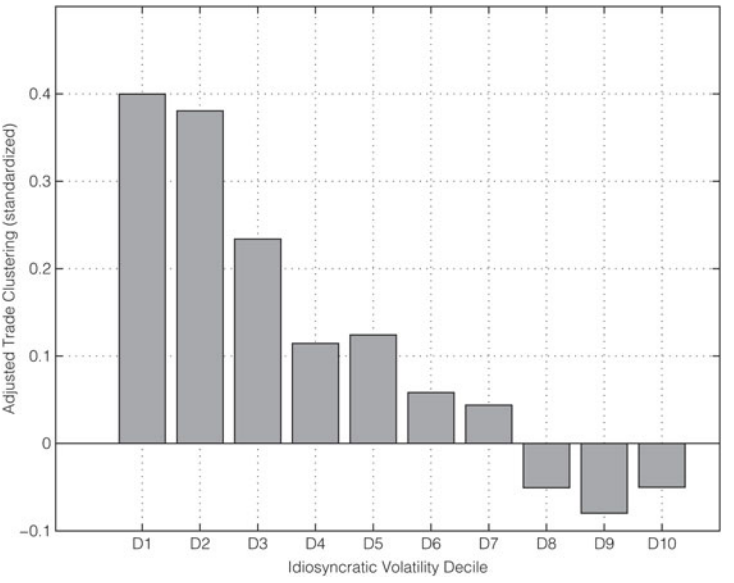
## Valuation Uncertainty, Investor Overconfidence, and Narrow Framing

Graph A of Figure 2 shows the 252-day post-trade sell-buy return differential (PTSBD) for idiosyncratic volatility deciles. Stocks with fewer than five buy and sell trades are not included in the analysis. Investor trades from the entire sample period are used to obtain stock-level overconfidence measures. Panel B shows the trading frequency-adjusted trade clustering (TC) for idiosyncratic volatility deciles. The stock-level TC measure is the proportion of trades that are executed simultaneously (i.e., on the same day by the same investor) in a given month. The adjusted TC measure is obtained by dividing the raw monthly TC measure by the number of trades executed during the month. This measure is standardized, and the sample period averages of the standardized, adjusted TC measures are shown in the figure. The idiosyncratic volatility for each stock is estimated each month using daily returns data.

*Graph A. Overconfidence*




*Graph B. Narrow Framing*




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about the true valuation of a stock. However, when idiosyncratic volatility is higher, the stocks that investors sell outperform the stocks they buy. For instance, the highest idiosyncratic volatility decile portfolio has a mean one-year PTSBD of 8.60%. The results are quite similar for other choices of $k$. The mean as well as the median $k$-day PTSBD is positive (negative) for lower (higher) idiosyncratic volatility stock portfolios.

## C. Overconfidence Regression Estimates

To examine the uncertainty-overconfidence relation more accurately, I estimate panel regression models with year fixed effects. In this specification, the dependent variable is the mean $k$-day PTSBD measure for a stock in year $t$. The independent variables are the three measures of VU, along with several stock-specific control variables. All independent variables are measured in year $t - 1$, and the dependent variable is measured in year $t$.

The regression estimates are presented in Table 2. In the first regression specification, I use the mean 252-day PTSBD as the dependent variable and the three uncertainty measures as independent variables. Consistent with the results from the univariate tests, I find that individual investors exhibit greater overconfidence when uncertainty is higher (see column (1)). The coefficient estimates of idiosyncratic volatility and firm age variables are statistically significant, but the estimate of the monthly turnover variable is statistically insignificant.

When I employ firm-specific variables as independent variables and use the same dependent variable (see column (2)), I find that investor overconfidence is higher among stocks that have lower market capitalization, have lower BM ratio, and do not pay dividends. These smaller, non-dividend-paying growth stocks are usually perceived as being more difficult to value. Thus, these estimates are consistent with the conjecture that behavioral biases are stronger when stocks are harder to value.

When I estimate the regression model with both uncertainty measures and stock-specific controls as independent variables, the results change only slightly. Interestingly, the monthly volume turnover coefficient estimate becomes positive and significant (see column (3)), and all three uncertainty measures paint a consistent picture. The estimate of the dividend-paying dummy becomes insignificant but retains the expected negative sign. The coefficient estimate for the analyst coverage measure is negative, which indicates that greater availability of public information is associated with weaker behavioral biases. Collectively, the full regression estimates indicate that investor overconfidence is higher among stocks that are harder to value. These stocks are younger and have higher idiosyncratic volatility, higher turnover, lower market capitalization, and lower BM.

In economic terms, the panel regression estimates are significant. For instance, PTSBD has a mean of 2.15% and a standard deviation of 22.56%, and in column (3), idiosyncratic volatility has a coefficient estimate of 0.078. This estimate implies that, all else being equal, a one-standard-deviation increase in the idiosyncratic volatility level of a stock would induce a $0.078 \times 22.56 = 1.76\%$ increase in the PTSBD measure for that stock. Relative to the mean of PTSBD, this corresponds to an economically significant 82% increase in PTSBD.

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To examine whether these results are robust to the post-trade window size used to measure overconfidence, I reestimate the overconfidence panel regression with the mean 126-day PTSBD measure as the dependent variable. These estimates are also reported in column (4) of Table 2. The coefficient estimates with the mean 126-day PTSBD measure are very similar to those obtained with the mean 252-day PTSBD measure. In particular, the estimates of the three uncertainty measures have the expected signs and are statistically significant.

To gather additional support for the overconfidence hypothesis, I estimate an additional regression model, where the mean stock holding period is the dependent variable. This regression specification examines whether, consistent with the overconfidence hypothesis, investors trade stocks with greater uncertainty more frequently. The regression estimates are reported in column (5) of Table 2. I find that stocks that have higher VU have lower mean holding periods and are traded more frequently. Two of the three uncertainty measures (idiosyncratic volatility

TABLE 2

Valuation Uncertainty and Investor Overconfidence: Regression Estimates

Table 2 reports panel regression estimates in which the annual measure of investor overconfidence in a given stock is the dependent variable. Investor overconfidence is defined as the *k*-day post-trade sell-buy return differential (PTSBD) in year *t*. All independent variables are measured in year $t-1$ and have been previously defined in Table 1. 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. In column (5), the dependent variable is the mean holding period of a stock in year *t*. Panel A reports the baseline estimates, and Panel B reports the results from several robustness tests where only the estimates of the three uncertainty measures are reported. I winsorize all variables at their 0.5 and 99.5 percentile levels, and both the dependent and the independent variables have been standardized. The *t*-statistics, obtained using firm- and year-clustered standard errors, are reported in parentheses.

*Panel A. Baseline Estimates*

| Variable | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Idiosyncratic volatility | 0.113 | | 0.078 | 0.065 | –0.054 |
| | (6.25) | | (3.46) | (3.32) | (–3.37) |
| Monthly volume turnover | –0.008 | | 0.057 | 0.042 | –0.102 |
| | (–1.05) | | (5.14) | (4.31) | (–6.55) |
| Firm age | –0.040 | | –0.061 | –0.031 | 0.016 |
| | (–3.89) | | (–4.78) | (–2.44) | (1.33) |
| Market beta | | –0.016 | –0.022 | –0.013 | –0.104 |
| | | (–1.05) | (–1.55) | (–0.90) | (–8.27) |
| log(firm size) | | –0.122 | –0.127 | –0.142 | –0.010 |
| | | (–7.02) | (–5.77) | (–6.07) | (–0.40) |
| BM ratio | | –0.037 | –0.031 | –0.049 | 0.098 |
| | | (–2.50) | (–3.17) | (–2.62) | (8.60) |
| Past 12-month stock returns | | 0.022 | –0.024 | –0.060 | –0.105 |
| | | (1.15) | (–1.30) | (–3.03) | (–8.22) |
| Dividend-paying dummy | | –0.037 | –0.015 | –0.020 | 0.076 |
| | | (–3.90) | (–1.47) | (–1.96) | (5.33) |
| NASDAQ dummy | | –0.007 | 0.023 | 0.017 | –0.008 |
| | | (–0.40) | (1.88) | (1.74) | (–0.75) |
| Institutional ownership | | –0.004 | 0.005 | –0.026 | 0.087 |
| | | (–0.33) | (0.38) | (–1.73) | (6.09) |
| Stock price | | –0.032 | –0.035 | –0.022 | 0.042 |
| | | (–1.60) | (–1.32) | (–0.85) | (1.98) |
| Bid-ask spread | | 0.041 | 0.037 | 0.036 | –0.060 |
| | | (2.56) | (2.91) | (2.04) | (–3.59) |
| log(1 + analyst coverage) | | –0.044 | –0.050 | –0.056 | –0.070 |
| | | (–2.73) | (–5.85) | (–4.02) | (–5.83) |
| Number of observations | 12,336 | 11,487 | 11,487 | 11,487 | 12,885 |
| Adjusted $R^2$ | 0.015 | 0.019 | 0.028 | 0.032 | 0.091 |

*(continued on next page)*

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TABLE 2 (continued)

Valuation Uncertainty and Investor Overconfidence: Regression Estimates

*Panel B. Robustness Test Results*

| Robustness Test | Idiosyncratic Volatility | Monthly Volume Turnover | Firm Age | Adj. $R^2$ |
|---|---|---|---|---|
| *Estimates with Other Estimation Methods* | | | | |
| Panel with year fixed effects | 0.075 | 0.046 | –0.073 | 0.039 |
| | (6.00) | (2.92) | (–5.85) | |
| Panel with year and industry fixed effects | 0.070 | 0.045 | –0.071 | 0.054 |
| | (5.44) | (3.67) | (–5.61) | |
| Idiosyncratic volatility using industry-adjusted returns | 0.101 | 0.052 | –0.076 | 0.060 |
| | (6.78) | (3.76) | (–6.10) | |
| Fama-MacBeth regression | 0.087 | 0.025 | –0.019 | 0.011 |
| | (2.93) | (2.96) | (–1.85) | |
| Single cross-sectional regression | 0.077 | 0.022 | –0.078 | 0.020 |
| | (6.15) | (2.55) | (–6.31) | |
| *Subsample Estimates* | | | | |
| Minimum $5 stocks | 0.050 | 0.052 | –0.073 | 0.013 |
| | (2.53) | (3.58) | (–4.66) | |
| Low measurement error | 0.048 | 0.053 | –0.073 | 0.014 |
| | (2.68) | (4.10) | (–3.81) | |
| 1991–1993 period | 0.071 | 0.061 | 0.004 | 0.017 |
| | (3.22) | (2.61) | (1.59) | |
| 1994–1996 period | 0.151 | 0.036 | –0.076 | 0.022 |
| | (4.07) | (3.05) | (–3.94) | |
| No entry or exit | 0.073 | 0.036 | –0.033 | 0.023 |
| | (4.05) | (3.57) | (–2.23) | |

and monthly volume turnover) have negative and significant coefficient estimates. In conjunction with the evidence from the PTSBD regressions, these results provide strong support for the main hypothesis.

## D. Robustness of Overconfidence Regression Estimates

To further examine the robustness of the overconfidence regression estimates, I conduct additional tests that are similar to the disposition effect robustness tests. The results are summarized in Panel B of Table 2.

In the first set of tests, I employ different methods to estimate the overconfidence regression. Specifically, I estimate the panel regression with time and industry fixed effects and compute the idiosyncratic volatility measure using industry-adjusted returns. I also estimate a cross-sectional regression and monthly Fama-MacBeth (1973) regressions. In all instances, I find that the uncertainty measures have statistically significant estimates, and the results are similar to the baseline estimates.

In the second set of tests, I estimate the overconfidence panel regression for two subsamples in which measurement errors are likely to be lower: i) stocks with prices above $5 and ii) stocks with low (bottom three deciles) bid-ask spreads. I find that the two subsample estimates are very similar to the full-sample estimates. Interestingly, the coefficient estimate for firm age becomes statistically significant in both subsamples. These subsample estimates indicate that the

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overconfidence-uncertainty relation is not mechanically induced by microstructure effects.

Next, to examine whether the uncertainty-overconfidence relation is sensitive to the rising market during the second half of the sample period, I reestimate the overconfidence regression separately for the 1991–1993 and 1994–1996 subperiods. I find that the subperiod coefficient estimates for the uncertainty measures are similar to the full-sample results, except for firm age, which does not always have statistically significant coefficient estimates. As before, to examine whether the insignificant subperiod estimates of firm age reflect the changing composition of the sample, I estimate the overconfidence regression by considering only the decisions of investors who are present throughout the sample period. Again, I find that the results are similar to the baseline estimates, which indicates that entry and exit of investors from the sample do not bias the overconfidence regression estimates.[12]

## IV. Market-Level Uncertainty and Behavioral Biases

If stock-level uncertainty amplifies investors' behavioral biases, it is natural to ask whether uncertainty at an aggregate level (i.e., market-level or economy-wide uncertainty) induces stronger behavioral biases. If investors are sensitive to uncertainty in stock valuation, it is likely that during times when market-level uncertainty is higher and the valuation of *all* stocks becomes more difficult, investors will also exhibit stronger behavioral biases.

### A. Time-Series Regression Estimates

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

$$\begin{aligned}(3)\qquad \mathrm{BIAS}_t \;=\; & b_0 + b_1\mathrm{IDIOVOL}_{t-1} + b_2\mathrm{VIX}_{t-1} + b_3\mathrm{SENTI}_{t-1} \\ & + b_4\mathrm{UNEMP}_{t-1} + b_5\mathrm{UEI}_{t-1} + b_6\mathrm{MP}_{t-1} + b_7\Delta\mathrm{RP}_{t-1} \\ & + b_8\Delta\mathrm{TS}_{t-1} + b_9\mathrm{BIAS}_{t-1} + \varepsilon_t.\end{aligned}$$

In this specification, $\mathrm{BIAS}_t$ is the aggregate level of behavioral bias in a given month. I consider four proxies for the level of market-wide uncertainty. $\mathrm{IDIOVOL}_t$ is the mean idiosyncratic volatility of all stocks in month $t$, where all CRSP common stocks (share codes 10 and 11) are used to obtain the aggregate volatility measure. For robustness, I consider two alternative measures of market-level uncertainty obtained from very different sources: the Chicago Board Options Exchange VIX and the Michigan consumer sentiment index (SENTI). VIX is a measure of the market's expectation of market volatility over the next 30 days, and the sentiment index captures people's opinions about the state of current and future

[12] Given the robust nature of the overconfidence and the disposition effect regression estimates, one might be concerned that the overconfidence and disposition effect measures represent similar aspects of investment decisions. I find that although the two measures are positively correlated, the correlation is very weak (= 0.045).

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economic conditions. Last, $UNEMP_t$ is the month-$t$ national unemployment rate and serves as another proxy for aggregate uncertainty.

Examining the correlations among the market-wide uncertainty measures, I find that the correlation between VIX and the consumer sentiment measure is −0.446. This makes intuitive sense. The consumer sentiment is low when the market-wide uncertainty is high. Moreover, as expected, the mean idiosyncratic volatility measure is positively correlated with the VIX (= 0.297), but negatively correlated with the sentiment index (= −0.515).

To ensure that shifts in investors' biases do not simply reflect changes in broad macroeconomic conditions, following Chen, Roll, and Ross (1986) and Ferson and Schadt (1996), I include four macroeconomic variables in the regression specification as control variables. Specifically, $UEI_t$ is the unexpected inflation in month $t$, where the average of the 12 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 default 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 10-year Treasury bond and the yield of a 3-month Treasury bill. Among these macroeconomic variables, the UEI rate could also reflect the level of aggregate uncertainty in the economy.

The time-series estimation results are reported in Table 3. Consistent with the evidence from the panel regressions, I find that periods of high mean idiosyncratic volatility are associated with stronger behavioral biases. The levels of both the overconfidence and the disposition biases are higher when mean idiosyncratic volatility is higher, VIX is higher, consumer sentiment is lower, or unemployment is higher. Among the four aggregate uncertainty measures, VIX appears to be the strongest, while the consumer sentiment measure has the weakest coefficient estimates. The UEI variable also has the expected positive coefficient estimates, but the estimates are statistically insignificant.

## B. Do Investors Seek Familiar Local and Domestic Stocks During Uncertain Times?

To examine the robustness of the uncertainty-bias time-series relation, I examine whether investors' aggregate LB and home bias measures increase when the market-level uncertainty increases. Previous studies (e.g., Huberman (2001), Grinblatt and Keloharju (2001), Zhu (2002), Ivković and Weisbenner (2005), and Bailey, Kumar, and Ng (2008)) find that individual investors exhibit a preference for both domestic and local stocks. This preference could at least partially be induced by investors' familiarity bias, where they perceive domestic and local stocks as being less risky, or they might simply have a perception of superior information about those stocks. In either scenario, investors might gravitate more toward familiar domestic and local stocks during times of greater aggregate uncertainty.

To examine the relation between the market-level uncertainty and familiarity bias, I estimate the time-series model where the dependent variable ($BIAS_t$) is the

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TABLE 3

Market-Level Uncertainty and Behavioral Biases: Time-Series Regression Estimates

Table 3 reports the estimation results for the time-series regression model specified in equation (3). The dependent variable is an aggregate behavioral bias (BIAS) (investor overconfidence or the disposition effect) measure in a given month. Both measures have been defined before in Tables 1 and 2. The independent variables include the mean idiosyncratic volatility (IDIOVOL) of all stocks in month $t$, the month-$t$ level of the VIX, the level of Michigan consumer sentiment index (SENTI) in month $t$, the national unemployment (UNEMP) rate in month $t$, the unexpected inflation (UEI) in month $t$, the monthly growth in industrial production (MP), the monthly default risk premium (RP), and the term spread (TS). Additional details on the regression specification are available in Section IV.A. Both the dependent and the independent variables have been standardized. The Newey and West (1987) adjusted $t$-statistics (with three lags) of the coefficient estimates are reported in parentheses.

| | Overconfidence | | | Disposition Effect | | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| Intercept | –0.050<br>(–0.40) | –0.055<br>(–0.44) | –0.044<br>(–0.35) | 0.001<br>(0.11) | 0.001<br>(0.12) | –0.041<br>(–0.47) |
| Lagged IDIOVOL | 0.283<br>(2.45) | 0.240<br>(2.13) | 0.228<br>(2.61) | 0.404<br>(2.76) | 0.205<br>(2.94) | 0.188<br>(2.68) |
| Lagged VIX | | 0.404<br>(2.18) | 0.292<br>(2.35) | | 0.394<br>(3.64) | 0.346<br>(2.52) |
| Lagged SENTI | | –0.385<br>(–2.62) | –0.164<br>(–1.73) | | –0.287<br>(–2.38) | –0.107<br>(–1.39) |
| Lagged UNEMP | | | 0.118<br>(2.01) | | | 0.349<br>(2.64) |
| Lagged UEI | | | 0.212<br>(1.37) | | | 0.088<br>(0.86) |
| Lagged MP | | | 0.122<br>(1.42) | | | –0.042<br>(–0.40) |
| Lagged $\Delta$RP | | | 0.118<br>(0.82) | | | 0.090<br>(0.81) |
| Lagged $\Delta$TS | | | –0.173<br>(–1.98) | | | –0.103<br>(–1.30) |
| Lagged BIAS | | | –0.101<br>(–0.76) | | | 0.252<br>(2.25) |
| Number of months | 71 | 71 | 70 | 71 | 71 | 70 |
| Adjusted $R^2$ | 0.074 | 0.155 | 0.277 | 0.151 | 0.401 | 0.461 |

aggregate LB or the home bias of brokerage investors.[13] The aggregate bias in month $t$ is the average bias of all investors in the sample. In untabulated results, I find that, similar to the results for the overconfidence and the disposition biases, LB is stronger when there is greater market-level uncertainty. Specifically, the coefficient estimates for idiosyncratic volatility, VIX, consumer sentiment index, and the unemployment rate are 0.105 ($t$-statistic = 2.19), 0.364 ($t$-statistic = 3.52), −0.152 ($t$-statistic = −1.35), and 0.140 ($t$-statistic = 1.99), respectively. When the dependent variable is a home bias proxy, the respective estimates are 0.244 ($t$-statistic = 2.74), 0.202 ($t$-statistic = 2.48), −0.074 ($t$-statistic = −0.65), and 0.103 ($t$-statistic = 2.68).

Overall, the time-series regression estimates are consistent with the main conjecture and indicate that higher levels of market-level uncertainty amplify investors' behavioral biases. Furthermore, the robustness test results indicate that

[13]The LB measure is defined as $\text{LB} = D_{\text{act}} - D_{\text{mkt}}$, where $D_{\text{act}}$ is the distance between an investor's location and her stock portfolio, and $D_{\text{mkt}}$ is the distance between an investor's location and the market portfolio. A proxy for home bias is the negative of the proportion of the total investor portfolio allocated to foreign securities.

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the positive relation between the market-level uncertainty and behavioral biases generalizes to other types of biases.

## V. Additional Robustness Tests

In this section, I conduct further tests to show that the uncertainty-bias relation is strong and robust.

### A. Panel Regression Estimates with Alternative Uncertainty Measures

In the first set of tests, to further ensure that my evidence reflects the relation between behavioral biases and difficulty in stock valuation, I consider three alternative measures of uncertainty. These measures attempt to capture the level of uncertainty reflected in the fundamentals of the firm. They are only weakly correlated with the three original uncertainty proxies. In absolute terms, the correlations are below 0.17.

The first measure is earnings volatility, which is the standard deviation of realized earnings from the past 20 quarters. The earnings measure used to compute earnings volatility is the diluted earnings per share (Compustat quarterly data item 9). The second uncertainty proxy is the cash flow volatility measure, which is defined as the standard deviation of cash flow from operations during the past 20 quarters.[14] Third, I consider the level of intangible assets of a firm as another proxy for VU. It is defined as $1 - \text{PPE}/\text{ASSETS}$, where PPE is the total net value of property, plant, and equipment (Compustat quarterly data item 42), and ASSETS is the total value of a firm's assets (Compustat quarterly data item 44).

The disposition effect and overconfidence regression estimates with the new uncertainty proxies are presented in Table 4. The estimates for the full sample period, the 1991–1993 subperiod, and the 1994–1996 subperiod are reported in columns (2) and (6), (3) and (7), and (4) and (8), respectively. The results indicate that all three alternative measures of uncertainty have positive and significant coefficient estimates, even when I include the previously employed uncertainty measures in the regression specifications. Among the three new uncertainty measures, the level of intangible assets has the strongest influence on the bias measures. Furthermore, the three new uncertainty proxies have statistically significant coefficient estimates in both subperiods. Taken together, the estimates with the new uncertainty proxies indicate that the bias-uncertainty relations are strong and robust.

### B. Valuation Uncertainty and Correlated Trading

The tests so far have focused on familiarity, overconfidence, and disposition biases. However, investors are also known to exhibit other types of biases, such as limited attention (Barber and Odean (2008)) and representativeness (e.g., Kahneman and Tversky (1973), Barberis, Shleifer, and Vishny (1998)). In this

[14]Specifically, the cash flow per share is computed as (Compustat quarterly data item 108)/(Compustat quarterly data item 61 $\times$ Compustat quarterly data item 17).

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TABLE 4

Disposition Effect and Overconfidence Panel Regression Estimates with Alternative Uncertainty Measures

Table 4 reports the disposition effect and overconfidence regression estimates with alternative measures of valuation uncertainty. The details of the disposition effect and overconfidence regression specifications are provided in Tables 1 and 2, respectively. The three new uncertainty measures are: i) earnings volatility (standard deviation of the earnings from the previous 20 quarters), ii) cash flow volatility (standard deviation of cash flow from the previous 20 quarters), and iii) the level of intangible assets. In columns (3) and (7), the estimates for the 1991–1993 subperiod are presented. In columns (4) and (8), the estimates for the 1994–1996 subperiod are presented. Additional details on the regression specifications are available in Section V.A. The *t*-statistics, obtained using firm- and year-clustered standard errors, are reported in parentheses.

| | Disposition Effect | | | | Overconfidence | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Earnings volatility | 0.035 | 0.048 | 0.038 | 0.049 | 0.044 | 0.039 | 0.053 | 0.030 |
| | (2.69) | (3.31) | (3.85) | (3.35) | (2.20) | (2.87) | (3.48) | (2.44) |
| Cash flow volatility | 0.042 | 0.034 | 0.031 | 0.042 | 0.034 | 0.044 | 0.065 | 0.033 |
| | (2.01) | (2.29) | (2.09) | (2.49) | (3.12) | (2.80) | (3.03) | (2.92) |
| Intangible assets | 0.052 | 0.042 | 0.039 | 0.044 | 0.043 | 0.043 | 0.026 | 0.054 |
| | (3.10) | (2.81) | (2.99) | (2.61) | (2.12) | (2.09) | (2.26) | (2.34) |
| Idiosyncratic volatility | | 0.130 | 0.143 | 0.105 | | 0.074 | 0.064 | 0.131 |
| | | (6.36) | (7.59) | (5.61) | | (3.14) | (2.96) | (5.58) |
| Monthly volume turnover | | 0.110 | 0.109 | 0.113 | | 0.050 | 0.052 | 0.047 |
| | | (5.56) | (5.63) | (3.11) | | (3.29) | (2.94) | (2.77) |
| Firm age | | –0.031 | –0.035 | 0.005 | | –0.036 | –0.009 | –0.040 |
| | | (–1.51) | (–1.07) | (1.06) | | (–2.78) | (–1.16) | (–3.00) |
| (Coefficient estimates of control variables have been suppressed.) | | | | | | | | |
| Number of observations | 12,545 | 12,545 | 6,361 | 6,184 | 11,056 | 11,056 | 5,606 | 5,450 |
| Adjusted $R^2$ | 0.053 | 0.159 | 0.083 | 0.075 | 0.019 | 0.035 | 0.021 | 0.026 |

section, I investigate whether these other biases are also amplified in more uncertain environments. Specifically, motivated by the evidence presented by Barber et al. (2009), who argue that behavioral biases (e.g., limited attention, representativeness) induce correlated trading among individual investors, I use trading correlation as a proxy for other behavioral biases. I examine whether the mean trading correlation is higher among stocks that are relatively more difficult to value.

I follow the Kumar and Lee (2006) methodology to measure trading correlations. First, I identify low (quintiles 1–2) and high (quintiles 4–5) VU stock categories, where the mean idiosyncratic volatility of a stock at the beginning of the sample period is used to measure uncertainty. Next, within each of the low and high VU stock categories, I randomly identify 1,000 non-overlapping *k*-stock portfolio pairs ($k = 25$, 50, 75, and 100) and compute the buy-sell imbalance (BSI) for each portfolio at the end of each month ($BSI_{pt}$). Last, I obtain the BSI time series for each *k*-stock portfolio pair, compute the correlation between the two time series, and measure the means of the 1,000 correlation estimates. For robustness, I also measure the correlations between residual BSI measures, where the residual BSI is obtained by removing the common dependence of portfolio BSI on the market. The BSI measures are defined in the caption of Table 5.

Consistent with the previous evidence, I find that the mean portfolio correlations are stronger among stocks that are more difficult to value. For instance, when 50-stock portfolios are randomly chosen, the mean BSI correlation is 0.272 for high uncertainty stocks and significantly lower (= 0.173) for low uncertainty stocks (see Panel A of Table 5). The mean raw correlation difference of 0.099

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TABLE 5

Valuation Uncertainty and Mean Trading Correlations

Table 5 reports the mean trading correlations for low (quintiles 1–2) and high (quintiles 4–5) valuation uncertainty (VU) stock portfolios. VU of a stock is proxied by its idiosyncratic volatility. The idiosyncratic volatility for each stock is estimated each month using daily returns data. The mean monthly volatility measure at the beginning of the sample period is used to measure the VU 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 $BSI_{pt} = (100/N_{pt}) \sum_{i=1}^{N_{pt}} BSI_{it}$ 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: $BSI_{pt} = b_0 + b_1 RMRF_t + \varepsilon_{pt}$. 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 risk-free rate in month $t$, and $\varepsilon_{pt}$ is the residual BSI for portfolio $p$ in month $t$.

*Panel A. Raw Buy-Sell Imbalance Correlations*

| Portfolio Size | Low VU | High VU | High−Low | *t*-Statistic |
|---|---|---|---|---|
| 25 | 0.092 | 0.151 | 0.059 | 7.85 |
| 50 | 0.173 | 0.272 | 0.099 | 13.04 |
| 75 | 0.349 | 0.472 | 0.123 | 20.02 |
| 100 | 0.419 | 0.547 | 0.128 | 27.45 |

*Panel B. Residual Buy-Sell Imbalance Correlations*

| Portfolio Size | Low VU | High VU | High−Low | *t*-Statistic |
|---|---|---|---|---|
| 25 | 0.086 | 0.144 | 0.058 | 7.76 |
| 50 | 0.162 | 0.266 | 0.104 | 13.55 |
| 75 | 0.330 | 0.463 | 0.133 | 21.36 |
| 100 | 0.398 | 0.538 | 0.140 | 28.73 |

is statistically significant ($p$-value $< 0.001$). The mean residual BSI correlations paint a similar picture (see Panel B of Table 5). Overall, the results from randomization tests indicate that other behavioral biases such as limited attention and representativeness will also get amplified in more uncertain environments.

## C. Valuation Uncertainty and Narrow Framing

In the third test, I investigate the relation between VU and narrow framing. Using TC as a proxy for narrow framing, I examine whether the framing bias is stronger among stocks that are more difficult to value.[15] I compute the mean level of TC for stocks in the 10 idiosyncratic volatility deciles. To measure stock-level TC, I assume that trades that are executed simultaneously with other trades by the same investor on the same day are likely to be broadly framed. In contrast, trades that are executed separately are likely to be narrowly framed. The stock-level TC measure in a given month is the proportion of trades that are executed simultaneously in that month.[16] I divide the raw TC measure by the number of monthly

[15]The choice of TC as a narrow framing proxy is motivated by experimental research, which finds that people's decision frames are affected by the manner in which different alternatives are presented to them (e.g., Tversky and Kahneman (1981), (1986)). Specifically, decisions that are made simultaneously are more likely to be framed broadly than decisions that are temporally separated (e.g., Read and Loewenstein (1995)). See Kumar and Lim (2008) for details.

[16]The TC measure is only weakly correlated with the previously examined biases. The maximum correlation with overconfidence, disposition effect, and LB measures is less than 0.20 in absolute terms.

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trades to obtain adjusted TC, and to facilitate graphical analysis, I standardize the adjusted TC measure.

The results presented in Graph B of Figure 2 indicate that the degree of TC is lower among stocks that are harder to value. Specifically, when stocks are more difficult to value, the average adjusted TC is below the average (standardized measure is negative). But when the level of uncertainty is low (e.g., decile 1), adjusted TC is positive and about 0.4 standard deviations above the mean. In untabulated results, I find that the uncertainty-narrow framing relation is positive and significant even in a multivariate setting in which multiple VU measures and stock-specific control variables are used as independent variables. Overall, the narrow framing estimates indicate that investors are likely to adopt focused and narrower decision frames in more uncertain environments.

## VI. Valuation Uncertainty and Informed Trading

If individual investors exhibit stronger behavioral biases among harder-to-value stocks, relatively better informed investors might avoid those stocks due to greater perceived noise trader risk (e.g., DeLong, Shleifer, Summers, and Waldmann (1990)). But opportunistic informed investors could also try to exploit these biases using their private information. In this section, I examine how better informed investors respond to higher VU and the amplified behavioral biases of individual investors.

I use the PIN measure developed in Easley et al. (2002) as a proxy for the intensity of informed trading.[17] The PIN measure for a given stock for a certain time period is the ratio of the arrival rates of information-induced orders and all orders, which includes both informed and uninformed orders. In other words, PIN measures the proportion of all orders that might be information-induced.

I estimate panel regressions, where the annual PIN measure for year $t$ is the dependent variable. The set of independent variables includes the two behavioral bias measures (overconfidence and disposition effect), along with the stock-specific control variables employed in the disposition effect and overconfidence regressions (see Sections II.E and III.C). To examine whether VU also influences the intensity of informed trading through a direct channel, I use the three uncertainty measures as additional independent variables. All independent variables are measured in year $t - 1$. Following previous studies (e.g., Easley, Hvidkjaer, and O'Hara (2009)), only NYSE and AMEX stocks are included in the sample.

The regression estimates are reported in Table 6, where, for brevity, the coefficient estimates of all control variables except firm size are suppressed. The evidence indicates that both the overconfidence and disposition effect measures have positive and significant coefficient estimates. Even when I control for the direct effects of uncertainty and other firm characteristics, the bias measures have

[17] I thank Soeren Hvidkjaer for providing the annual PIN estimates. The data are available at his Web site: http://sites.google.com/site/hvidkjaer/data.

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positive and statistically significant estimates. This evidence indicates that harder-to-value stocks induce stronger behavioral biases among individual investors and simultaneously attract more informed trading.

TABLE 6

Valuation Uncertainty, Behavioral Biases, and Informed Trading: Panel Regression Estimates

Table 6 reports the panel regression estimates, where the annual degree of informed trading (PIN) in a given stock in year $t$ is the dependent variable. Only NYSE/AMEX stocks are included in the analysis. The main independent variables are: i) the level of investor overconfidence, and ii) the disposition effect (DE), both measured over the same annual period. Investor overconfidence is defined as the 252-day post-trade sell-buy return differential (PTSBD), where stocks with fewer than five buy and sell trades are not included in the analysis. DE is defined as PGR − PLR, where PGR is the proportion of gains realized and PLR is the proportion of losses realized. To ensure that the bias estimates are less noisy, stocks with fewer than 10 trades during a year are excluded. Additionally, three measures of valuation uncertainty—namely, idiosyncratic volatility, monthly volume turnover, and firm age—are used as independent variables. The control variables are same as the disposition effect and overconfidence regression specifications. All independent variables are measured in year $t - 1$ and have been previously defined in Table 1. I winsorize all variables at their 0.5 and 99.5 percentile levels and both the dependent and the independent variables have been standardized. The $t$-statistics, obtained using firm- and year-clustered standard errors, are reported in parentheses.

| Variable | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intercept | 0.002 | 0.001 | 0.002 | –0.001 |
| | (0.10) | (0.11) | (0.09) | (–0.08) |
| Retail overconfidence | 0.075 | | 0.043 | 0.047 |
| | (3.51) | | (2.16) | (2.63) |
| Retail disposition effect | 0.208 | | 0.093 | 0.068 |
| | (9.68) | | (4.36) | (2.01) |
| Idiosyncratic volatility | | 0.379 | 0.355 | 0.029 |
| | | (17.99) | (16.48) | (1.57) |
| Monthly volume turnover | | –0.161 | –0.171 | –0.101 |
| | | (–7.93) | (–8.46) | (–6.50) |
| Firm age | | 0.155 | 0.137 | 0.024 |
| | | (7.45) | (6.41) | (1.44) |
| log(firm size) | | | | –0.767 |
| | | | | (–28.66) |
| (Coefficient estimates of other control variables have been suppressed.) | | | | |
| Number of observations | 12,438 | 12,204 | 12,174 | 11,286 |
| Adjusted $R^2$ | 0.048 | 0.199 | 0.229 | 0.342 |

The PIN measure is also higher for stocks with higher idiosyncratic volatility, which indicates that greater VU is directly associated with higher levels of informed trading (see columns (2) and (3)). But the other two VU measures (monthly volume turnover and firm age) portray a contradictory picture. Furthermore, in the full regression specification (see column (4)), the presence of the firm size variable considerably reduces the statistical significance of idiosyncratic volatility. Overall, firm size is the strongest determinant of informed trading intensity, while the uncertainty measures have relatively weaker coefficient estimates. Thus, the direct relation between VU and PIN is somewhat ambiguous.

Collectively, the PIN regression estimates indicate that informed trading intensity is higher among stocks where individual investors exhibit stronger behavioral biases. While the direct relation between VU and informed trading is ambiguous, informed investors appear to exploit individual investors' uncertainty-amplified behavioral biases.

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## VII. Summary and Conclusion

This paper uses investor-level data to provide direct evidence for an intuitive but surprisingly untested proposition that investors make larger investment mistakes when valuation uncertainty is higher and stocks are more difficult to value. Using a 6-year panel of retail stock holdings and trades, I show that individual investors exhibit stronger disposition effect and greater overconfidence when stocks are more difficult to value. This positive bias-uncertainty relation generalizes to other biases such as familiarity, representativeness, and limited attention. I also find that informed trading intensity is higher among stocks where individual investors exhibit stronger behavioral biases. This evidence indicates that relatively better informed investors attempt to exploit individual investors' behavioral biases.

Taken together, my findings extend the known relation between investor characteristics and behavioral biases and indicate that both stock characteristics and the market environment are likely to be common determinants of a wide range of behavioral biases. The findings are consistent with the psychological evidence and provide *direct* empirical support for recent behavioral models (Daniel et al. (1998), (2001), Hirshleifer (2001)), which posit that behavioral biases are stronger among stocks that operate in informationally sparse environments and are more difficult to value.

I also consider an extension of Hirshleifer's (2001) basic conjecture and examine whether greater market-level uncertainty induces stronger behavioral biases. I find that both the overconfidence and disposition biases are stronger when market-level uncertainty is higher. Investors also gravitate more toward familiar domestic and local stocks during times of greater market-wide uncertainty. These results support the extended conjecture and indicate that uncertainty at both stock and market levels amplifies individual investors' behavioral biases. In sum, these results indicate that investors' misperceptions are stronger not only in the "dusty corners of the market place" where valuation uncertainty is greater, but also during "dark and uncertain times" when the market-level uncertainty is higher.

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