Positive Shocks, Lower Stock Demand: Asymmetric Volatility Timing*

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March 24, 2026

Abstract

Using a large panel of roughly 6,000 firms, we develop a parametric portfolio framework that directly estimates stock-level demand and yields an implementable volatility-timing strategy with transaction costs and monthly rebalancing. Our findings are threefold. First, portfolios that optimally reduce demand for more volatile stocks earn certainty-equivalent returns roughly 10% per year higher than benchmarks, both in-sample and out-of-sample; these gains are economically large, robust to trading frictions, and exceed those from standard characteristics and systematic volatility timing. Second, the gains are driven primarily by idiosyncratic rather than systematic volatility. Third, volatility timing exhibits a novel asymmetry: positive shocks dominate negative shocks, contrary to the standard leverage-effect view. This pattern is consistent with learning-about-profitability models.

Keywords: Idiosyncratic volatility; Firm-level volatility; Portfolio allocation

*We thank Federico Bandi, Kim Christensen, Allan Timmermann, and Viktor Todorov for valuable discussions.

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1 Introduction

Firm-specific stock return volatility, distinct from market, factor, or industry components, has attracted growing attention for the role it plays and the information it conveys in financial decision making. Beginning with Campbell et al. (2001), much of the literature has examined aggregate measures of idiosyncratic volatility, emphasizing their time-series dynamics and asset-pricing implications (Goyal and Santa-Clara, 2003; Brandt et al., 2010; Herskovic et al., 2016; Bekaert et al., 2025).[1] The evidence to date suggests that idiosyncratic volatility contains valuable information about firms' corporate decisions (Campbell et al., 2023). This naturally raises the question of whether, from the perspective of active investors and arbitrageurs trading individual stocks rather than aggregate fluctuations, firm-specific volatility offers timely and relevant information for portfolio allocation. More broadly, the extent to which firm-level volatility can be systematically exploited in volatility-timing strategies has received limited attention in the literature and remains an open question.

Among active portfolio allocation strategies, volatility timing is arguably the most straightforward to understand. In any modern optimal portfolio framework, dating back to Markowitz (1952, 1959), portfolio weights are proportional to assets' expected returns and inversely proportional to their volatilities. Because expected returns are generally persistent and exhibit only limited short-term variation (Campbell and Shiller, 1988; Fama and French, 1988; Cochrane, 2008), while volatility is highly time-varying and strongly predictable (Schwert, 1989; Engle and Patton, 2001; Andersen et al., 2003), optimal portfolio weights should be inversely related to volatility. This logic applies not only at the aggregate level, for market or factor portfolios, but also at the level of individual firm returns. Yet the empirical literature on volatility timing has focused almost exclusively on aggregate market volatility or the volatility of common risk factors (Fleming et al., 2001, 2003; Moreira and Muir, 2017; DeMiguel et al., 2024). This emphasis reflects, in part, the curse of dimensionality that arises when extending the analysis to a large cross-section of assets, and in part the limited attention given to idiosyncratic risk discussed above. As a result, the question of whether cross-sectional variation in volatility can be systematically exploited in portfolio allocation remains largely unexplored, leaving an important gap in the empirical finance literature.

In this paper, we ask whether firm-level volatility improves portfolio allocation

[1] A smaller strand of research focuses on firm-level variation in idiosyncratic risk (Vuolteenaho, 2002).

across individual stocks, and if so, why. Specifically, when two stocks are alike in observable characteristics (e.g., size, book-to-market, momentum) but differ in their volatilities, the question is how investors should incorporate that information into their allocations. To answer this question, we use an approach that builds on directly estimating portfolio weights (Brandt et al., 2009), where individual firms' weights are economically motivated functions of company characteristics, with firm volatility playing a central role. This framework offers a tractable way to evaluate firm-level volatility timing relative to a benchmark and under realistic transaction costs, without requiring a full model of the joint distribution of returns and characteristics. It makes it feasible to consider a portfolio of up to 6,000 publicly listed firms rebalanced monthly, a scale typically prohibitive in standard portfolio settings. Because volatility is more variable than other state variables and prone to jumps, volatility-timing strategies entail higher transaction costs (Barroso and Detzel, 2021). A key feature of our approach is that transaction costs are embedded directly in the optimization, serving as an economic regularization mechanism that disciplines trading activity, produces tradeable portfolios, and enhances out-of-sample stability.

The main finding is that firm-level volatility delivers substantial risk-adjusted gains even after accounting for transaction costs, in- and out-of-sample. Portfolios that assign lower weights to more volatile stocks, both across firms and over time, achieve certainty-equivalent returns roughly 10% higher than strategies that ignore volatility timing. In other words, to obtain these gains, investors should place less weight on stocks whose volatility is above the cross-sectional mean, conditional on other characteristics. These core result obtain either with simple and transparent realized variance (Schwert, 1989; Fleming et al., 2003) or absolute variance (Forsberg and Ghysels, 2007) measures. The in-sample results are economically large and statistically significant, underscoring the importance and timeliness of the information embedded in firm-level volatility. Out of sample, the gains remain sizable, with volatility-timing portfolios producing certainty-equivalent returns about 10% above the benchmark, net of transaction costs. These improvements double those generated by commonly used characteristics such as size, book-to-market, and momentum, and are distinct from those generated by recent factor-based approaches to volatility management (DeMiguel et al., 2024).

To understand the economic mechanism behind firm-level volatility timing, we extend the analysis in several directions. First, decomposing firm-level volatility into idiosyncratic and systematic components, we find that performance gains are driven mainly by the idiosyncratic part, setting our results apart from prior work focused on systematic risk (e.g., market, industry, or factor volatility). The systematic

component has the same sign as in Moreira and Muir (2017) and DeMiguel et al. (2024), but its effect is significant only for certain measures and remains much smaller than that of the idiosyncratic component, after transaction costs. Overall, the evidence points to idiosyncratic volatility as the key driver of our results.

Second, our main analysis shows that realized volatility measures based on a longer 252-day history deliver higher after-transaction-cost gains than those based on 22 days. The advantage of longer windows stems from the smoother nature of the estimates: they reduce the variability of portfolio weights, lower turnover, and thereby enhance net performance. Following this result, the natural next step is to investigate which specification of firm-level volatility most accurately captures the conditional risk dynamics relevant for optimal volatility-timing strategies. Whereas the volatility forecasting literature seeks measures that minimize prediction error for future volatility (e.g., Bekaert et al. (2025)), our objective is to maximize portfolio performance net of trading costs. To address this, we adopt a MIDAS framework that jointly estimates the weighting of past daily returns and the portfolio weights based on monthly data, allowing the data to determine which lags of daily returns are most informative for volatility timing. The results point to a bias–variance tradeoff: more recent squared or absolute returns capture firm-specific news and announcements more effectively, but they yield noisier estimates that raise turnover; in contrast, longer-horizon measures are smoother and reduce trading costs, but are less responsive to recent information.

Third, we explore the role of positive and negative volatility components into the overall volatility-timing. When it comes to forecasting future volatility, it is well known that asymmetries play an important role. Specifically, volatility associated with negative shocks is associated with higher future volatility, a phenomenon that is commonly referred to as the leverage effect. We decompose firm-level volatility into components driven by positive and negative shocks—analogous to realized semi-variances (Barndorff-Nielsen et al. (2010)) or to the news impact curves (Engle and Ng (1993); Chen and Ghysels (2011))—and allow portfolio weights to load separately on each. We find that there is clear evidence of asymmetries, with positive and negative returns having a different impact, an empirical fact well documented in the literature. What is new, however, is that, unlike in volatility forecasting, within the context of volatility timing, positive shocks result in higher portfolio gains relative to negative shocks.

We focus on two competing hypotheses: (1) the leverage hypothesis of Black (1976) and (2) the learning-about-profitability framework of Pástor and Veronesi (2003). The key distinction is that a learning mechanism predicts higher volatility

following positive shocks, in contrast to leverage-based explanations, which imply the opposite. We report novel empirical evidence discriminating between the two theoretical models by focusing on two testable implications. The first implication is that when the variance is decomposed into components driven by positive and negative shocks, the leverage hypothesis predicts a stronger effect from negative shocks on portfolio weights, whereas the learning-about-profitability hypothesis predicts the opposite. The second is that under the leverage view, high book-to-market (value) firms should display this asymmetry more strongly due to higher leverage, while low book-to-market (growth) firms, being less leveraged, should exhibit little or none. Under the learning-about-profitability mechanism, volatility timing should be concentrated among firms with high profitability uncertainty.

Regarding the first test, we report a new and provocative result: the positive component of volatility explains most of the negative relation between volatility and portfolio weights. The negative component contributes only marginally. In other words, the learning-about-profitability mechanism appears to play a dominant role in volatility timing, while the leverage effect, although present, is considerably weaker. To our knowledge, we are the first to document this result. This interpretation is also consistent with our firm-level evidence.

Regarding the second test, consistent with our second testable implication, we partition firms into high- and low-profitability-uncertainty groups. If the learning-about-profitability mechanism drives our results, volatility timing should be strongest among firms whose profitability is most uncertain. This is precisely what we find: volatility timing is substantially larger for firms with higher profitability uncertainty. By contrast, value firms do not display stronger volatility timing; instead, the effect is concentrated in growth firms. To the extent to which growth firms tend to exhibit greater uncertainty about future profitability, this pattern is also consistent with the Pástor and Veronesi (2003) framework. Together, these results support the interpretation that learning about profitability is the primary mechanism behind firm-level volatility timing.

One outstanding question is why the learning effect is not purely idiosyncratic and diversifiable? A possible explanation is cross-firm learning: firms update their beliefs not only from their own cash flows but also from information about their competitors and suppliers. This interdependence in the learning process induces correlation across firms, making the effect aggregate rather than purely idiosyncratic.

Related Literature: Our paper contributes to three strands of literature. First, it extends the volatility timing literature, with notable contributions by Fleming et al. (2001, 2003); Moreira and Muir (2017); DeMiguel et al. (2024). These studies

typically rely on aggregate volatility measures—at the market or factor level—and directly specify the return process. By contrast, we examine volatility at the firm level, exploiting cross-sectional variation, and show that the resulting portfolio gains are substantially higher than previously documented. Our parametric portfolio approach is also markedly different from existing methods in that we do not explicitly specify the returns process. Finally, we take at heart the concerns raised in this literature by Cederburg et al. (2020) regarding out-of-sample performance and by Barroso and Detzel (2021) regarding transaction costs.

Second, our paper contributes to the literature on idiosyncratic volatility (Campbell et al., 2001; Goyal and Santa-Clara, 2003; Brandt et al., 2010; Bekaert et al., 2012; Herskovic et al., 2016; Campbell et al., 2023) which relies on aggregate measures of idiosyncratic risk and emphasizes time-series dynamics. By contrast, we exploit cross-sectional variation in firm-level volatility, which is predominantly idiosyncratic in nature. Existing studies also highlight the asset-pricing implications, whereas our central message is that idiosyncratic volatility is crucial for portfolio selection. A related contribution is Ang et al. (2006), who show that stocks with low idiosyncratic volatility earn higher expected returns based on portfolio sorts. Our approach differs by developing parametric, tradeable strategies that explicitly incorporate transaction costs, which are especially salient given the turnover associated with volatility timing. Taken together, our findings underscore a distinct dimension of the broader message: firm-level volatility is a key input into financial decision making, particularly portfolio allocation.

Third, the MIDAS models that distinguishes between positive and negative volatility components shed light on the economic mechanisms driving the asymmetries: (1) the leverage hypothesis of Black (1976) and (2) the learning-about-profitability framework of Pástor and Veronesi (2003).

The paper is organized as follows. Section 2 covers the methods used to study firm-level volatility timing. Section 3 documents the main empirical results of firm-level volatility timing. Section 4 documents the novel asymmetries in volatility timing. Section 5 tests various economic mechanisms that might give rise to asymmetries. Section 6 concludes.

2 Firm-Level Volatility Timing: Methodology

The investable universe consists of N_t stocks in month t, with associated monthly returns $r_{i,t}$, $i = 1, \ldots, N_t$, monthly return volatility $\sigma_{i,t}$, and a vector of baseline characteristics, $x_{i,t}$ (such as size, book-to-market, and momentum) of dimension p.

We consider the entire cross-section of individual publicly traded stocks and, in our sample, N_t ranges from 3,116 to 5,996 stocks in a given month.

An investor chooses a portfolio of the N_t stocks to maximize her expected utility

$$\max_{\theta} E[u(r_{p,t+1} - TC_t)], \tag{1}$$

where $r_{p,t+1} = \sum_{i=1}^{N} w(x_{i,t}, \sigma_{i,t}; \theta) r_{i,t+1}$ is the portfolio return, $w(x_{i,t}, \sigma_{i,t}; \theta)$ are the portfolio weight for stock i at time t parameterized as a function of the asset's characteristics $x_{i,t}$, its volatility, and an parameter vector θ. The portfolio transaction costs are $TC_t = \sum_{i=1}^{N} c_{i,t} |w(x_{i,t}; \theta) - w(x_{i,t-1}; \theta)|$, where $c_{i,t}$ is the one-way trading cost of stock i at time t.

2.1 Portfolio Weights as a Function of Firm-Level Volatility

Following the framework of Brandt et al. (2009), we specify the portfolio weights $w(x_{i,t}, \sigma_{i,t}; \theta)$ directly as a linear function of the firm's baseline characteristics and volatility:

$$w(x_{i,t}; \theta) = \bar{w}_{i,t} + (\theta_x' x_{i,t} + \theta_\sigma \sigma_{i,t})/N_t \tag{2}$$

where $\bar{w}_{i,t}$ represents benchmark weights (e.g., value-weighted or equal-weighted). The investor observes or estimates the conditioning information $[x_{i,t}, \sigma_{i,t}]$ from past accounting data or market returns. Specifically, while the volatility of returns is unobservable, a large literature suggests that it can be reliably estimated. Given $[x_{i,t}, \sigma_{i,t}]$, the investor estimates the parameters $[\theta_x', \theta_\sigma]$ by maximizing the sample analogue of the expected utility function (1). These estimates fully characterize the optimal portfolio policy under specification (2). As we investigate whether, and to what extent, firm-level return volatility $\sigma_{i,t}$ affects portfolio allocation, our focus is on the volatility-timing parameter θ_σ.

2.1.1 Normalization of variables

The variables $x_{i,t}$ and $\sigma_{i,t}$ in (2) are normalized by subtracting their cross-sectional mean and dividing by their cross-sectional standard deviation at each t, ensuring that they have a zero mean and unit standard deviation across stocks. This normalization guarantees that the optimal portfolio weights sum to one and allows the magnitudes of the parameters θ_x and θ_σ to be directly comparable.

In the context of volatility timing, the normalization provides two additional advantages. It emphasizes deviations of firm-level volatility from the cross-sectional average volatility, aligning with the average volatility measure studied in Campbell

et al. (2001) and Goyal and Santa-Clara (2003). As such, θ_σ effectively captures fluctuations in idiosyncratic risk. Moreover, because the transformation yields unitless deviations, the scale of dispersion is inconsequential; consequently, either variance or standard deviation (or any transformation of the second moment) may be used in the weight specification (2).

2.1.2 Transaction costs as an economic regularization of the portfolio

In (1), gains in portfolio performance are evaluated net of transaction costs, as the parameters θ influence both portfolio returns and trading costs. Specifically, they determine turnover, $\sum_{i=1}^{N} |w(x_{i,t}, \sigma_{i,t}; \theta) - w(x_{i,t-1}, \sigma_{i,t}; \theta)|$, which generates an economic penalty through transaction costs TC_t. The severity of this penalty is proportional to the one-way trading costs $c_{i,t}$ and disappears when $c_{i,t} = 0$. Hence, the transaction cost term acts as an economic regularization, penalizing large deviations from benchmark weights and excessive trading. This role is particularly important when working with the entire cross-section of individual stocks: without such regularization, extreme realizations of returns or conditioning variables can produce large estimated θs, leading to portfolios that are difficult to implement and that perform poorly out-of-sample. For this reason, it is essential to optimize the after-transaction-cost portfolio return, rather than ignoring trading costs or subtracting a fixed cost ex post.

Economic portfolio regularization through transaction costs is particularly important when volatility is included among the conditioning variables. Cross-sectional differences in volatility often reflect firm-specific news events that materialize as large return jumps (see e.g. Todorov and Tauchen (2011)). In addition, volatility displays substantial time-series variation, often exceeding that of the baseline characteristics $x_{i,t}$. Incorporating transaction costs mitigates overfitting concerns and delivers volatility-timing portfolio policies that are both economically plausible and implementable.

We next turn to the measurement of firm-level volatility in (2), which is essential for implementing the volatility-timing strategy. Our analysis builds on the extensive volatility literature, beginning with two of the most widely used model-free measures of variance. These measures provide a transparent and broadly applicable benchmark, requiring minimal distributional assumptions and offering a natural starting point before considering alternative approaches.

2.2 Simple Measures of Firm-Level Volatility

We start off with two well-established and model-free measures of monthly $\sigma_{i,t}$, the realized volatility, $RV_{i,t}$, and absolute volatility, $AV_{i,t}$. These are estimated from daily returns for each firm i in month t, as follows:[2]

$$RV_{i,t}(D) = \sqrt{22} \times \left[\frac{1}{D} \sum_{d=1}^{D} r_{i,t-\frac{d}{22}}^2 \right]^{1/2}, \quad AV_{i,t}(D) = \sqrt{22} \times \left[\frac{1}{D} \sum_{d=1}^{D} |r_{i,t-\frac{d}{22}}| \right], \quad (3)$$

where daily returns are indexed with fraction of month t, such that $r_{i,t-\frac{d}{22}}$ is the daily return d days before the end of month t and D is the window of past daily returns used in the estimation. The realized volatility is a widely-used estimator, with a long-standing history tracing back to French et al. (1987) and Schwert (1989). It is a well-established measure and predictor of return variation, capturing both smooth dynamics and jumps when high-frequency data are used (Andersen et al., 2003). The absolute variance estimator is also commonly used; Forsberg and Ghysels (2007) show that it primarily captures the continuous component of return variability.[3]

We estimate $RV_{i,t}(D)$ and $AV_{i,t}(D)$ with firm-level daily stock returns of all companies listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ obtained from the Center for Research on Security Prices (CRSP) for the period 2003–2023. The sample is restricted to firms with share codes 10 and 11. For each firm, we compute monthly $RV_{i,t}$ and $AV_{i,t}$ using windows of length $D = 22$ and $D = 252$ days. The choice of window length D balances responsiveness and noise reduction. Short horizons (e.g., $D = 22$) place greater weight on recent information and yield non-overlapping estimates but are noisier and, as we will see below, induce higher turnover. Longer horizons (e.g., $D = 252$) smooth transitory fluctuations and capture persistent variance dynamics, at the cost of requiring overlapping observations. To address this trade-off more systematically, we later consider MIDAS-type weighting schemes that flexibly combine information across horizons to systematically evaluate the window length that yields the best volatility-timing performance.

Figure 1 shows the 25th and 75th cross-sectional percentiles and mean of $RV_{i,t}(22)$,

[2] We use daily returns because of the overwhelming evidence that high-frequency data leads to better estimates of monthly volatility (cfr. Merton (1980)). We astrain from the use of even higher-frequency returns given that for most stocks intra-daily returns are not available and/or characterized by staleness. Alternatively, is possible to use monthly returns and a GARCH model to estimate the monthly variance.

[3] We square the sum of absolute returns such that $AV_{i,t}$ is expressed in the same units as the realized variance. Its analogue in the ARCH/GARCH literature is the absolute GARCH family of models (see Ding et al. (1993)).

$AV_{i,t}(22)$, $RV_{i,t}(252)$, and $AV_{i,t}(252)$ over time. The spread of the interquartile range captures substantial cross-sectional heterogeneity, while changes in the mean indicates pronounced time-series variation. Our portfolio framework incorporates both cross-sectional and time-series variation in volatilities. Table 1 contains summary statistics of the $RV_{i,t}$ and $AV_{i,t}$ estimates.

2.3 Decomposing Firm-Level Volatility: Idiosyncratic and Systematic Components

The total firm-level volatility $RV_{i,t}$ can be decomposed into idiosyncratic and systematic components as

$$RV_{i,t}^2 = SYS_{i,t}^2 + IDIO_{i,t}^2, \tag{4}$$

where $SYS_{i,t}^2$ denotes systematic variance, $IDIO_{i,t}^2$ denotes idiosyncratic variance, and we suppress the estimation window notation for simplicity. Goyal and Santa-Clara (2003) demonstrate, via a simple variance decomposition, that the total variance of individual firm returns is predominantly attributable to idiosyncratic fluctuations. Campbell et al. (2001) and Campbell et al. (2023) show, using market models and cross-sectional restrictions that avoid direct estimation of betas, that the bulk of firm-level volatility is idiosyncratic. In particular, Campbell et al. (2023) estimate that roughly 70–80% of total firm volatility reflects idiosyncratic risk, with the remainder attributable to industry- and market-level components (see Figure 4 in Campbell et al. (2023)).

In general, the identification of the systematic component requires making modeling choices about systematic risk, such as the selection of factors, the estimation of factor loadings, and the choice of the estimation window, that inevitably introduce model dependence. We use state-of-the-art estimates of firm-level idiosyncratic risk from Jensen et al. (2023) implicitly conditioning our decomposition on the specification choices in that study. Jensen et al. (2023) construct four measures of idiosyncratic volatility for the full cross-section of listed firms. Three are based on the most recent 22 trading days and rely, respectively, on the CAPM, the Fama and French (1993) three-factor model (FF), and the Hou et al. (2015) multi-factor model (HXZ). Using (4), each of these idiosyncratic measures can be subtracted from the total volatility measure $RV_{i,t}(22)$ to obtain three alternative estimates of systematic risk. A fourth measure, based on the past 252 trading days and the CAPM, aligns with our long-horizon benchmark, $RV_{i,t}(252)$. Together, these yield four decompositions, which we denote $CAPM(22)$, $FF(22)$, $HXZ(22)$, and $CAPM(252)$.

Figure 2 shows the cross-sectional mean of systematic and idiosyncratic volatili-

ties over time, along with their unconditional averages (dotted lines). In all four decompositions, idiosyncratic volatility is substantially larger than systematic volatility, accounting for about 70% of total volatility, in line with Campbell et al. (2023). The share of idiosyncratic volatility declines during the Global Financial Crisis (2007–2009) and again in early 2020 during the Covid-19 shock, when systematic risk rose sharply. The four decompositions deliver broadly similar results on average, although cross-sectional differences may exist. Since the idiosyncratic volatility measures are produced externally to our study, we remain agnostic as to which specification is preferable and therefore employ all four in our analysis.

3 Firm-Level Volatility Timing: Main Results

To estimate the volatility-timing strategy, we employ, in addition to the $RV_{i,t}$ and $AV_{i,t}$ measures, monthly returns, stock prices, and shares outstanding from CRSP for the same set of firms and time span. Stock prices and shares outstanding are used to construct the benchmark value-weighted portfolio weights, $\bar{w}_{i,t}$. We further augment the information set with baseline firm characteristics $x_{i,t}$—size, book-to-market, and momentum—obtained from Jensen et al. (2023). These characteristics are lagged by one month to ensure they are included in investors' information set at time t and are predetermined with respect to subsequent returns $r_{i,t+1}$. Summary statistics for the characteristics are provided in Table 1.

We begin by presenting estimates of the simple volatility-timing strategy, followed by an analysis of its in-sample and out-of-sample performance. Throughout, we assume an investor with CRRA preferences and a relative risk aversion parameter of five, as in Brandt et al. (2009). Note that our sample starts exactly when the Brandt et al. (2009) ends, so the baseline case constitutes an external validation of their results.

3.1 Volatility Timing Strategies: In-Sample Results

We estimate the volatility-timing strategy in (2) by optimizing the sample analogue of (1), using monthly firm returns $r_{i,t+1}$, baseline characteristics $x_{i,t}$, and the volatility estimates from Section 2.2. As a benchmark, we first compute portfolio weights in the absence of transaction costs ($c_{i,t} = 0$), and then re-estimate the weights under transaction costs of 10 and 25 basis points (bps).[4] For simplicity, we assume identical costs across stocks, or average trading costs, and interpret them as average

[4] As additional robustness check, the Appendix reports results with also 50 basis points of transaction costs.

trading costs, while noting that our framework can readily incorporate stock-specific variation in $c_{i,t}$ when such data are available, which unfortunately, we do not have at the firm level. The 10-basis-point level is consistent with the empirical evidence in Frazzini et al. (2018), who document average equity trading costs of about 10 bps. They further report that small-cap stocks face trading costs of roughly 20–25 bps. Accordingly, the $c_{i,t} = 0.0025$ is a conservative upper bound, as it assumes that the trading costs of all stocks—large, medium, and small—are uniformly set at 25 bps. For each cost specification, portfolio weights are re-estimated since the parameters θ jointly determine both the allocation and the resulting turnover. As discussed in Section 2.1, in the presence of trading costs the optimization naturally incorporates an economic form of regularization; while stronger signals can improve expected returns, they also increase turnover and thereby reduce net-of-cost performance.

Table 2 displays the estimates of θ for $c_{i,t} = 0$ (Panel A), $c_{i,t} = 0.001$ (Panel B), and $c_{i,t} = 0.0025$ (Panel C). In each panel, as benchmarks, column (1) presents the value-weighted portfolio ($\theta = 0$) and column (2) shows the optimal portfolio based on the three baseline characteristics in $x_{i,t}$ but without volatility timing.[5] The final four columns display the estimates of the volatility-timing strategy, where the parameter θ_σ captures the effect of each of the four volatility measures – $RV_{i,t}(22)$, $AV_{i,t}(22)$, $RV_{i,t}(252)$, and $AV_{i,t}(252)$ – on optimal portfolio weights.

The results yield three main insights. First, the estimated θ_σ is negative across all volatility measures and trading-cost specifications. This implies that firms with higher-than-average variance receive lower portfolio weights, after controlling for other characteristics, The result is consistent with standard portfolio choice models, where investors optimally allocate away from high-variance stocks and with prior studies that use systematic volatility measures (Fleming et al. (2001, 2003); Moreira and Muir (2017)). Second, the magnitude of θ_σ is comparable to that of the baseline characteristics and is statistically significant. As trading costs increase, all estimated θs shrink toward zero due to the stronger turnover penalty. Consequently, the inclusion of even a single volatile signal induces shrinkage across all estimated coefficients. The shrinkage effect is especially pronounced for $RV_{i,t}(22)$ and $AV_{i,t}(22)$, which are inherently noisier and generate higher turnover. In general, θ_σ is larger for smoother volatility measures, underscoring the importance of the choice of volatility measure in volatility-timing strategies. The choice of volatility measure corresponds to the length of the return window D used in its construction, which raises the question

[5]The estimated θ on market capitalization is negative, while those on book-to-market and momentum are positive, indicating that small-cap, value, and high-momentum stocks receive larger weights than in the market portfolio. These estimates are similar in sign and magnitude to those in Brandt et al. (2009), and essentially replicate their results on an updated, non-overlapping sample.

of what constitutes the optimal D for volatility timing. We address this question in the next section.

Third, the volatility-timing effect is both economically meaningful and straightforward to interpret. Consider two stocks with identical market weights, characteristics and transaction costs of 10 bps (Panel B). One has an $RV_{i,t}(22)$ equal to the cross-sectional mean, while the other is one standard deviation above it. The optimal weight of the higher-variance stock is $(-4.053 \times 1)/N_t$. Using the time-series average of $N_t = 3{,}953$, this corresponds to $-4.053/3953 \approx -0.001$. Put differently, the higher-RV stock receives a portfolio weight that is about 11 basis points lower. This difference captures the incremental adjustment in optimal weights due to volatility. Aggregated across all N_t stocks at time t, these adjustments generate the total portfolio effect of volatility timing.

A more informative gauge of economic significance, however, comes from comparing realized portfolio performance. The in-sample performance of the optimal portfolios is reported in Table 3. Without transaction costs (Panel A), the value-weighted portfolio delivers a certainty-equivalent return (CE(r)) of 4.4%, with an average return of 10.5%, volatility of 15.3%, and a Sharpe ratio of 0.601, all annualized. Conditioning only on baseline characteristics substantially improves performance, raising the CE(r) to 18.4%. Adding variance as an additional conditioning variable further increases the CE(r) to between 27.8% ($RV_{i,t}(22)$) and 29.5% ($RV_{i,t}(252)$), nearly doubling the incremental risk-adjusted gains. In absolute terms, the gains in CE(r) amount to roughly 10% or more per year, which is economically significant. The Sharpe ratio increases to as high as 1.654 ($AV_{i,t}(22)$), driven primarily by higher average returns without a commensurate rise in volatility. The turnover and average short positions of the volatility-timing portfolios are broadly similar to those of the baseline case.

Introducing transaction costs attenuates performance for all portfolios, but does not eliminate the gains from volatility timing. With 10 bps costs (Panel B), the CE(r) of the baseline portfolio falls to 0.160, while the volatility-timing portfolios deliver CE(r) values between 0.243 and 0.272. In absolute terms, the gains in CE(r) are again around 10% or higher annually, representing a sizable economic effect. The $RV_{i,t}(22)$ and $AV_{i,t}(22)$ strategies are affected more strongly, reflecting the higher turnover induced by their noisier volatility estimates. With 25 bps costs (Panel C), the CE(r) of the baseline portfolio declines further to 0.129, while the volatility-timing portfolios continue to outperform with CE(r) values between 0.197 and 0.241. Overall, incorporating variance timing yields increases in CE(r) of about 10% relative to the benchmarks, even after accounting for trading costs.

3.2 Volatility Timing Strategies: Out-of-Sample Results

Table 4 reports the out-of-sample (OOS) performance. Portfolio policies are estimated over the period 2003–2012 under three cost scenarios—no trading costs (Panel A), 10 basis points (Panel B), and 25 basis points (Panel C)—and re-estimated annually using an expanding-window procedure for the evaluation period 2013–2023. Portfolio weights are updated monthly based on signals derived from firm characteristics. We focus our discussion on the 10 bps results in Panel B. The OOS CE(r) of the baseline portfolio is 10.3%, with a Sharpe ratio of 0.977. By contrast, the volatility-timing portfolios deliver substantially higher CE(r). The most modest gains, at 16.4%, arise from the most variable measure, $RV_{i,t}(22)$. The gains increase to as high as 28.0% for $RV_{i,t}(252)$, which closely matches the in-sample results and indicates that the strategy is stable out-of-sample. The Sharpe ratio also rises markedly, reaching 1.523 for $RV_{i,t}(252)$. These represent large and economically meaningful out-of-sample improvements. Similar patterns hold under both zero and higher trading costs.

Figure 5 plots the cumulative OOS CE(r) of the portfolios. Focusing on the 10 bps case (Panel B), the volatility-managed portfolios outperform the baseline allocation, which itself delivers strong performance. The outperformance is steady and sustained throughout the evaluation period. A dollar invested in the baseline portfolio at the start of 2013 grows to just over 16 dollars by the end of 2023, on a risk-adjusted basis. In contrast, the cumulative value rises to more than 26 dollars for $RV_{i,t}(252)$ and about 23 dollars for $AV_{i,t}(252)$. The results in Panels A and C are qualitatively similar. The portfolio returns (not risk-adjusted) are even larger, and are shown in the appendix. Overall, the OOS performance improvement is about 10%, comparable in magnitude to the in-sample results.

To strengthen the robustness of our results, we repeat the out-of-sample analysis under alternative sample splits. Specifically, we extend the estimation sample back to January 1995 and conduct the same out-of-sample exercise described above, varying the initial date of the out-of-sample period from January 2010 through January 2022. This approach generates 13 distinct out-of-sample validation exercises, each implemented following the procedure outlined above. Table 5 reports the OOS CE(r) from this exercise. The results largely corroborate the superior performance of our volatility timing strategies. Regardless of the sample considered, the volatility-timing CE(r) is positive and larger than that of the baseline portfolio.[6] These results

[6] We also assess the statistical significance of the utility gains from the volatility timing strategies using a Diebold and Mariano (1995) test, finding that they are statistically significant at the 1% level for most of the OOS periods. We report the results of these tests in Table A.2.

are particularly important to further mitigate the Cederburg et al. (2020)'s critique on the deteriorating OOS performance of the volatility timing strategy.

3.3 Idiosyncratic and Systematic Volatility

Building on prior evidence that firm-level volatility is predominantly idiosyncratic (Campbell et al., 2001; Goyal and Santa-Clara, 2003; Campbell et al., 2023), we conjecture that idiosyncratic risk is central to our findings. To test this conjecture, we draw on the four decompositions introduced in Section 2.3, which partition total firm-level volatility into systematic and idiosyncratic components. As a first step, we replace the $RV(22)$ and $RV(252)$ benchmarks with four measures of idiosyncratic volatility, $CAPM(22)$, $FF(22)$, $HXZ(22)$, and $CAPM(252)$, and denote the corresponding parameter $\theta_{\sigma_{IDIO}}$.

Table 6 reports the results alongside the benchmarks $RV(22)$ and $RV(252)$, all including transaction costs of 10 bps. Panel (A) shows that the estimates of $\theta_{\sigma_{IDIO}}$ for $CAPM(22)$, $FF(22)$, and $HXZ(22)$ are negative and slightly larger in magnitude than θ_{VOL}. A similar pattern emerges when comparing the $CAPM(252)$ to $RV(252)$ specifications. None of these differences are statistically significant. To gauge their relevance we turn to the portfolio performance results.

In Panel (B), the in-sample CE(r) of the idiosyncratic measures exceeds that of the corresponding total volatility benchmarks by 60 to 190 basis points. These gains, however, come with higher portfolio volatility, mixed changes in Sharpe ratios (slightly lower or higher than those of $RV(22)$ and $RV(252)$), and increased turnover. Panel (C) presents the out-of-sample results, which broadly mirror the in-sample findings. The CE(r) remains in the 16.3%–25.8% range, occasionally below the total volatility benchmarks. The largest discrepancy arises for $CAPM(252)$ relative to $RV(252)$. Overall, total and idiosyncratic volatility yield comparable results at short horizons, consistent with $RV(22)$ largely reflecting idiosyncratic risk. At longer horizons, however, $RV(252)$ delivers higher certainty-equivalent returns and Sharpe ratios than the idiosyncratic benchmarks, suggesting that systematic risk may contribute to the volatility-timing gains at this frequency.

Table 6 reports results for both idiosyncratic and systematic components from the four decompositions, again including 10 bps transaction costs. Adding systematic risk does not change qualitatively the estimates on $\theta_{\sigma_{IDIO}}$. The coefficient on systematic volatility, $\theta_{\sigma_{SYS}}$, is consistently negative, indicating that the optimal strategy reduces weight on stocks with higher systematic risk exposure, holding other factors constant. This result echoes the volatility-managed portfolio evidence in Moreira and Muir (2017); DeMiguel et al. (2024), though obtained here with in-

dividual stocks, a different methodology, and a distinct sample. The coefficients are insignificant at short horizons but reach the 5% significance level at longer horizons. Panel (B) shows that including the systematic component improves in-sample CE(r) only for the long-horizon specifications, where the increase is about 1.7%. Out-of-sample, CE(r) increases by 1.4%, though it remains below the CE(r) of $RV(252)$, likely because the latter relies on fewer parameters while capturing similar information.

Overall, the evidence suggests that the timing gains from $RV(22)$ and $RV(252)$ are primarily driven by idiosyncratic risk, with systematic risk playing a role only at longer horizons. Importantly, the explicit decomposition does not yield material improvements over using $RV(22)$ and $RV(252)$ directly. In fact, the strongest out-of-sample performance arises from $RV(252)$ rather than from the $CAPM(252)$ decomposition.

3.4 Additional Controls

We extend the baseline set of firm characteristics $x_{i,t}$ by adding three widely used variables: the beta from Frazzini and Pedersen (2014), the illiquidity measure of Amihud (2002), and the investment ratio of Hou et al. (2015). These additions are motivated by their low correlation across firms and time, their established role in explaining the cross-section of returns, and their relevances for firm-level volatility timing. The beta tests the Frazzini and Pedersen (2014) "betting-against-beta" hypothesis, implying a negative θ as the portfolio tilts away from high-beta stocks. The illiquidity measure captures either trading frictions (Amihud, 2002) or systematic liquidity risk (Acharya and Pedersen, 2005), while the investment ratio reflects the negative relation between expected returns and investment intensity (Hou et al., 2015). We concentrate on these key variables and report results for additional factors in the appendix.

Table 8 reports the results with 10 basis points transaction costs. Column (1) presents the expanded baseline specification with six characteristics, including the three newly added variables. The estimated θ on beta is negative, indicating that the portfolio tilts away from high-beta stocks, consistent with the betting-against-beta effect, though obtained through a different empirical approach than in Frazzini and Pedersen (2014). The θ on the illiquidity measure is positive, implying larger weights on illiquid stocks and underscoring the need to control for transaction costs to ensure implementability. The θ on investment is negative and of the largest magnitude among all characteristics, consistent with Hou et al. (2015) who show that high-investment firms earn lower expected returns.

Adding firm-level volatility to the expanded baseline specification yields consistent results. The coefficients on both $RV(252)$ and $AV(252)$ remain negative, statistically significant, and comparable in magnitude to those reported in the preceding tables. Notably, controlling for volatility renders the θ on beta insignificant, with its sign reversing. This pattern reinforces the evidence from the previous subsection, indicating that the negative relation between portfolio weights and risk is primarily driven by idiosyncratic rather than systematic components. The coefficients on illiquidity and investment remain stable and unaffected by the inclusion of volatility.

Including the three additional characteristics leads to improvement to both in-sample and out-of-sample portfolio performance, with CE(r) increasing to 0.364 and 0.194, respectively. Incorporating firm-level volatility timing further enhances performance, particularly out-of-sample, with CE(r) rising to 0.337 for $RV(252)$ and 0.255 for $AV(252)$. Thus, even relative to a specification including a rich set of "state-of-the-art" characteristics, volatility timing captures distinct cross-sectional variation in expected returns and materially improves portfolio performance.

3.5 Joint Volatility and Weights Estimates via MIDAS

The estimators in equation (3) assign equal weight to daily observations within a fixed window D, which we collectively refer to as *equal-weights* volatility measures. The window length had a significant effect on the results. Volatility estimates computed with $D = 252$ outperformed those based on $D = 22$, primarily because the latter specification induces greater short-term variability. Although these window lengths follow standard practice, in our context they are arbitrary in the sense that they are not selected to maximize portfolio performance.

As an alternative, we estimate volatility by jointly choosing the weighting scheme on past daily squared or absolute returns together with the portfolio weights that maximize an investor's expected utility. The objective is to construct a volatility measure that is optimal in the sense of maximizing volatility-timing performance net of transaction costs. The main challenge is the mixed frequency of the data, *daily* squared or absolute returns versus *monthly* firm returns and characteristics, which calls for a mixed-data sampling (MIDAS) approach, outlined below.

We consider the following two specifications to estimate firm-level volatility:

$$\text{MIDAS-RV}_{i,t}(\kappa) = \sqrt{22} \times \left[\sum_{d=1}^{D} \upsilon_d(\kappa) r^2_{i,t-\frac{d}{22}} \right]^{1/2}, \tag{5}$$

$$\text{MIDAS-AV}_{i,t}(\kappa) = \sqrt{22} \times \left[\sum_{d=1}^{D} \upsilon_d(\kappa) |r_{i,t-\frac{d}{22}}| \right], \tag{6}$$

where the MIDAS weights $\upsilon_d(\kappa)$ on past daily squared or absolute returns are parameterized by a flexible but parsimonious function whose parameters κ will be estimated from the data and K is chosen to be large enough not to influence the parameter estimates. Following Ghysels et al. (2005), we use an exponential Almon polynomial weights:

$$\upsilon_d(\kappa) = \frac{\exp(\kappa_1 d + \kappa_2 d^2)}{\sum_{l=0}^{D-1} \exp(\kappa_1 l + \kappa_2 l^2)}, \tag{7}$$

where $\kappa = (\kappa_1, \kappa_2)$.[7] We write the portfolio weights and the MIDAS volatility specification (5) as

$$w(x_{i,t}; \theta, \kappa) = \bar{w}_{i,t} + (\theta_x' x_{i,t} + \theta_\sigma \text{MIDAS-RV}_{i,t}(\kappa))/N_t, \tag{8}$$

and analogously for the MIDAS-AV specification (6). The portfolio weights are functions of two parameter vectors, θ and κ, which we estimate jointly by maximizing the utility function (1). This setup naturally combines data at different frequencies: firm returns and characteristics $x_{i,t}$ are monthly, while lagged squared returns in the MIDAS specification are daily. The vector κ determines the weights assigned to daily lags of squared or absolute returns that define the optimal portfolio policy. The equal-weighted measures in equation (3) are nested as the special case $\kappa_1 = \kappa_2 = 0$.

By estimating θ and κ jointly, we ask which lags of daily squared or absolute returns yield volatility measures that deliver the strongest after-transaction-costs portfolio gains. The focus here is on portfolio performance, in contrast to the volatility forecasting literature, which targets proxies that minimize mean-squared or QLIKE loss when predicting future realized volatility (Patton, 2011).

The volatility timing MIDAS results are reported in Table 9 using 10 basis points transaction costs. Panel A presents the estimates of θ and κ. To interpret the κ coefficients, we substitute the estimated values into (7) and plot the implied weights on lagged daily returns in Figure 4. Relative to the equal-weighted $RV(252)$ benchmark (dashed line), the MIDAS specifications assign greater weight to more recent observations, an effect that is especially pronounced for the MIDAS-AV. At the same time, the weights are not concentrated solely within the first month, and thus differ markedly from the equal-weighted $RV(22)$ benchmark (dotted line). Hence, the MIDAS weights strike a balance between recency, by emphasizing recent returns,

[7] Other parameterizations of MIDAS weights $\upsilon_d(\kappa)$ are discussed in Ghysels et al. (2006). For an overview of the MIDAS literature, see Ghysels et al. (2025).

and efficiency, by incorporating longer lags in a parsimonious form, thereby managing the bias–variance tradeoff in volatility estimation. Most of the mass of the MIDAS weights is concentrated in the first three months (approximately 66 trading days), suggesting that $RV(D)$ and $AV(D)$ with $D = 66$ may deliver stronger volatility-timing performance than either $D = 22$ or $D = 252$. Finally, the estimated volatility-timing coefficient, $\theta_{\sigma_{MIDAS}}$, is negative and comparable in magnitude to those obtained from the RV measures.

Turning to Panel B, the in-sample performance of the MIDAS specifications, measured by CE(r) and Sharpe ratios, is slightly higher than that of the RV and AV benchmarks. This is expected, as the MIDAS framework introduces additional flexibility through two extra parameters in the portfolio weight specification. The improvement, however, comes at the cost of higher turnover. Out-of-sample results are mixed. For the MIDAS-RV specifications, CE(r) and Sharpe ratios are below those of the RV benchmark, while for the MIDAS-AV they are essentially indistinguishable. To better understand these patterns, Figure 6 plots the implied OOS weights in the second and third subplots. For some OOS periods, the MIDAS weights are heavily concentrated in the first month, resembling the equal-weighted $RV(22)$ and $AV(22)$. This concentration leads to higher turnover, which in turn explains the weaker after-transaction-cost performance.

To summarize, the MIDAS results highlight the importance of the bias–variance tradeoff in volatility timing. The evidence points to a sweet spot around three months of lagged daily returns, suggesting that either MIDAS or $RV(66)$ and $AV(66)$ provide more effective volatility proxies within our volatility-timing framework.

4 Exploiting Asymmetries in Firm-Level Volatility Timing

One of the most robust stylized facts in the volatility literature is the presence of asymmetries: volatility tends to rise more following negative return shocks than after positive ones. The earliest observation of this phenomenon is often attributed to Black (1976) and is known as the leverage effect. The asymmetric response of volatility has since been extensively documented in the GARCH literature (e.g., Glosten et al. (1993); Campbell and Hentschel (1993)). Barndorff-Nielsen et al. (2010) and Patton and Sheppard (2015) develop realized-semivariance estimators that decompose realized variance into components associated with positive and negative returns, providing a nonparametric measure of this asymmetry. Ghysels et al.

(2005) document evidence of volatility asymmetry in the MIDAS framework, highlighting that the sensitivity of volatility to past returns depends on the sign and magnitude of the underlying shocks.

4.1 Realized Semivariances and Volatility Timing

We begin with the realized semivariance estimators of Barndorff-Nielsen et al. (2010), which in our notation can be expressed as

$$RV^{+}_{i,t}(252) = \sqrt{22} \times \left[\frac{1}{D} \sum_{d=1}^{D} r^{2}_{i,t-\frac{d}{22}} \mathbb{1}^{+}_{i,t-\frac{d}{22}} \right]^{1/2}, \tag{9}$$

$$RV^{-}_{i,t}(252) = \sqrt{22} \times \left[\frac{1}{D} \sum_{d=1}^{D} r^{2}_{i,t-\frac{d}{22}} \mathbb{1}^{-}_{i,t-\frac{d}{22}} \right]^{1/2}, \tag{10}$$

where $\mathbb{1}^{+}_{i,t-\frac{d}{22}}$ ($\mathbb{1}^{-}_{i,t-\frac{d}{22}}$) is an indicator function that is equal to one if $r_{i,t-\frac{d}{22}} \geq 0$ ($r_{i,t-\frac{d}{22}} < 0$), and zero otherwise. This provides an exact decomposition of total variance into components attributable to positive and negative return shocks.[8] Analogously, we define $AV^{+}_{i,t}(252)$ and $AV^{-}_{i,t}(252)$ by replacing $r^{2}_{i,t-\frac{d}{22}}$ with $|r_{i,t-\frac{d}{22}}|$ in the expressions above. We then employ the resulting semi-variance measures $RV^{+}_{i,t}(252)$, $RV^{-}_{i,t}(252)$, $AV^{+}_{i,t}(252)$, and $AV^{-}_{i,t}(252)$ in estimating the portfolio-weight specification (2). The objective is to examine whether positive and negative semivariances induce systematically different portfolio allocation responses.

The results are reported in Table 10. Consistent with the earlier tables, all estimates of θ on the volatility measures are negative. The novel finding here is that the coefficient on the positive semivariance has a larger magnitude for the RV measures. The difference remains present, although less pronounced, for the average AV measures. Hence, volatility rebalancing following positive return shocks induces more pronounced portfolio adjustments than rebalancing after negative shocks.

Panel B further highlights this asymmetry: for RV, the in-sample CE(r) associated with positive shocks is roughly twice as large, at 0.322, as that associated with negative shocks, 0.179, while turnover remains comparable. This pattern is even more evident in the out-of-sample results in Panel C, where CE(r) for positive shocks (0.333) again exceeds that for negative shocks (0.154) by a factor of two. The magnitudes for the AV-based measures are smaller but follow a similar pattern.

To the best of our knowledge, this is the first evidence that volatility timing responds more strongly to volatility arising from positive rather than negative return

[8] Each component is scaled by a factor of $\sqrt{2}$ to ensure that its magnitude matches that of $RV_{i,t}(252)$. This scaling is necessary because each one of the components converges to one-half of the quadratic variation, as shown by Barndorff-Nielsen et al. (2010).

innovations. This finding is surprising, given that the volatility-forecasting literature has consistently documented that negative shocks generate higher future volatility than positive shocks. Since portfolio weights are inversely related to volatility, one might therefore expect negative shocks to have the stronger impact on portfolio rebalancing.

We caution that this intuition does not hold in our setting. Our framework differs fundamentally from the volatility-forecasting literature in both the object of modeling, portfolio weights rather than volatility, and the relevant loss function, expected utility rather than statistical forecast accuracy. The observed asymmetry thus reflects not differences in volatility predictability per se, but differences in how volatility affects optimal portfolio decisions.

4.2 Realized MIDAS Semivariances and Volatility Timing

We next turn to the MIDAS volatility where we can do a similar decomposition and jointly estimate the portfolio weights and the semivariances. Specifically, we decompose the MIDAS volatility measures into positive and negative components and examine their separate effects on portfolio weights by considering:

$$MIDAS - RV^{+}_{i,t}(\kappa_{+}) = \sqrt{22}\left[\sum_{d=1}^{D}\left(\upsilon_d(\kappa_{+})r^2_{i,t-\frac{d}{22}}\mathbb{1}^{+}_{i,t-\frac{d}{22}}\right)\right]^{1/2}, \tag{11}$$

$$MIDAS - RV^{-}_{i,t}(\kappa_{-}) = \sqrt{22}\left[\sum_{d=1}^{D}\left(\upsilon_d(\kappa_{-})r^2_{i,t-\frac{d}{22}}\mathbb{1}^{-}_{i,t-\frac{d}{22}}\right)\right]^{1/2}. \tag{12}$$

This is the MIDAS version of the realized semi-variance of Barndorff-Nielsen et al. (2010) and relates to the Chen and Ghysels (2011) MIDAS version of news impact curves introduced by Engle and Ng (1993).

Equations (11)-(12) provide a more flexible specification than the semivariances in (9), as the two lag functions $\upsilon_d(\kappa_{+})$ and $\upsilon_d(\kappa_{-})$ allow positive and negative shocks to load differently on squared or absolute daily returns. These specifications allow the sign of returns to convey information that is not captured by equation (5). By using $|r_{i,t-\frac{d}{22}}|$ instead of the squared returns in equations (11)-(12), we obtain the $MIDAS - AV^{+}_{i,t}$ and $MIDAS - AV^{-}_{i,t}$.

The asymmetric volatility timing weights using $MIDAS - RV^{+}_{i,t}$ and $MIDAS - RV^{-}_{i,t}$ are specified as

$$w(x_{i,t};\theta,\kappa_{+}) \quad = \quad \bar{w}_{i,t} + \theta'_x x_{i,t}/N_t + \theta_{\sigma+} MIDAS - RV^{+}_{i,t}(\kappa_{+})/N_t, \tag{13}$$

and

$$w(x_{i,t};\theta,\kappa_-) \;=\; \bar{w}_{i,t} + \theta_x' x_{i,t}/N_t + \theta_{\sigma-} MIDAS - RV^-_{i,t}(\kappa_-)/N_t, \tag{14}$$

and we can write similar specifications for $MIDAS - AV^+_{i,t}$ and $MIDAS - AV^-_{i,t}$.[9]

We report the results of these portfolios in Table 11, columns (1)-(4). First, $\theta_{\sigma+}$ and $\theta_{\sigma-}$ are both negative. Second, and perhaps more strikingly, the magnitude of $\theta_{\sigma+}$ is approximately three times that of $\theta_{\sigma-}$ across the specifications. The result that positive shocks exert a stronger influence on portfolio weights echoes the earlier evidence in Table 10, though the difference is even more pronounced here. We attribute this amplification to the MIDAS framework's flexibility, which permits distinct lag-weighting functions for positive and negative returns and the joint estimation of both the portfolio-weight coefficients and the MIDAS lag structures. Allowing asymmetric shocks to affect portfolio weights separately increases the in-sample CE(r) to between 48.1 and 52.3 percent for the positive volatility timing, representing a sizable improvement relative to the symmetric specifications. The corresponding Sharpe ratios all exceed 2. Out-of-sample, the CE(r) of the positive volatility ranges from 35.2 to 38.0 percent, again outperforming the specifications that do not account for asymmetries. Overall, allowing positive and negative return shocks to affect portfolio weights asymmetrically improves portfolio performance, with the dominant contribution stemming from positive shocks. This finding appears robust across alternative specifications of the asymmetry.

The MIDAS framework enables us to further disentangle whether the observed asymmetry arises from differences in the lag weighting functions, $\upsilon_d(\kappa_+)$ and $\upsilon_d(\kappa_-)$, associated with positive and negative return innovations, or from differences in the sensitivity of portfolio weights to semi-variances, captured by the parameters $\theta_{\sigma+}$ and $\theta_{\sigma-}$. To assess this, we estimate an asymmetric MIDAS volatility model where positive and negative shocks have different MIDAS lag weights:

$$\begin{aligned}&\text{MIDAS-RV}_{i,t}(\kappa_+,\kappa_-) = \\ &\quad \sqrt{22}\left[\textstyle\sum_{d=1}^{D} \upsilon_d(\kappa_+)\, r^2_{i,t-\frac{d}{22}}\, \mathbb{1}^+_{i,t-\frac{d}{22}} + \sum_{d=1}^{D} \upsilon_d(\kappa_-)\, r^2_{i,t-\frac{d}{22}}\, \mathbb{1}^-_{i,t-\frac{d}{22}}\right]^{1/2},\end{aligned} \tag{15}$$

but their impact on the weights is captured by one parameter θ_σ:

$$w(x_{i,t};\theta,\kappa_+,\kappa_-) = \bar{w}_{i,t} + (\theta_x' x_{i,t} + \theta_\sigma \text{MIDAS-RV}_{i,t}(\kappa_+,\kappa_-))/N_t. \tag{16}$$

[9] Although in principle one could combine (11) and (12) within the same portfolio strategy, the two volatility measures are highly correlated (approximately 0.8), since both converge to the same volatility measure (see Barndorff-Nielsen et al. (2010)). This high correlation gives rise to identification issues when they are included jointly.

The parameter θ_σ captures the overall volatility timing effect taking into account the asymmetric impact of positive and negative shocks. This specification represents a restricted version of equations (11)-(12), imposing the constraint $\theta_{\sigma+} = \theta_{\sigma-} = \theta_\sigma$. An analogous restriction can be applied to the MIDAS-AV$_{i,t}(\kappa+)$ and MIDAS-AV$_{i,t}(\kappa_-)$ volatility estimates.

The results from estimating the parameters in (15)-(16) are reported in columns (5) and (6) of Table 11. The estimate of θ_σ is negative and its magnitude exceeds that reported in Table 9 for the non-asymmetric MIDAS specification, indicating a stronger sensitivity of portfolio weights to volatility due to the asymmetry. The estimates of κ_+ and κ_- differ notably, suggesting asymmetric weighting of past positive and negative shocks. Figure 7 illustrates the resulting lag profile implied by these estimates when substituted into the exponential Almon polynomial given in equation (7).

Panel B reports the in-sample CE(r) values and the incremental improvements relative to the symmetric MIDAS specification in Table 9. Allowing for asymmetries in volatility alone raises CE(r) by roughly 10.2–21.3 percentage points, with corresponding Sharpe ratios increasing to 1.81 and 2.11 for the MIDAS-RV and MIDAS-AV models, respectively. Nonetheless, the improvement in performance remains smaller than that obtained under the unrestricted specification.

Out-of-sample results, presented in Panel C, reveal a similar pattern. The asymmetric MIDAS volatility models yield CE(r) values between 28.1 and 33.7 percent, representing gains of 8.6–12.2 percentage points relative to the symmetric benchmark, and translate into substantially higher risk-adjusted performance. These results indicate that incorporating volatility asymmetries meaningfully enhances portfolio efficiency, though the even larger gains observed under the unrestricted specifications in columns (1) and (3) underscore the importance of allowing positive and negative volatility shocks to exert differential effects on portfolio weights.

Overall, the evidence strongly indicates that accounting for asymmetries in volatility timing substantially enhances portfolio efficiency and should be viewed as an essential component of dynamic allocation strategies. In particular, positive shocks lead to volatility timing that is more exploitable from a volatility-timing perspective.

Finally, we emphasize that our results do not contradict the well-established leverage effect of Black (1976). Our data confirm the familiar asymmetry whereby negative return shocks are followed by larger increases in volatility than positive shocks. In the appendix, we document the firm-level distribution of the asymmetry parameter, confirming the classical negative-dominated asymmetry but revealing

substantially richer dynamics at the firm level.[10] In addition, within the context of portfolio volatility timing, positive volatility shocks predominantly drive the strong negative relation between firm-level volatility and optimal portfolio weights. These results are consistent with Bollerslev et al. (2019), who show that stocks with high relative good-to-bad realized weekly volatility earn lower returns than those with low good-to-bad volatility. In the next section, we explore economic mechanisms consistent with these findings, highlighting how the asymmetric influence of volatility on portfolio weights may provide new insights into the broader economic forces shaping firm-level volatility timing.

5 Using Asymmetries to Identify the Economic Mechanism of Firm-Level Volatility Timing

In a modern portfolio framework, optimal asset weights rise with expected returns and fall with volatility. Moreira and Muir (2017) show that volatility-timing strategies based on systematic risk, such as factor or market volatility, challenge the traditional risk–return tradeoff, since expected returns vary far less over time than volatility. As discussed above, our results depart from theirs, as our volatility-timing framework is grounded in idiosyncratic rather than systematic risk.[11] A second novel dimension of our findings is the presence of asymmetries in the volatility-timing strategy. Building on the results in the previous section, we next examine the economic mechanisms that (1) operate at the firm level and (2) generate asymmetric responses of volatility to return shocks.

5.1 Direction of Volatility Timing Asymmetries

Perhaps the most obvious explanation that incorporates asymmetry in volatility is Black's (1976) leverage hypothesis which operates through firms' financial leverage: a decline in equity value following a negative return mechanically raises the firm's debt-to-equity ratio, thereby increasing the equity's risk and expected volatility. In contrast, positive return shocks reduce leverage and thus lower volatility. This

[10] We report the distribution of the firm-level asymmetry parameter in Figure A.1. Most of the empirical finance studies examine asymmetries either at the aggregate or portfolio level, or in relatively small cross-sections (e.g., Patton and Sheppard (2015) consider 105 stocks). Earlier firm-level analyses using EGARCH specifications include Braun et al. (1995), Duffee (1995), and Choi and Richardson (2016). By contrast, our use of a large cross-section combined with realized measures allows us to exploit richer firm-level dynamics.

[11] Indeed, Moreira and Muir (2017) note that "if a return is largely driven by idiosyncratic risk, then volatility timing will not be informative about the broader price of risk in the economy."

leverage-induced asymmetry implies that volatility rises following negative shocks and falls after positive shocks, producing the well-documented negative correlation between returns and volatility. In a portfolio context, this means that when volatility increases as a result of negative shocks, optimal portfolio weights should decline more sharply than when volatility rises due to positive shocks.

Another influential explanation for volatility asymmetry is provided by Pástor and Veronesi (2003), who develop a model in which stock prices reflect investors' learning about the profitability of cash flows generated by new technologies. In their framework, volatility depends on both the conditional variance of expected cash flows and the sensitivity of prices to uncertainty about future profitability. Positive cash flow shocks raise expected profitability and increase this sensitivity, leading to higher volatility, whereas negative shocks reduce both profitability and volatility. Consequently, volatility responds asymmetrically to news, rising with positive shocks and falling with negative shocks, opposite to Black's (1976) leverage effect.

Framed through the lens of Campbell et al. (2001), Black (1976) emphasizes the amplification of discount-rate shocks, with asymmetry arising from financial leverage, whereas Pástor and Veronesi (2003) focus on cash-flow shocks, where asymmetry stems from the convexity of prices with respect to profitability. Both mechanisms generate asymmetry between positive and negative shocks, yet they differ in their implications for returns and portfolio weights. This distinction yields two testable implications.

The first implication is that when the variance is decomposed into components driven by positive and negative shocks, the leverage hypothesis predicts a stronger effect from negative shocks on portfolio weights, whereas the learning-about-profitability hypothesis predicts the opposite. In Tables 10 and 11, the volatility timing is more pronounced for positive shocks, which is consistent with the learning-about profitability mechanism. These results are robust to various ways of specifying the asymmetry and, remarkably, hold out of sample.

The second implication concerns conditioning volatility timing on variables that proxy for either leverage or uncertainty about profitability. Under the leverage hypothesis, conditioning on book-to-market provides a natural test: high book-to-market (value) firms, which tend to be more highly levered, should display stronger volatility asymmetry, whereas low book-to-market (growth) firms, being less levered, should exhibit little or none.

Similarly, conditioning on a measure that captures uncertainty about profitability yields complementary predictions. For firms with high profitability uncertainty,

there is greater scope for learning about underlying profitability, and thus volatility asymmetry should be more pronounced. Conversely, firms with low profitability uncertainty offer limited scope for learning, implying weaker volatility asymmetry. In the next section, we implement these tests by conditioning the volatility-timing strategy on book-to-market and on uncertainty about profitability.

5.2 Leverage Hypothesis: Volatility Timing in Value vs Growth

Consider two companies, one has high BTM (value) and the other a low BTM (growth). The value firm has a significant amount of debt relative to the growth firm (Myers (1977), Rajan and Zingales (1995), Baker and Wurgler (2002), among others). A negative shock increases leverage and the magnitude of the sensitivity increases with debt; for higher debt levels, leverage responds more strongly to changes in price.[12] Hence the value firm (high D) ought to exhibit a higher volatility asymmetry to negative shocks. Following this logic, if we split the sample of companies into value versus growth, the leverage effect implies we should observe a larger in absolute value impact of volatility timing on the portfolio weights.

The opposite holds under the learning-about-profitability hypothesis, albeit for a different reason. Growth (low BTM) firms have more uncertain long-run prospects. A positive cash-flow shock raises expected profitability and amplifies the sensitivity of prices to posterior beliefs, as distant future cash flows become more valuable. Consequently, volatility increases sharply. In contrast, for value (high BTM) firms, whose cash flows are less uncertain, the same effect is much weaker.

This discussion motivates examining volatility timing separately across value and growth firms. We partition the cross section by BTM ratios, classifying the top 30% as value firms and the bottom 30% as growth firms. Within each subsample, we estimate the volatility-timing strategy and present the results in Table 12. For low BTM firms, we report a strong volatility-timing effect, with θ_σ estimates of –7.589 (RV) and –6.760 (AV), both statistically significant. For high BTM firms, the effect remains negative but is economically smaller and statistically insignificant, with θ_σ estimates of –1.707 (RV) and –1.536 (AV). The performance of the low BTM portfolios improves markedly, as reflected in higher CE(r) and Sharpe ratios relative to the benchmark. In contrast, for high BTM firms, portfolio performance gains are limited, if any. The same pattern holds out of sample: volatility timing

[12] This is straight forward. If leverage is $L = \frac{D}{P}$, where D is the level of debt and V is the value of the company, then $\frac{dL}{dP} = \frac{-D}{P^2}$, or the higher D, the higher is the absolute sensitivity of leverage to price.

among low BTM firms outperforms the benchmark by roughly 20%, whereas no such improvement is observed for high book-to-market firms. These findings provide further evidence that the learning-about-profitability mechanism of Pástor and Veronesi (2003) plays an important role in explaining the negative relation between firm-level volatility and optimal portfolio performance.

5.3 Learning-about-Profitability and Volatily Timing

We use the profitability measures of Fama and French (1993) and Hou et al. (2015) to construct a firm-level measure of profitability uncertainty, which is defined as the cross-sectional deviation of a firm's profitability from the average level of profitability in that period. For firms whose profitability is highly uncertain, investors have greater scope to revise their beliefs about underlying fundamentals, which should amplify the asymmetric response of volatility to return shocks. In contrast, when profitability is relatively predictabe (low uncertainty), few such revisions are needed, and the resulting volatility asymmetry should be muted. The prediction is that, when conditioning on profitability uncertainty, firms with high uncertainty should exhibit stronger volatility timing than firms with low profitability uncertainty.

To test this prediction, we sort firms into high- and low-profitability-uncertainty groups (top and bottom 30 percent of the cross-section) and re-estimate the volatility-timing portfolio within each subsample. Table 13 reports the results. The loading on volatility, θ_σ, is larger in absolute value and statistically significant for high–profitability-uncertainty firms, whereas it is substantially smaller for the low-uncertainty group.

In-sample certainty-equivalent returns (Panel B) reinforce this pattern. For high-uncertainty firms, CE(r) ranges from 21.7% to 23.4%, a sizable improvement over the benchmark of 11.6%. For low-uncertainty firms, certainty equivalents are markedly lower, between 16.9% and 17.9%. Sharpe ratios follow the same ordering. Turnover is also slightly lower for the high-uncertainty group.

Out-of-sample results (Panel C) display an even sharper contrast. The CE(r) for high-uncertainty firms lies between 12.6% and 19.2%, compared with essentially zero for the corresponding benchmark. Low-uncertainty firms yield out-of-sample certainty equivalents of only 5.9% to 6.7%. Taken together, these findings indicate that the gains from volatility timing are concentrated among firms with high profitability uncertainty, consistent with the predictions of the Pástor and Veronesi (2003) learning framework.

6 Conclusion

We quantify the role of firm-level volatility timing in large cross-sections of US stocks using parametric portfolio policies. We report gains of about 10% in-sample. This is economically significant and larger than previous volatility timing estimates. Out-of-sample gains are also economically large and robust. We emphasize the importance of transaction costs in penalizing the performance when turnover is high. From a methodological perspective, we provide analytic results for the parametric estimator and show that a large cross-section is crucial to compute precise estimates of the parametric weights. We argue that the after transaction costs portfolio estimation can be seen as a penalized utility estimator, again emphasizing the importance of including transaction costs within the optimization problem, rather than to subtract them from an already computed portfolio.

We attribute the performance gains to the firm-level volatility timing to learning about cash-flow news. Allowing sign asymmetry, permitting positive and negative shocks to load differently on the weights, is essential for unlocking these gains. That cash-flow fluctuations systematically move portfolio weights and realized utility suggests a common component in such shocks that merits further measurement. It might suggest that a firm might learn about its cash flow prospects from the cash-flow innovations of other firms. This is a promising venue for expanding the Pastor and Veronesi framework.

References

Acharya, V. V. and Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77(2):375–410.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica*, 71(2):579–625.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance*, 61(1):259–299.

Baker, M. and Wurgler, J. (2002). Market timing and capital structure. *The Journal of Finance*, 57(1):1–32.

Barndorff-Nielsen, O. E., Kinnebrock, S., and Shephard, N. (2010). Measuring downside risk: Realised semivariance. In Andersen, T. G., Davis, R. A., Kreiss, J.-P., and Mikosch, T., editors, *Volatility and Time Series Econometrics: Essays in Honor of Robert Engle*, pages 117–136. Oxford University Press.

Barroso, P. and Detzel, A. L. (2021). Do limits to arbitrage explain the benefits of volatility-managed portfolios? *Journal of Financial Economics*, 140:744–767.

Bekaert, G., Bergbrant, M., and Kassa, H. (2025). Expected idiosyncratic volatility. *Journal of Financial Economics*, 167(C):1–20.

Bekaert, G., Hodrick, R. J., and Zhang, X. (2012). Aggregate idiosyncratic volatility. *Journal of Financial and Quantitative Analysis*, 47:1155–1185.

Black, F. (1976). Studies of stock price volatility changes. *Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economic Statistics Section*, pages 177–181.

Bollerslev, T., Li, S. Z., and Zhao, B. (2019). Good volatility, bad volatility, and the cross section of stock returns. *Journal of Financial and Quantitative Analysis*, 55(3):751–781.

Brandt, M. W., Brav, A., Graham, J. R., and Kumar, A. (2010). The idiosyncratic volatility puzzle: Time trend or speculative episodes? *Review of Financial Studies*, 23:863–899.

Brandt, M. W., Santa-Clara, P., and Valkanov, R. (2009). Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns. *The Review of Financial Studies*, 22(9):3411–3447.

Braun, P. A., Nelson, D. B., and Sunier, A. M. (1995). Good news, bad news, volatility, and betas. *The Journal of Finance*, 50(5):1575–1603.

Campbell, J. Y. and Hentschel, L. (1993). No news is good news: An asymmetric model of changing volatility in stock returns. *Journal of Financial Economics*, 31(3):281–318.

Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y. (2001). Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk. *Journal of Finance*, 56(1):1–43.

Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y. (2023). Idiosyncratic equity risk two decades later. *Critical Finance Review*, 12:203–223.

Campbell, J. Y. and Shiller, R. J. (1988). Stock prices, earnings, and expected dividends. *Journal of Finance*, 43(3):661–676.

Cederburg, S., O'Doherty, M. S., Wang, F., and Yan, X. S. (2020). On the performance of volatility-managed portfolios. *Journal of Financial Economics*, 138:95–117.

Chen, X. and Ghysels, E. (2011). News—good or bad—and its impact on volatility predictions over multiple horizons. *Review of Financial Studies*, 24(1):46–81.

Choi, J. and Richardson, M. (2016). The volatility of a firm's assets and the leverage effect. *Journal of Financial Economics*, 121(2):254–277.

Cochrane, J. H. (2008). The dog that did not bark: A defense of return predictability. *Review of Financial Studies*, 21(4):1533–1575.

DeMiguel, V., Martín-Utrera, A., and Uppal, R. (2024). A multifactor perspective on volatility-managed portfolios. *The Journal of Finance*, 79(6).

Diebold, F. X. and Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 20(1):134–144.

Ding, Z., Granger, C. W. J., and Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, 1(1):83–106.

Duffee, G. R. (1995). Stock returns and volatility a firm-level analysis. *Journal of financial Economics*, 37(3):399–420.

Engle, R. F. and Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *Journal of Finance*, 48(5):1749–1778.

Engle, R. F. and Patton, A. J. (2001). What good is a volatility model? In Heckman, J. J. and Leamer, E. E., editors, *Handbook of Econometrics*, volume 5, chapter 40, pages 3369–3439. Elsevier.

Fama, E. F. and French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics*, 22(1):3–25.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fleming, J., Kirby, C., and Ostdiek, B. (2001). The economic value of volatility timing. *The Journal of Finance*, 56(1):329–352.

Fleming, J., Kirby, C., and Ostdiek, B. (2003). The economic value of volatility timing using "realized" volatility. *Journal of Financial Economics*, 67:473–509.

Forsberg, L. and Ghysels, E. (2007). Why do absolute returns predict volatility so well? *Journal of Financial Econometrics*, 5(1):31–67.

Frazzini, A., Israel, R., and Moskowitz, T. J. (2018). Trading costs. Working Paper 24505, National Bureau of Economic Research.

Frazzini, A. and Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, 111(1):1–25.

French, K. R., Schwert, G. W., and Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, 19(1):3–30.

Ghysels, E., Marcellino, M., and Valkanov, R. (2025). The econometric analysis of mixed frequency data. University of North Carolina at Chapel Hill, Bocconi University, and University of California San Diego.

Ghysels, E., Santa-Clara, P., and Valkanov, R. (2005). There is a risk-return tradeoff after all. *Journal of Financial Economics*, 76:509–548.

Ghysels, E., Santa-Clara, P., and Valkanov, R. (2006). Predicting volatility: Getting the most out of return data sampled at different frequencies. *Journal of Econometrics*, 131:59–95.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, 48(5):1779–1801.

Goyal, A. and Santa-Clara, P. (2003). Idiosyncratic risk matters! *Journal of Finance*, 58(3):975–1007.

Herskovic, B., Kelly, B., Lustig, H., and Van Nieuwerburgh, S. (2016). The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics*, 119(2):249–283.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3):650–705.

Jensen, T. I., Kelly, B., and Pedersen, L. H. (2023). Is there a replication crisis in finance? *Journal of Finance*, 78(5):2465–2518.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, 7(1):77–91.

Markowitz, H. (1959). *Portfolio Selection: Efficient Diversification of Investments*. Yale University Press, New Haven, CT.

Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of Financial Economics*, 8(4):323–361.

Moreira, A. and Muir, T. (2017). Volatility-managed portfolios. *The Journal of Finance*, 72(4):1611–1644.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5(2):147–175.

Newey, W. K. and West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4):631–653.

Pástor, Ľ. and Veronesi, P. (2003). Stock valuation and learning about profitability. *Journal of Finance*, 58(5):1749–1789.

Patton, A. J. (2011). Volatility forecast comparison using imperfect volatility proxies. *Journal of Econometrics*, 160(1):246–256.

Patton, A. J. and Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics*, 97(3):683–697.

Rajan, R. G. and Zingales, L. (1995). What do we know about capital structure? some evidence from international data. *The Journal of Finance*, 50(5):1421–1460.

Schwert, G. W. (1989). Why does stock market volatility change over time? *Journal of Finance*, 44(5):1115–1153.

Todorov, V. and Tauchen, G. (2011). Volatility jumps. *Journal of Business and Economic Statistics*, 29(3):356–371.

Vuolteenaho, T. (2002). What drives firm-level stock returns? *Journal of Finance*, 57(1):233–264.

7 Tables and Figures

	Exc. Returns and Baseline Characteristics			
	r	ME	BTM	MOM
μ	0.008	6.170	0.504	0.120
σ	0.164	2.144	0.339	0.672
skew	3.906	0.200	1.752	5.503
AR(1)	0.115	0.994	0.952	0.918
	Total Volatility			
	$RV(22)$	$AV(22)$	$RV(252)$	$AV(252)$
μ	0.104	0.077	0.120	0.079
σ	0.062	0.043	0.066	0.036
skew	1.657	1.340	1.743	0.955
AR(1)	0.813	0.807	0.990	0.992
	Systematic Volatility			
	$CAPM(22)$	$FF3(22)$	$HXZ(22)$	$CAPM(252)$
μ	0.041	0.053	0.055	0.055
σ	0.032	0.039	0.040	0.066
skew	4.109	4.743	4.681	5.742
AR(1)	0.679	0.716	0.726	0.979
	Idiosyncratic Volatility			
	$CAPM(22)$	$FF3(22)$	$HXZ(22)$	$CAPM(252)$
μ	0.099	0.111	0.096	0.095
σ	0.091	0.080	0.090	0.090
skew	7.482	4.940	7.544	7.607
AR(1)	0.879	0.994	0.893	0.892

Table 1: Summary Statistics Jan 2000 - Nov 2023 . ME is log of size, BTM is log of 1 plus book to market, and MOM is the 12 month momentum obtained as the arithmetic return of between 12 months returns. μ, σ, skew and AR(1) are the time-series mean, standard deviation, skewness and first-order autocorrelation coefficient, respectively.

Volatility Timing Portfolio Weights: Estimates

Panel A: Transaction Costs of 0 bps

	Benchmarks		Volatility Timing			
	VW	Baseline	$RV(22)$	$AV(22)$	$RV(252)$	$AV(252)$
θ_{ME}	—	-0.912	-3.774	-4.237	-5.413	-5.256
Std. Err.	—	(1.077)	(1.317)	(1.334)	(1.607)	(1.516)
θ_{BTM}	—	5.796	5.499	6.089	5.605	5.566
Std. Err.	—	(1.539)	(1.653)	(1.642)	(1.634)	(1.562)
θ_{MOM}	—	5.960	4.807	5.231	4.973	4.935
Std. Err.	—	(1.443)	(1.469)	(1.501)	(1.538)	(1.497)
θ_{σ}	—	—	-4.349	-4.074	-4.793	-3.909
Std. Err.	—	—	(1.213)	(0.995)	(1.292)	(1.013)

Panel B: Transaction Costs of 10 bps

θ_{ME}	—	-0.812	-3.706	-4.150	-5.587	-5.018
Std. Err.	—	(1.064)	(1.315)	(1.332)	(1.604)	(1.505)
θ_{BTM}	—	5.459	5.288	5.774	5.024	5.163
Std. Err.	—	(1.504)	(1.620)	(1.608)	(1.590)	(1.522)
θ_{MOM}	—	5.532	4.744	4.968	4.096	4.381
Std. Err.	—	(1.411)	(1.453)	(1.477)	(1.510)	(1.465)
θ_{σ}	—	—	-4.053	-3.891	-5.153	-3.861
Std. Err.	—	—	(1.201)	(0.988)	(1.293)	(1.007)

Panel C: Transaction Costs of 25 bps

θ_{ME}	—	-0.554	-3.193	-3.472	-5.192	-4.473
Std. Err.	—	(1.048)	(1.303)	(1.316)	(1.591)	(1.491)
θ_{BTM}	—	4.740	4.877	4.942	4.692	4.861
Std. Err.	—	(1.435)	(1.553)	(1.511)	(1.547)	(1.487)
θ_{MOM}	—	4.483	4.265	4.158	3.730	3.913
Std. Err.	—	(1.360)	(1.414)	(1.408)	(1.479)	(1.433)
θ_{σ}	—	—	-3.518	-3.289	-4.848	-3.602
Std. Err.	—	—	(1.179)	(0.969)	(1.275)	(0.995)

Table 2: In-Sample Portfolio Policies. This table reports the in-sample portfolio policies estimated over the sample from January 2003 to November 2023 under different levels of transaction costs.

Volatility Timing Portfolio Performance: In Sample

Panel A: Transaction Costs of 0 bps

	Benchmarks		Volatility Timing			
	VW	Baseline	$RV(22)$	$AV(22)$	$RV(252)$	$AV(252)$
CE(r)	0.044	0.184	0.278	0.294	0.295	0.279
$\bar{r}$	0.105	0.410	0.496	0.528	0.519	0.483
$\sigma(r)$	0.153	0.314	0.296	0.311	0.306	0.292
SR	0.601	1.264	1.633	1.654	1.652	1.611
$\sum \lvert w_i - w_i^h \rvert$	0.918	24.649	34.629	35.521	24.011	23.045
$\sum w_i I(w_i < 0)$	0.000	-2.166	-2.360	-2.635	-2.676	-2.576

Panel B: Transaction Costs of 10 bps

CE(r)	0.043	0.160	0.243	0.259	0.272	0.256
$\bar{r}$	0.105	0.362	0.449	0.475	0.475	0.437
$\sigma(r)$	0.153	0.294	0.287	0.299	0.289	0.273
SR	0.601	1.188	1.516	1.547	1.602	1.555
$\sum \lvert w_i - w_i^h \rvert$	0.918	22.240	33.000	33.862	21.344	21.012
$\sum w_i I(w_i < 0)$	0.000	-1.959	-2.268	-2.500	-2.513	-2.381

Panel C: Transaction Costs of 25 bps

CE(r)	0.042	0.129	0.197	0.212	0.241	0.225
$\bar{r}$	0.105	0.294	0.372	0.377	0.421	0.384
$\sigma(r)$	0.153	0.262	0.264	0.259	0.271	0.254
SR	0.601	1.071	1.358	1.405	1.509	1.463
$\sum \lvert w_i - w_i^h \rvert$	0.918	18.160	29.217	28.608	19.716	19.148
$\sum w_i I(w_i < 0)$	0.000	-1.571	-2.009	-2.064	-2.310	-2.161

Table 3: In-Sample Portfolio Performance. This table reports the in-sample portfolio performance of the volatility timing strategy over the sample January 2003 — November 2023 under different levels of transaction costs.

Volatility Timing Portfolio Performance: Out-of-Sample

Panel A: Transaction Costs of 0 bps

	Benchmarks		Volatility Timing			
	VW	Baseline	$RV(22)$	$AV(22)$	$RV(252)$	$AV(252)$
CE(r)	0.067	0.122	0.182	0.231	0.291	0.227
$\bar{r}$	0.120	0.420	0.627	0.627	0.652	0.554
$\sigma(r)$	0.151	0.401	0.443	0.431	0.421	0.404
SR	0.795	1.047	1.415	1.454	1.550	1.371
$\sum \lvert w_i - w_i^h \rvert$	9.024	22.271	34.774	33.355	24.326	24.117
$\sum w_i I(w_i < 0)$	0.000	-2.573	-3.465	-3.527	-3.412	-3.349

Panel B: Transaction Costs of 10 bps

CE(r)	0.067	0.103	0.164	0.206	0.280	0.216
$\bar{r}$	0.120	0.358	0.549	0.547	0.600	0.499
$\sigma(r)$	0.151	0.367	0.411	0.398	0.394	0.372
SR	0.795	0.977	1.335	1.376	1.523	1.341
$\sum \lvert w_i - w_i^h \rvert$	9.024	19.543	31.608	30.411	21.804	21.506
$\sum w_i I(w_i < 0)$	0.000	-2.252	-3.142	-3.191	-3.111	-3.036

Panel C: Transaction Costs of 25 bps

CE(r)	0.065	0.076	0.140	0.171	0.258	0.209
$\bar{r}$	0.120	0.279	0.440	0.447	0.513	0.424
$\sigma(r)$	0.151	0.322	0.361	0.355	0.347	0.320
SR	0.795	0.868	1.217	1.258	1.478	1.327
$\sum \lvert w_i - w_i^h \rvert$	9.024	15.473	26.615	26.001	17.968	17.579
$\sum w_i I(w_i < 0)$	0.000	-1.775	-2.621	-2.687	-2.661	-2.567

Table 4: Out-of-Sample Portfolio Performance. This table reports the out-of-sample portfolio performance of the volatility timing strategy. The out-of-sample evaluation period goes from February 2013 to November 2023 with an expanding window scheme, and a warm-up window of 120 months (January 2003-January 2013).

Out-of-Sample CE(r) for Different Starting Years

Starting Yr.	Baseline	$RV(252)$	$AV(252)$
2010	0.056	0.119	0.117
2011	0.113	0.175	0.173
2012	0.150	0.212	0.205
2013	0.098	0.195	0.162
2014	0.005	0.078	0.075
2015	0.046	0.121	0.116
2016	0.039	0.115	0.104
2017	-0.059	0.019	0.008
2018	0.048	0.113	0.103
2019	0.096	0.165	0.158
2020	0.095	0.197	0.179
2021	0.539	0.576	0.556
2022	0.438	0.469	0.442
mean	0.128	0.196	0.185

Table 5: Out-of-Sample Robustness. This table reports the out-of-sample CE(r) for different starting years. The toal sample spans from January 1995 to to November 2023. The first warm-up window is 15 years of monthly data spanning from January 1995 to December 2009, and the first out-of-sample period January 2010 to November 2023. In all cases we consider 10 bps of transaction costs.

Idiosyncratic Volatility Timing: Estimates and Performance

Panel A: Portfolio Policies

	Total Volatility		Idiosyncratic Volatility wrt model			
	$RV(22)$	$RV(252)$	$CAPM(22)$	$FF(22)$	$HXZ(22)$	$CAPM(252)$
θ_{ME}	-3.706	-5.587	-5.809	-5.546	-5.632	-7.425
Std. Err.	(1.315)	(1.604)	(1.698)	(1.722)	(1.734)	(2.039)
θ_{BTM}	5.288	5.024	4.885	4.582	4.620	4.370
Std. Err.	(1.620)	(1.590)	(1.580)	(1.558)	(1.564)	(1.561)
θ_{MOM}	4.744	4.096	4.728	4.599	4.531	4.282
Std. Err.	(1.453)	(1.510)	(1.519)	(1.491)	(1.492)	(1.526)
θ_{σ}	-4.053	-5.153	—	—	—	—
Std. Err.	(1.201)	(1.293)	—	—	—	—
$\theta_{\sigma_{IDIO}}$	—	—	-5.512	-5.204	-5.380	-6.171
Std. Err.	—	—	(1.546)	(1.582)	(1.603)	(1.664)

Panel B: In-Sample Results

CE(r)	0.243	0.272	0.262	0.249	0.251	0.281
$\bar{r}$	0.449	0.475	0.504	0.475	0.480	0.489
$\sigma(r)$	0.287	0.289	0.319	0.307	0.310	0.293
SR	1.516	1.602	1.537	1.502	1.507	1.625
$\sum \lvert w_i - w_i^h \rvert$	33.000	21.344	41.086	39.120	40.003	21.781
$\sum w_i I(w_i < 0)$	-2.268	-2.513	-2.546	-2.391	-2.418	-2.594

Panel C: Out-of-Sample Results

CE(r)	0.164	0.280	0.186	0.163	0.173	0.258
$\bar{r}$	0.549	0.600	0.571	0.544	0.555	0.581
$\sigma(r)$	0.411	0.394	0.430	0.430	0.431	0.400
SR	1.335	1.523	1.327	1.266	1.286	1.452
$\sum \lvert w_i - w_i^h \rvert$	31.608	21.804	37.950	37.304	37.792	21.815
$\sum w_i I(w_i < 0)$	-3.142	-3.111	-3.296	-3.214	-3.238	-3.277

Table 6: Idiosyncratic Volatility Timing. This table reports the results of the volatility timing strategy implemented using measures of idiosyncratic volatility and transaction costs of 10 bps. $ivol_1$ is the idiosyncratic volatility from CAPM using 22 daily observations, $ivol_2$ is the idiosyncratic volatility from FF3 using 22 daily observations $ivol_3$ is the idiosyncratic volatility from Hou et al. (2015) factor model using 22 daily observations, finally $ivol_4$ is the idiosyncratic volatility from CAPM using 252 daily observations. All the idiosyncratic volatilities are sourced from Jensen et al. (2023).

Systematic vs Idiosyncratic Volatility Timing: Estimates and Performance

Panel A: Portfolio Policies

	Systematic Model			
	$CAPM(22)$	$FF3(22)$	$HXZ(22)$	$CAPM(252)$
θ_{ME}	-5.546	-4.362	-4.463	-5.179
Std. Err.	(1.941)	(1.848)	(1.890)	(2.288)
θ_{BTM}	4.749	5.237	5.179	5.149
Std. Err.	(1.567)	(1.567)	(1.574)	(1.594)
θ_{MOM}	4.744	4.772	4.855	4.099
Std. Err.	(1.512)	(1.464)	(1.478)	(1.629)
$\theta_{\sigma_{IDIO}}$	-5.018	-3.731	-3.948	-4.157
Std. Err.	(1.947)	(1.906)	(1.954)	(1.955)
$\theta_{\sigma_{SYS}}$	-0.302	-1.533	-1.040	-3.121
Std. Err.	(1.241)	(1.185)	(1.252)	(1.753)

Panel B: In-Sample Portfolio Results

CE(r)	0.263	0.261	0.255	0.298
ΔCE(r)	0.001	0.012	0.004	0.017
$\bar{r}$	0.490	0.481	0.475	0.520
$\sigma(r)$	0.310	0.305	0.304	0.304
SR	1.539	1.535	1.521	1.666
$\sum \lvert w_i - w_i^h \rvert$	39.070	36.602	35.837	21.995
$\sum w_i I(w_i < 0)$	-2.464	-2.418	-2.382	-2.610

Panel C: Out-of-Sample Portfolio Results

CE(r)	0.178	0.186	0.178	0.272
ΔCE(r)	-0.008	0.023	0.005	0.014
$\bar{r}$	0.564	0.557	0.554	0.589
$\sigma(r)$	0.431	0.422	0.426	0.392
SR	1.309	1.319	1.301	1.502
$\sum \lvert w_i - w_i^h \rvert$	38.866	36.036	36.314	21.850
$\sum w_i I(w_i < 0)$	-3.322	-3.212	-3.213	-3.277

Table 7: Dissected Volatility. This table reports the results of the volatility timing strategy under volatility decomposition and transaction costs of 10 bps. We refer to Table 6 for an explanation of the idiosyncratic measures used to decompose volatility into systematic and idiosyncratic components.

Volatility Timing with Multiple Characteristics

	BAB & (IL)LIQ			BAB & (IL)LIQ & INV		
	BASE	$RV(252)$	$AV(252)$	BASE	$RV(252)$	$AV(252)$
Panel A: Portfolio Policies						
θ_{ME}	0.846	-5.053	-4.782	0.876	-4.997	-4.544
Std. Err.	(1.067)	(2.588)	(3.006)	(1.056)	(2.134)	(2.673)
θ_{BTM}	5.477	4.404	4.702	4.043	3.594	3.398
Std. Err.	(1.461)	(1.731)	(1.643)	(1.668)	(1.691)	(1.675)
θ_{MOM}	3.595	3.433	4.107	3.396	3.867	4.192
Std. Err.	(1.315)	(1.544)	(1.346)	(1.310)	(1.350)	(1.358)
θ_{BAB}	-2.033	1.001	1.150	-1.711	1.264	1.342
Std. Err.	(0.885)	(1.272)	(1.545)	(0.899)	(1.264)	(1.557)
$\theta_{(IL)LIQ}$	7.982	9.273	8.388	6.470	7.540	6.795
Std. Err.	(2.213)	(2.283)	(2.255)	(2.223)	(2.280)	(2.258)
θ_{INV}	—	—	—	-8.052	-8.152	-8.350
Std. Err.	—	—	—	(2.561)	(2.677)	(2.670)
θ_{σ}	—	-6.823	-5.327	—	-6.810	-4.970
Std. Err.	—	(2.070)	(2.189)	—	(2.058)	(2.215)
Panel B: In-Sample Portfolio Results						
CE(r)	0.303	0.393	0.357	0.364	0.450	0.409
$\bar{r}$	0.563	0.719	0.648	0.650	0.826	0.742
$\sigma(r)$	0.361	0.395	0.374	0.371	0.427	0.402
SR	1.524	1.787	1.698	1.716	1.905	1.814
$\sum \lvert w_i - w_i^h \rvert$	20.086	22.690	22.750	23.387	28.166	26.951
$\sum w_i I(w_i < 0)$	-2.183	-2.480	-2.362	-2.503	-3.066	-2.797
Panel C: Out-of-Sample Portfolio Results						
CE(r)	0.142	0.305	0.221	0.194	0.337	0.255
$\bar{r}$	0.510	0.724	0.623	0.609	0.809	0.702
$\sigma(r)$	0.477	0.492	0.487	0.487	0.515	0.499
SR	1.068	1.473	1.278	1.250	1.569	1.406
$\sum \lvert w_i - w_i^h \rvert$	22.016	23.382	24.253	25.343	26.672	26.850
$\sum w_i I(w_i < 0)$	-2.875	-3.017	-3.065	-3.239	-3.371	-3.327

Table 8: Volatility Timing with Multiple Characteristics. This table reports the results of the volatility timing strategy when additional characteristics are included in the portfolio construction. BASE refers to the portfolio constructed using the three baseline characteristics and adding multiple additional characteristic. The results reported are for 10 bps of transaction costs.

MIDAS Volatility Timing: Estimates and Performance

Panel A: Portfolio Policies

	EW Volatility		MIDAS Volatility	
	$RV(252)$	$AV(252)$	$\mathcal{M}_{RV(252)}$	$\mathcal{M}_{AV(252)}$
θ_{ME}	-5.587	-5.018	-5.462	-4.599
Std. Err.	(1.604)	(1.505)	(1.499)	(1.386)
θ_{BTM}	5.024	5.163	5.126	5.682
Std. Err.	(1.590)	(1.522)	(1.604)	(1.590)
θ_{MOM}	4.096	4.381	4.112	4.690
Std. Err.	(1.510)	(1.465)	(1.435)	(1.417)
$\theta_{\sigma_{MIDAS}}$	-5.153	-3.861	-4.992	-3.873
Std. Err.	(1.293)	(1.007)	(1.146)	(0.917)
$\kappa_1 * 100$	—	—	-0.839	-3.2439
$\kappa_2 * 100$	—	—	-0.0004	-0.0008

Panel B: In-Sample Results

CE(r)	0.272	0.256	0.277	0.272
$\bar{r}$	0.475	0.437	0.487	0.479
$\sigma(r)$	0.289	0.273	0.294	0.292
SR	1.602	1.555	1.611	1.595
$\sum \lvert w_i - w_i^h \rvert$	21.344	21.012	22.088	25.720
$\sum w_i I(w_i < 0)$	-2.513	-2.381	-2.496	-2.484

Panel C: Out-of-Sample Results

CE(r)	0.280	0.216	0.195	0.215
$\bar{r}$	0.600	0.499	0.592	0.561
$\sigma(r)$	0.394	0.372	0.426	0.403
SR	1.523	1.341	1.388	1.393
$\sum \lvert w_i - w_i^h \rvert$	21.804	21.506	30.456	28.146
$\sum w_i I(w_i < 0)$	-3.111	-3.036	-3.246	-3.242

Table 9: MIDAS Volatility Timing. This table reports the results of the volatility timing strategy implemented using MIDAS volatility and transaction costs of 10 bps. MIDAS volatility is estimated using an Almon polynomial and one year of daily observations. $\mathcal{M}_{RV(252)}$ refers to the MIDAS-RV specification while $\mathcal{M}_{AV(252)}$ refers to the MIDAS-AV specification.

Asymmetric Volatility Timing				
Panel A: Portfolio Policies				
	$RV(252)$		$AV(252)$	
	RV^+	RV^-	AV^+	AV^-
θ_{ME}	-6.742	-3.926	-5.259	-4.820
Std. Err.	(1.762)	(1.637)	(1.620)	(1.624)
θ_{BTM}	4.763	5.365	4.984	5.342
Std. Err.	(1.584)	(1.509)	(1.499)	(1.504)
θ_{MOM}	4.262	4.518	4.773	4.225
Std. Err.	(1.344)	(1.307)	(1.310)	(1.297)
θ_{σ_+}	-6.475	—	-4.162	—
Std. Err.	(1.536)	—	(1.155)	—
θ_{σ_-}	—	-3.275	—	-3.604
Std. Err.	—	(1.305)	—	(1.119)
Panel B: In-Sample Results				
CE(r)	0.322	0.179	0.276	0.235
ΔCE(r)	0.050	-0.093	0.020	-0.021
$\bar{r}$	0.556	0.370	0.455	0.415
$\sigma(r)$	0.319	0.281	0.279	0.276
SR	1.706	1.271	1.582	1.457
$\sum \lvert w_i - w_i^h \rvert$	22.598	21.411	21.991	20.631
$\sum w_i I(w_i < 0)$	-2.520	-2.165	-2.196	-2.211
Panel C: Out-of-Sample Results				
CE(r)	0.333	0.154	0.248	0.200
ΔCE(r)	0.053	-0.126	0.032	-0.016
$\bar{r}$	0.695	0.428	0.532	0.467
$\sigma(r)$	0.419	0.364	0.375	0.360
SR	1.658	1.172	1.419	1.297
$\sum \lvert w_i - w_i^h \rvert$	22.685	21.189	22.246	20.766
$\sum w_i I(w_i < 0)$	-3.264	-2.929	-3.006	-3.028

Table 10: Asymmetric Volatility Timing. This table reports the portfolio performance of the asymmetric volatility timing strategies using the semivariances defined in Section 4 under 10 bps of transaction costs.

Asymmetric-MIDAS — 10 bps TC

Panel A: Portfolio Policies

	MIDAS-RV^{asy}		MIDAS-AV^{asy}		MIDAS^{asy}	
	$RV^{+}(252)$	$RV^{-}(252)$	$AV^{+}(252)$	$AV^{-}(252)$	$RV(252)$	$AV(252)$
θ_{ME}	-5.946	-3.076	-5.750	-3.880	-5.627	-6.417
Std. Err.	(1.462)	(1.302)	(1.516)	(1.348)	(1.396)	(1.525)
θ_{BTM}	4.352	6.302	3.893	5.761	6.388	5.243
Std. Err.	(1.633)	(1.599)	(1.684)	(1.585)	(1.605)	(1.640)
θ_{MOM}	4.638	5.331	4.450	4.526	5.293	4.200
Std. Err.	(1.465)	(1.403)	(1.480)	(1.410)	(1.456)	(1.484)
θ_{σ_+}	-11.201	—	-11.784	—	—	—
Std. Err.	(1.886)	—	(2.042)	—	—	—
θ_{σ_-}	—	-3.311	—	-3.364	—	—
Std. Err.	—	(1.133)	—	(0.915)	—	—
θ_{σ}	—	—	—	—	-7.897	-9.758
Std. Err.	—	—	—	—	(1.410)	(1.683)

Panel B: In-Sample Portfolio Results

CE(r)	0.481	0.214	0.523	0.242	0.379	0.485
$\bar{r}$	0.895	0.411	0.965	0.431	0.703	0.875
$\sigma(r)$	0.426	0.290	0.434	0.278	0.382	0.409
SR	2.071	1.374	2.192	1.502	1.808	2.110
$\sum \lvert w_i - w_i^h \rvert$	89.425	29.154	98.192	25.051	57.400	76.497
$\sum w_i I(w_i < 0)$	-3.408	-2.441	-3.506	-2.363	-3.230	-3.411

Panel C: Out-of-Sample Portfolio Results

CE(r)	0.352	0.153	0.380	0.200	0.281	0.337
$\bar{r}$	0.912	0.439	0.982	0.496	0.767	0.898
$\sigma(r)$	0.522	0.377	0.536	0.385	0.497	0.540
SR	1.747	1.164	1.830	1.287	1.543	1.660
$\sum \lvert w_i - w_i^h \rvert$	79.455	27.316	87.773	25.328	52.910	70.166
$\sum w_i I(w_i < 0)$	-3.902	-3.146	-4.091	-3.257	-3.799	-4.073

Table 11: Asymmetric-MIDAS. This table reports the portfolio results of the Asymmetric-MIDAS under 10 bps of transaction costs.

Low vs High BTM						
Panel A: Portfolio Policies						
	Low BTM			High BTM		
	Baseline	$RV(252)$	$AV(252)$	Baseline	$RV(252)$	$AV(252)$
θ_{ME}	0.419	-5.826	-5.938	-2.993	-4.085	-3.977
Std. Err	(0.811)	(1.511)	(1.568)	(0.785)	(1.003)	(0.976)
θ_{BTM}	0.252	-3.386	-3.424	0.185	0.045	0.137
Std. Err	(0.429)	(0.858)	(0.913)	(0.463)	(0.482)	(0.483)
θ_{MOM}	-0.162	-0.739	-0.305	3.432	3.556	3.526
Std. Err	(0.693)	(0.766)	(0.763)	(0.810)	(0.824)	(0.818)
θ_{σ}	—	-7.589	-6.760	—	-1.707	-1.536
Std. Err	—	(1.598)	(1.496)	—	(0.968)	(0.903)
Panel B: In-Sample Portfolio Results						
CE(r)	0.061	0.248	0.229	0.164	0.189	0.188
$\bar{r}$	0.101	0.444	0.413	0.359	0.410	0.406
$\sigma(r)$	0.127	0.287	0.278	0.280	0.291	0.287
SR	0.688	1.500	1.439	1.238	1.366	1.372
$\sum \lvert w_i - w_i^h \rvert$	2.225	15.386	12.533	12.218	13.995	13.638
$\sum w_i I(w_i < 0)$	-0.227	-1.459	-1.213	-0.628	-0.823	-0.773
Panel C: Out-of-Sample Portfolio Results						
CE(r)	0.033	0.232	0.226	0.111	0.109	-0.047
$\bar{r}$	0.119	0.546	0.548	0.362	0.409	0.358
$\sigma(r)$	0.199	0.317	0.383	0.349	0.359	0.397
SR	0.595	1.719	1.432	1.037	1.138	0.900
$\sum \lvert w_i - w_i^h \rvert$	6.741	13.329	13.178	11.013	11.854	13.490
$\sum w_i I(w_i < 0)$	-0.524	-1.321	-1.427	-0.823	-0.865	-1.010

Table 12: Portfolio Results BTM Sorting. This table reports the in-sample results of the volatility timing for the cross-section of stocks sorted by the book-to-market (BTM). Low BTM are the stocks within the bottom 30% of the cross-section sorted by BTM, while High BTM are the stocks within the top 30% of the cross-section sorted by BTM. In all cases 10 bps of transaction costs are considered.

Learning about Profitability

Panel A: Portfolio Policies

	High Profitability Uncertainty			Low Profitability Uncertainty		
	Baseline	$RV(252)$	$AV(252)$	Baseline	$RV(252)$	$AV(252)$
θ_{ME}	-0.298	-3.584	-4.458	-4.727	-6.110	-6.178
Std. Err	0.444	0.564	0.541	1.252	1.384	1.382
θ_{BTM}	2.056	2.553	2.557	0.419	2.286	2.761
Std. Err	0.661	0.745	0.725	0.786	1.105	1.095
θ_{MOM}	1.390	1.631	2.001	1.815	1.636	1.788
Std. Err	0.680	0.734	0.733	1.122	1.135	1.132
θ_{σ}	—	-4.947	-4.966	—	-3.093	-3.098
Std. Err	—	0.582	0.568	—	1.726	1.726

Panel B: In-Sample Portfolio Results

CE(r)	0.116	0.234	0.217	0.127	0.169	0.179
$\bar{r}$	0.167	0.393	0.362	0.240	0.297	0.313
$\sigma(r)$	0.144	0.261	0.248	0.229	0.253	0.259
SR	1.070	1.457	1.409	0.994	1.122	1.157
$\sum \lvert w_i - w_i^h \rvert$	8.892	15.238	15.863	9.409	12.567	13.066
$\sum w_i I(w_i < 0)$	-0.898	-1.399	-1.409	-1.160	-1.512	-1.538

Panel C: Out-of-Sample Portfolio Results

CE(r)	-0.015	0.192	0.126	0.003	0.059	0.067
$\bar{r}$	0.105	0.507	0.400	0.160	0.291	0.301
$\sigma(r)$	0.254	0.400	0.364	0.294	0.357	0.365
SR	0.413	1.268	1.098	0.545	0.813	0.824
$\sum \lvert w_i - w_i^h \rvert$	9.126	14.835	14.939	9.657	12.811	14.078
$\sum w_i I(w_i < 0)$	-1.290	-1.786	-1.693	-1.666	-1.873	-1.895

Table 13: Learning about Profitability. This table reports the portfolio results of the volatility timing for the cross-section of stocks sorted by profitability uncertainty, defined as the cross-sectional volatility of operating profitability. High profitability uncertainty stocks are within the top 30% of the cross-section sorted by the volatility of operating profits, while low profitability uncertainty stocks are those within the bottom 30% of the cross-section sorted by the volatility of profitability. The level of transaction costs considered is 10 bps.

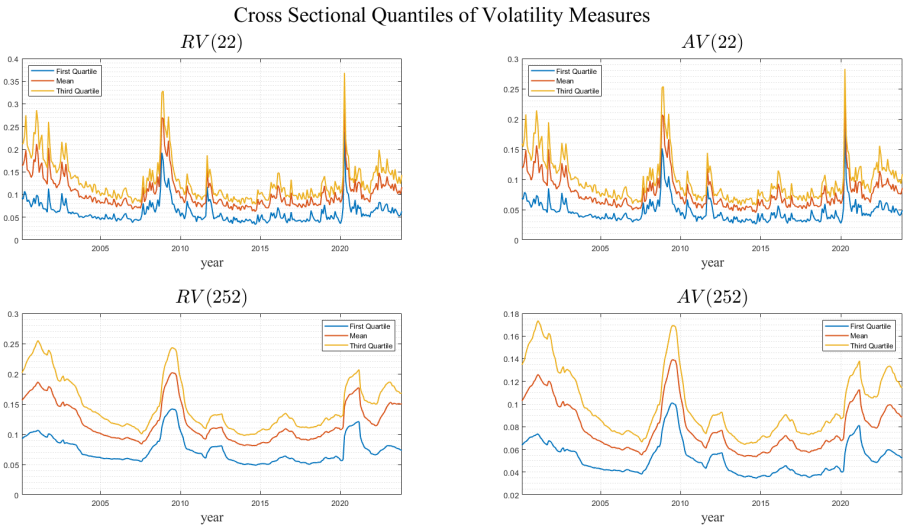


Figure 1: Cross-Section Quantiles of Volatility Measures. This figure plots the cross-sectional quantiles of the $RV(22)$, $AV(22)$, $RV(252)$ and $AV(252)$ volatility measures.

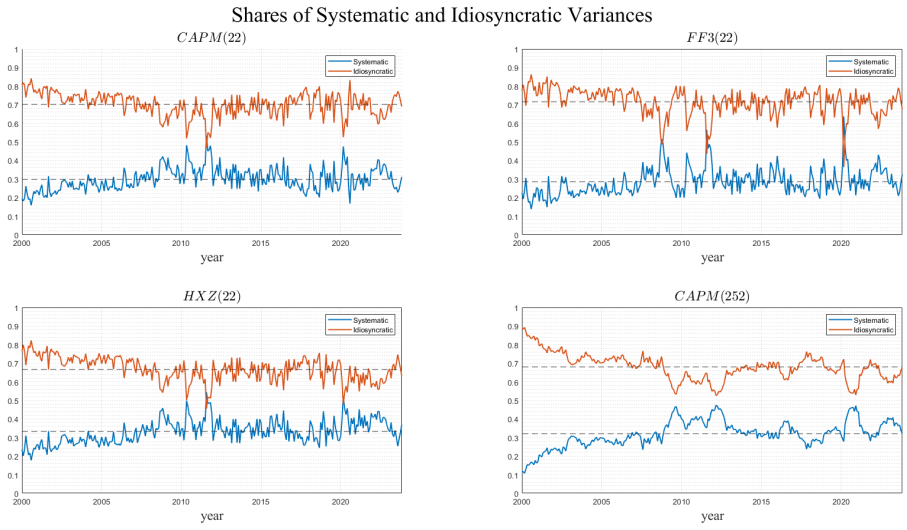


Figure 2: Share of systematic and Idiosyncratic Variance. This figure plots the share of the systematic and the idiosyncratic variance.

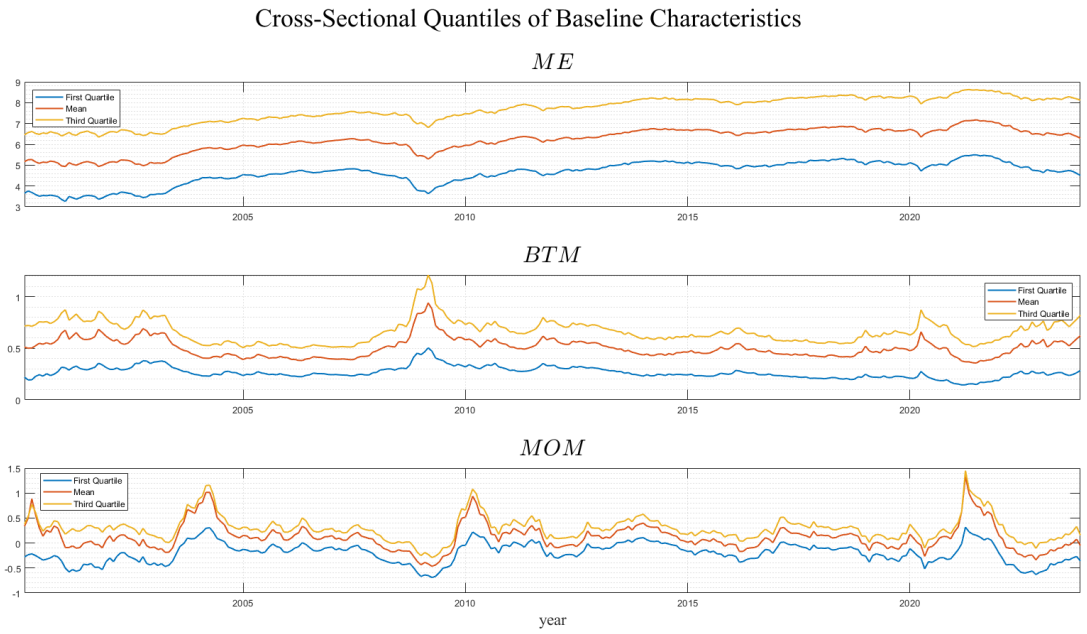


Figure 3: Cross-Sectional Quantiles of Characteristics. This figure plots the cross-sectional mean, the first and third quartile (25th and 75th percentile) of each of the baseline characteristics.

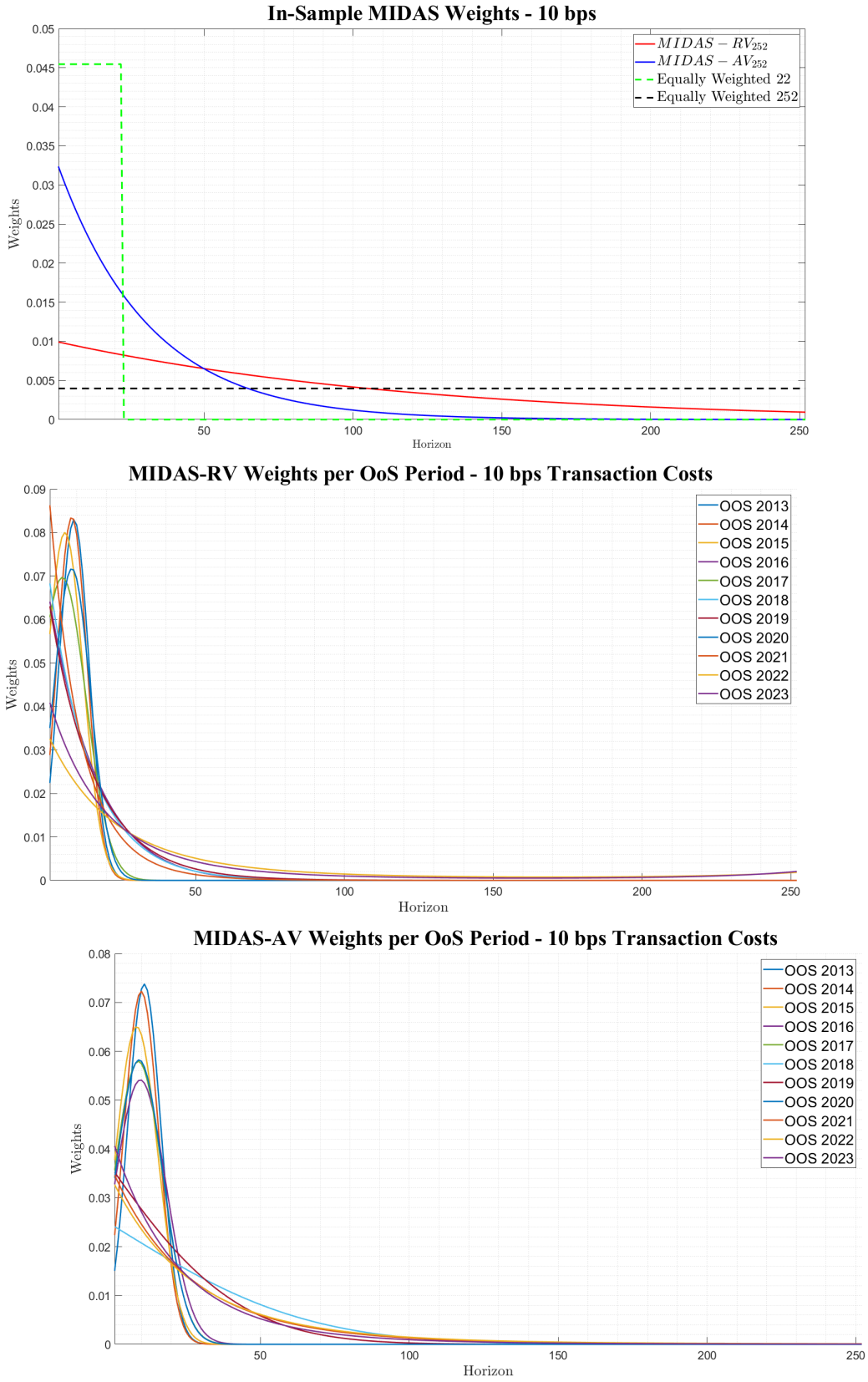


Figure 4: MIDAS Weights. This figure plots the in-sample MIDAS-RV(252) and MIDAS-AV(252) weights with 10 bps of transaction costs.

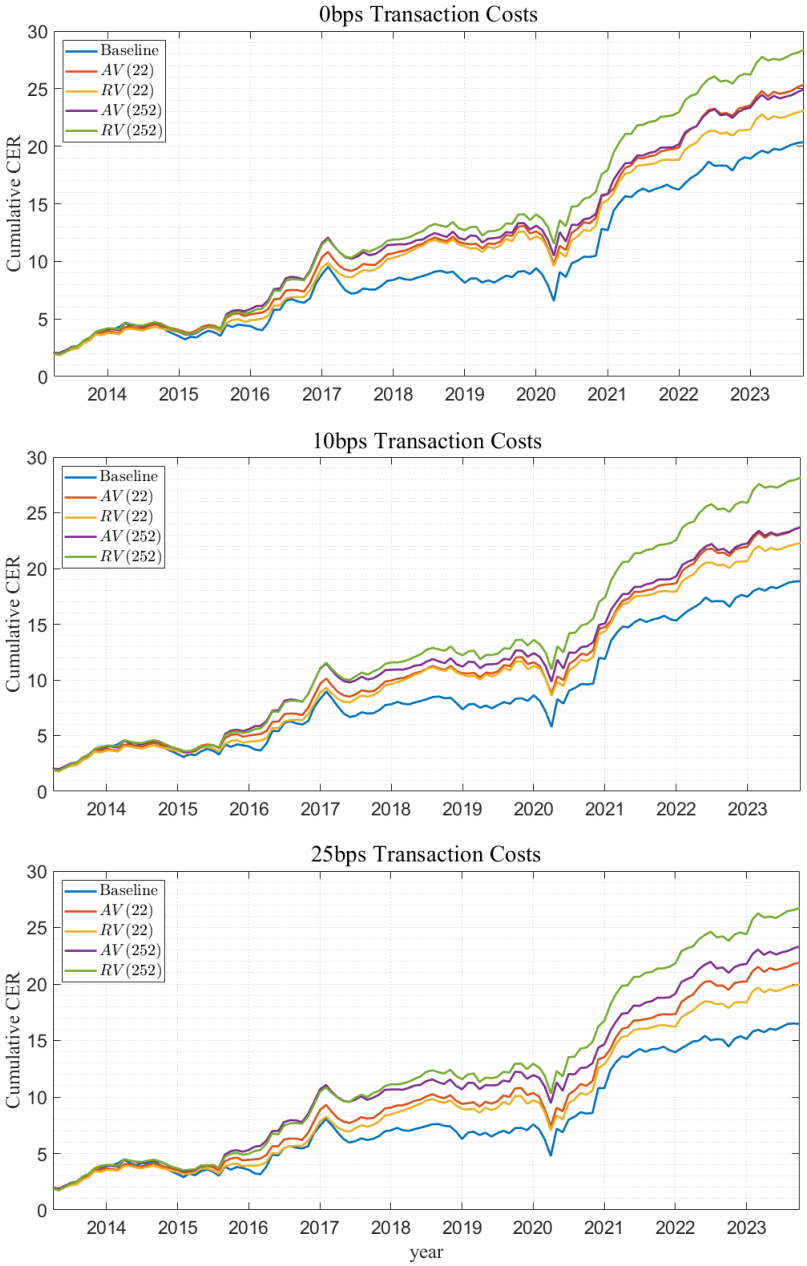


Figure 5: Out-of-Sample Cumulative CERs. This figure plots the out-of-sample cumulative CER of the volatility timing strategy and the baseline strategy under three levels of transaction costs. The top panel plots the 0bps transaction costs. The middle panel 10 bps. The bottom panel 25 bps. The volatility timing strategy is implemented using the $RV(22), AV(22), RV(252), AV(252)$ methods.

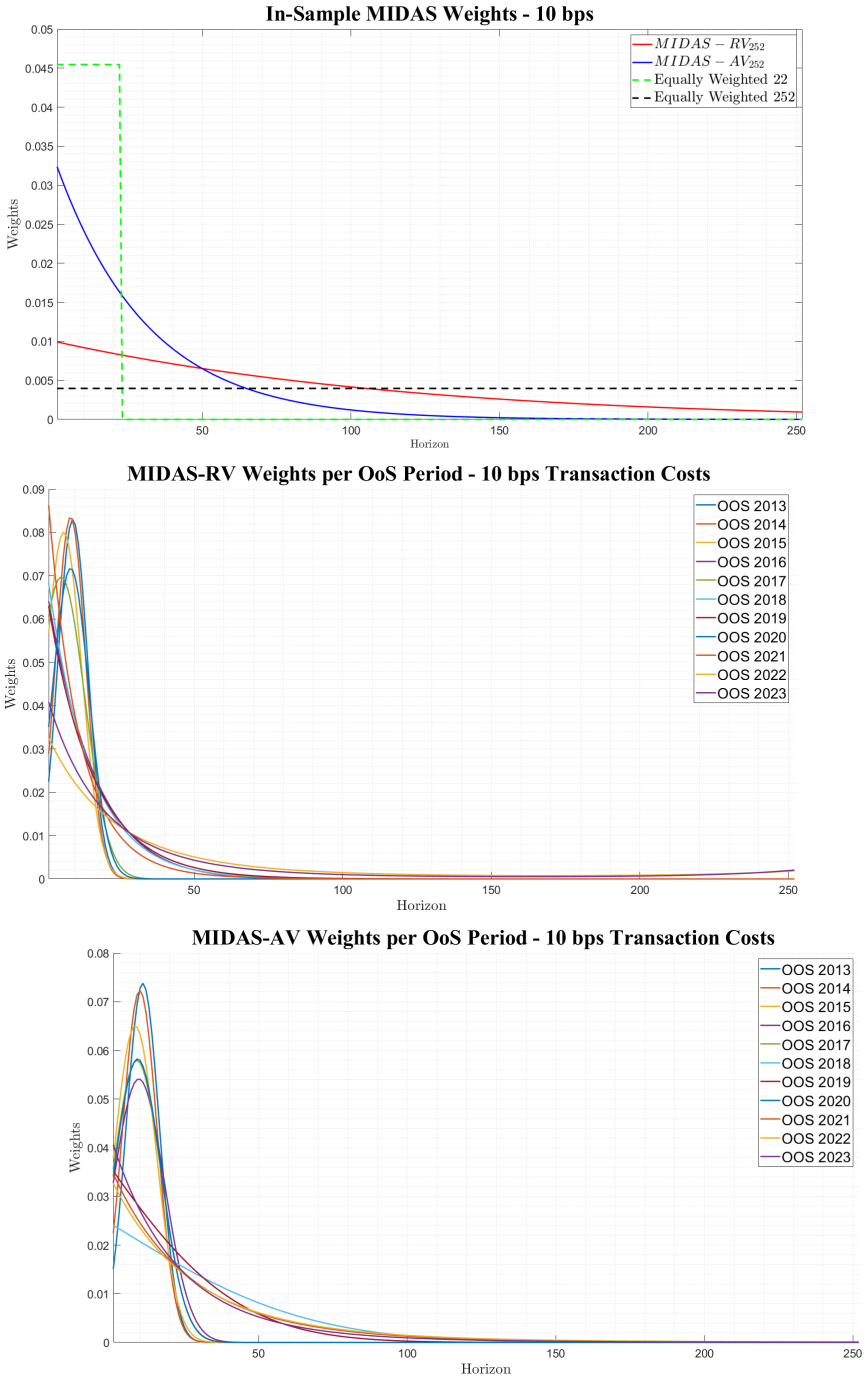


Figure 6: MIDAS Weights. This figure plots the out-of-sample MIDAS weights. In all cases 10 bps of transaction costs are considered. The top panel plots the out-of-sample MIDAS weights of the $MIDAS - RV(252)$ estimated over the expanding windows. The bottom panel plots the out-of-sample MIDAS weights of the $MIDAS - AV(252)$ estimated over the expanding windows.

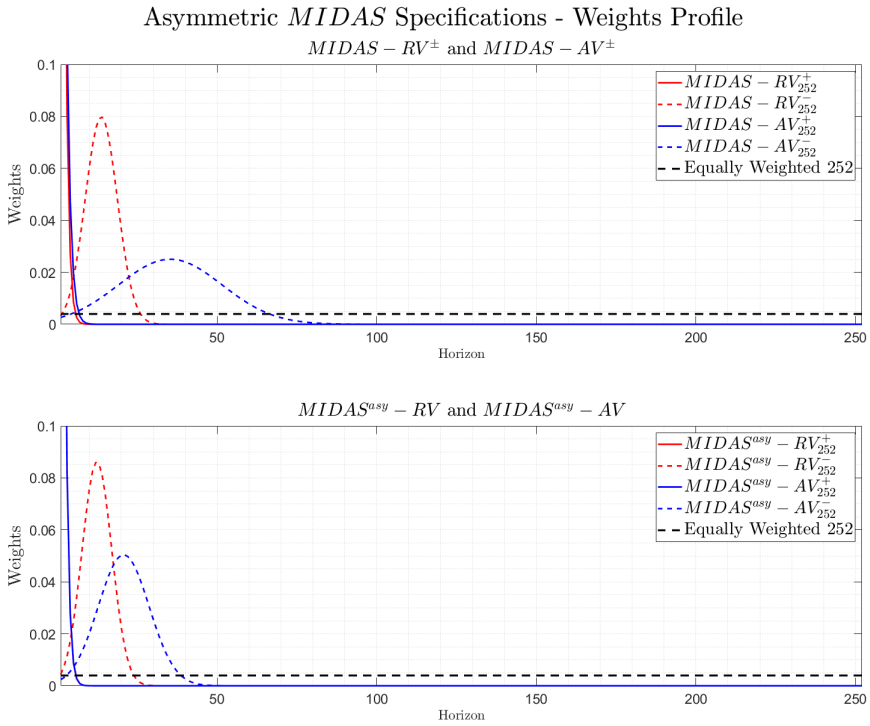


Figure 7: Asymmetric-MIDAS Weights. This figure plots the in-sample implied Asymmetric-MIDAS weights for the specifications in Section 4. The top panel plots the MIDAS weights of the $MIDAS-RV^{\pm}(252)$ and $MIDAS-AV^{\pm}(252)$, defined in equations (11)-(12). The bottom panel plots the MIDAS weights of the $MIDAS^{asy}-RV(252)$ and $MIDAS^{asy}-AV(252)$ defined in equation (15) (for RV). In all cases 10 bps of transaction costs are considered.

APPENDIX

A.1 Further Results

Volatility Timing Results — Transaction costs of 50 bps

Panel A: Portfolio Policies

	Benchmarks		Volatility Timing			
	VW	Baseline	$RV(22)$	$AV(22)$	$RV(252)$	$AV(252)$
θ_{ME}	—	-0.346	-2.410	-2.677	-5.202	-4.563
Std. Err.	—	(1.020)	(1.286)	(1.312)	(1.575)	(1.478)
θ_{BTM}	—	3.328	3.725	4.170	3.335	3.477
Std. Err.	—	(1.356)	(1.415)	(1.428)	(1.432)	(1.380)
θ_{MOM}	—	2.793	3.128	3.379	2.236	2.404
Std. Err.	—	(1.300)	(1.334)	1.349	(1.405)	(1.353)
θ_{σ}	—	—	-2.534	-2.495	-4.936	-3.729
Std. Err.	—	—	(1.135)	(0.955)	(1.251)	(0.981)

Panel B: In-Sample Results

CE(r)	0.039	0.090	0.134	0.147	0.200	0.185
$\bar{r}$	0.105	0.215	0.255	0.274	0.333	0.298
$\sigma(r)$	0.153	0.224	0.218	0.225	0.230	0.211
SR	0.601	0.899	1.111	1.160	1.391	1.355
$\sum \lvert w_i - w_i^h \rvert$	0.918	12.701	21.436	22.590	14.636	13.816
$\sum w_i I(w_i < 0)$	0.000	-1.084	-1.435	-1.625	-1.899	-1.727

Panel C: Out-of-Sample Results

CE(r)	0.064	0.041	0.100	0.123	0.214	0.168
$\bar{r}$	0.120	0.182	0.296	0.304	0.397	0.318
$\sigma(r)$	0.151	0.260	0.292	0.284	0.290	0.260
SR	0.795	0.697	1.012	1.069	1.369	1.220
$\sum \lvert w_i - w_i^h \rvert$	9.024	9.335	18.308	18.591	13.073	12.358
$\sum w_i I(w_i < 0)$	0.000	-1.069	-1.801	-1.893	-2.053	-1.946

Table A.1: Volatility Timing. This table reports the estimated portfolio policies, in-sample and out-of-sample portfolio results of the volatility timing strategy under 50bps of transaction costs.

Diebold-Mariano Out-of-Sample p-values

Starting Yr.	$RV(252)$	$AV(252)$
2010	0.002	0.039
2011	0.002	0.034
2012	0.003	0.058
2013	0.032	0.050
2014	0.002	0.047
2015	0.003	0.065
2016	0.008	0.179
2017	0.004	0.095
2018	0.014	0.149
2019	0.028	0.190
2020	0.012	0.131

Table A.2: Diebold-Mariano p-values. This table reports the results of the Diebold and Mariano (1995) test for comparing the out-of-sample utility gains of the volatility timing strategies against the baseline benchmark portfolio for the starting years for which at least three years of monthly evaluation sample is available. Specifically, we test H_0 : $E[u(r^{vol}_{p,t+1})] = E[u(r^{bmk}_{p,t+1})]$ against H_A : $E[u(r^{vol}_{p,t+1})] > E[u(r^{bmk}_{p,t+1})]$. We report results using HAC-robust standard errors computed with a Bartlett kernel with 4 lags. The utility gains are net of 10 bps transaction costs.

Idiosyncratic Volatility Timing — Transaction costs of 0 bps

Panel A: Portfolio Policies

	Baseline and Total Volatility		Idiosyncratic Volatility			
	$RV(22)$	$RV(252)$	$ivol_1$	$ivol_2$	$ivol_3$	$ivol_4$
θ_{ME}	-3.774	-5.413	-6.221	-5.707	-6.235	-7.744
Std. Err.	(1.317)	(1.607)	(1.714)	(1.737)	(1.757)	(2.059)
θ_{BTM}	5.499	5.605	4.945	5.161	4.902	4.929
Std. Err.	(1.653)	(1.634)	(1.600)	(1.610)	(1.602)	(1.617)
θ_{MOM}	4.807	4.973	4.680	5.229	4.927	4.987
Std. Err.	(1.469)	(1.538)	(1.537)	(1.531)	(1.528)	(1.564)
θ_{σ}	-4.349	-4.793				
Std. Err.	(1.213)	(1.292)				
$\theta_{\sigma_{IDIO}}$			-6.038	-5.382	-5.893	-6.269
Std. Err.			(1.566)	(1.601)	(1.628)	(1.680)
Panel B: In-Sample Results						
CE(r)	0.278	0.295	0.305	0.289	0.293	0.305
$\bar{r}$	0.496	0.519	0.564	0.547	0.553	0.545
$\sigma(r)$	0.296	0.306	0.330	0.330	0.331	0.317
SR	1.633	1.652	1.669	1.621	1.632	1.677
$\sum \lvert w_i - w_i^h \rvert$	34.629	24.011	43.791	41.644	43.646	24.362
$\sum w_i I(w_i < 0)$	-2.360	-2.676	-2.668	-2.630	-2.665	-2.849
Panel C: Out-of-Sample Results						
CE(r)	0.182	0.291	0.209	0.185	0.196	0.272
$\bar{r}$	0.627	0.652	0.655	0.628	0.640	0.640
$\sigma(r)$	0.443	0.421	0.463	0.463	0.465	0.431
SR	1.415	1.550	1.416	1.354	1.375	1.485
$\sum \lvert w_i - w_i^h \rvert$	34.774	24.326	42.047	41.546	42.166	24.242
$\sum w_i I(w_i < 0)$	-3.465	-3.412	-3.647	-3.567	-3.597	-3.561

Table A.3: Idiosyncratic Volatility Timing. This table reports the results of the volatility timing strategy implemented using measures of idiosyncratic volatility and transaction costs of 0 bps. We refer to Table 6 for an explanation of the idiosyncratic measures used to decompose volatility into systematic and idiosyncratic components.

Idiosyncratic Volatility Timing — Transaction costs of 25 bps

Panel A: Portfolio Policies

	Baseline and Total Volatility		Idiosyncratic Volatility			
	$RV(22)$	$RV(252)$	$ivol_1$	$ivol_2$	$ivol_3$	$ivol_4$
θ_{ME}	-3.193	-5.192	-4.716	-4.496	-4.540	-7.329
Std. Err.	(1.303)	(1.591)	(1.657)	(1.689)	(1.699)	(2.024)
θ_{BTM}	4.877	4.692	4.430	4.348	4.397	3.797
Std. Err.	(1.553)	(1.547)	(1.516)	(1.513)	(1.518)	(1.513)
θ_{MOM}	4.265	3.730	4.224	4.253	4.221	3.599
Std. Err.	(1.414)	(1.479)	(1.459)	(1.446)	(1.446)	(1.492)
θ_{σ}	-3.518	-4.848				
Std. Err.	(1.179)	(1.275)				
$\theta_{\sigma_{IDIO}}$			-4.481	-4.233	-4.338	-6.157
Std. Err.			(1.495)	(1.541)	(1.559)	(1.647)

Panel B: In-Sample Results

CE(r)	0.197	0.241	0.206	0.194	0.195	0.249
$\bar{r}$	0.372	0.421	0.398	0.384	0.387	0.433
$\sigma(r)$	0.264	0.271	0.284	0.281	0.283	0.274
SR	1.358	1.509	1.358	1.321	1.323	1.533
$\sum \lvert w_i - w_i^h \rvert$	29.217	19.716	34.462	33.269	33.824	19.423
$\sum w_i I(w_i < 0)$	-2.009	-2.310	-2.133	-2.062	-2.082	-2.396

Panel C: Out-of-Sample Results

CE(r)	0.140	0.258	0.153	0.133	0.139	0.238
$\bar{r}$	0.440	0.513	0.454	0.430	0.437	0.504
$\sigma(r)$	0.361	0.347	0.380	0.379	0.381	0.359
SR	1.217	1.478	1.194	1.133	1.147	1.403
$\sum \lvert w_i - w_i^h \rvert$	26.615	17.968	31.572	30.739	30.989	18.443
$\sum w_i I(w_i < 0)$	-2.621	-2.661	-2.760	-2.676	-2.687	-2.889

Table A.4: Idiosyncratic Volatility Timing. This table reports the results of the volatility timing strategy implemented using measures of idiosyncratic volatility and transaction costs of 25 bps. We refer to Table 6 for an explanation of the idiosyncratic measures used to decompose volatility into systematic and idiosyncratic components.

Idiosyncratic Volatility Timing — Transaction costs of 50 bps

Panel A: Portfolio Policies

	Baseline and Total Volatility		Idiosyncratic Volatility			
	$RV(22)$	$RV(252)$	$ivol_1$	$ivol_2$	$ivol_3$	$ivol_4$
θ_{ME}	-2.410	-5.202	-2.880	-2.567	-2.773	-6.898
Std. Err.	(1.286)	(1.575)	(1.600)	(1.637)	(1.648)	(1.989)
θ_{BTM}	3.725	3.335	3.490	3.792	3.748	2.896
Std. Err.	(1.415)	(1.432)	(1.409)	(1.432)	(1.430)	(1.435)
θ_{MOM}	3.128	2.236	3.096	3.389	3.410	2.540
Std. Err.	(1.334)	(1.405)	(1.359)	(1.365)	(1.366)	(1.430)
θ_{σ}	-2.534	-4.936				
Std. Err.	(1.135)	(1.251)				
$\theta_{\sigma_{IDIO}}$			-2.791	-2.452	-2.567	-5.933
Std. Err.			(1.411)	(1.467)	(1.481)	(1.609)
Panel B: In-Sample Results						
CE(r)	0.134	0.200	0.132	0.125	0.125	0.205
$\bar{r}$	0.255	0.333	0.259	0.262	0.264	0.349
$\sigma(r)$	0.218	0.230	0.227	0.237	0.238	0.241
SR	1.111	1.391	1.085	1.053	1.052	1.394
$\sum \lvert w_i - w_i^h \rvert$	21.436	14.636	23.015	22.318	22.905	15.656
$\sum w_i I(w_i < 0)$	-1.435	-1.899	-1.418	-1.465	-1.484	-2.037
Panel C: Out-of-Sample Results						
CE(r)	0.100	0.214	0.097	0.083	0.086	0.205
$\bar{r}$	0.296	0.397	0.288	0.271	0.273	0.401
$\sigma(r)$	0.292	0.290	0.301	0.300	0.300	0.304
SR	1.012	1.369	0.955	0.902	0.910	1.318
$\sum \lvert w_i - w_i^h \rvert$	18.308	13.073	20.447	19.336	19.260	13.786
$\sum w_i I(w_i < 0)$	-1.801	-2.053	-1.839	-1.751	-1.744	-2.338

Table A.5: Idiosyncratic Volatility Timing. This table reports the results of the volatility timing strategy implemented using measures of idiosyncratic volatility and transaction costs of 50 bps. We refer to Table 6 for an explanation of the idiosyncratic measures used to decompose volatility into systematic and idiosyncratic components.

Dissected Volatility — Transaction Costs of 0 bps

Panel A: Portfolio Policies

	Systematic Model			
	$CAPM(22)$	$FF3(22)$	$HXZ(22)$	$CAPM(252)$
θ_{ME}	-6.736	-4.833	-6.109	-5.246
Std. Err.	(2.002)	(1.874)	(1.944)	(2.300)
θ_{BTM}	4.937	5.539	4.927	5.591
Std. Err.	(1.612)	(1.608)	(1.598)	(1.634)
θ_{MOM}	5.011	5.117	4.862	4.643
Std. Err.	(1.561)	(1.492)	(1.517)	(1.653)
$\theta_{\sigma_{IVOL}}$	-6.270	-4.126	-5.470	-4.135
Std. Err.	(2.006)	(1.929)	(1.999)	(1.970)
$\theta_{\sigma_{SYSVOL}}$	0.138	-1.645	-0.649	-3.126
Std. Err.	(1.277)	(1.203)	(1.280)	(1.762)

Panel B: In-Sample Portfolio Results

CE(r)	0.305	0.300	0.296	0.320
ΔCE(r)	0.000	0.011	0.003	0.015
$\bar{r}$	0.578	0.549	0.552	0.565
$\sigma(r)$	0.340	0.325	0.329	0.321
SR	1.660	1.649	1.641	1.718
$\sum \lvert w_i - w_i^h \rvert$	45.468	39.749	42.281	23.895
$\sum w_i I(w_i < 0)$	-2.799	-2.634	-2.660	-2.775

Panel C: Out-of-Sample Portfolio Results

CE(r)	0.193	0.201	0.194	0.280
ΔCE(r)	-0.016	0.016	-0.002	0.008
$\bar{r}$	0.648	0.636	0.637	0.646
$\sigma(r)$	0.469	0.457	0.464	0.425
SR	1.382	1.391	1.373	1.520
$\sum \lvert w_i - w_i^h \rvert$	45.142	40.331	41.449	24.318
$\sum w_i I(w_i < 0)$	-3.736	-3.551	-3.582	-3.571

Table A.6: Dissected Volatility. This table reports the results of the volatility timing strategy under volatility decomposition and transaction costs of 0 bps. We refer to Table 6 for an explanation of the idiosyncratic measures used to decompose volatility into systematic and idiosyncratic components.

Dissected Volatility — Transaction Costs of 25 bps

Panel A: Portfolio Policies

	Systematic Model			
	$CAPM(22)$	$FF3(22)$	$HXZ(22)$	$CAPM(252)$
θ_{ME}	-4.183	-3.726	-3.659	-5.231
Std. Err.	(1.879)	(1.816)	(1.842)	(2.275)
θ_{BTM}	4.484	4.812	4.613	4.477
Std. Err.	(1.519)	(1.512)	(1.507)	(1.53)7
θ_{MOM}	4.014	4.298	4.134	3.372
Std. Err.	(1.450)	(1.426)	(1.424)	(1.594)
$\theta_{\sigma_{IVOL}}$	-3.947	-3.130	-3.216	-4.309
Std. Err.	(1.889)	(1.871)	(1.903)	(1.937)
$\theta_{\sigma_{SYSVOL}}$	-0.495	-1.358	-1.045	-2.908
Std. Err.	(1.217)	(1.167)	(1.219)	(1.739)

Panel B: In-Sample Portfolio Results

CE(r)	0.208	0.209	0.203	0.268
ΔCE(r)	0.002	0.015	0.008	0.019
$\bar{r}$	0.391	0.394	0.380	0.460
$\sigma(r)$	0.276	0.279	0.271	0.280
SR	1.371	1.366	1.357	1.595
$\sum \lvert w_i - w_i^h \rvert$	32.469	31.960	30.558	19.376
$\sum w_i I(w_i < 0)$	-2.054	-2.119	-2.011	-2.378

Panel C: Out-of-Sample Portfolio Results

CE(r)	0.153	0.159	0.151	0.258
ΔCE(r)	0.000	0.026	0.012	0.020
$\bar{r}$	0.452	0.448	0.442	0.514
$\sigma(r)$	0.378	0.372	0.373	0.349
SR	1.193	1.204	1.183	1.475
$\sum \lvert w_i - w_i^h \rvert$	31.228	29.900	29.703	18.394
$\sum w_i I(w_i < 0)$	-2.752	-2.698	-2.683	-2.863

Table A.7: Dissected Volatility. This table reports the results of the volatility timing strategy under volatility decomposition and transaction costs of 25 bps. We refer to Table 6 for an explanation of the idiosyncratic measures used to decompose volatility into systematic and idiosyncratic components.

Dissected Volatility — Transaction Costs of 50 bps

Panel A: Portfolio Policies

	Systematic Model			
	$CAPM(22)$	$FF3(22)$	$HXZ(22)$	$CAPM(252)$
θ_{ME}	-2.611	-2.511	-2.458	-5.327
Std. Err.	(1.809)	(1.763)	(1.783)	(2.247)
θ_{BTM}	3.849	3.898	3.773	3.112
Std. Err.	(1.431)	(1.421)	(1.416)	(1.434)
θ_{MOM}	3.324	3.223	3.181	1.886
Std. Err.	(1.374)	(1.354)	(1.353)	(1.530)
$\theta_{\sigma_{IVOL}}$	-2.298	-2.097	-2.085	-4.445
Std. Err.	(1.810)	(1.811)	(1.836)	(1.899)
$\theta_{\sigma_{SYSVOL}}$	-0.588	-1.032	-0.836	-2.985
Std. Err.	(1.179)	(1.140)	(1.184)	(1.723)

Panel B: In-Sample Portfolio Results

CE(r)	0.137	0.139	0.135	0.226
ΔCE(r)	0.005	0.014	0.010	0.021
$\bar{r}$	0.270	0.269	0.263	0.374
$\sigma(r)$	0.232	0.231	0.227	0.243
SR	1.104	1.110	1.097	1.489
$\sum \lvert w_i - w_i^h \rvert$	22.996	23.260	22.168	14.654
$\sum w_i I(w_i < 0)$	-1.523	-1.535	-1.469	-2.017

Panel C: Out-of-Sample Portfolio Results

CE(r)	0.104	0.108	0.101	0.236
ΔCE(r)	0.007	0.025	0.015	0.031
$\bar{r}$	0.293	0.292	0.286	0.418
$\sigma(r)$	0.300	0.296	0.296	0.290
SR	0.977	0.986	0.965	1.439
$\sum \lvert w_i - w_i^h \rvert$	20.221	19.925	19.598	13.596
$\sum w_i I(w_i < 0)$	-1.850	-1.839	-1.816	-2.275

Table A.8: Dissected Volatility. This table reports the results of the volatility timing strategy under volatility decomposition and transaction costs of 50 bps. We refer to Table 6 for an explanation of the idiosyncratic measures used to decompose volatility into systematic and idiosyncratic components.

MIDAS Volatility Timing — Transaction costs of 0 bps

Panel A: Portfolio Policies

	EW Volatility		MIDAS Volatility	
	$RV(252)$	$AV(252)$	$\mathcal{M}_{RV(252)}$	$\mathcal{M}_{AV(252)}$
θ_{ME}	-5.413	-5.256	-5.462	-4.599
Std. Err.	(1.607)	(1.516)	(1.499)	(1.386)
θ_{BTM}	5.605	5.566	5.126	5.682
Std. Err.	(1.634)	(1.562)	(1.604)	(1.590)
θ_{MOM}	4.973	4.935	4.112	4.690
Std. Err.	(1.538)	(1.497)	(1.435)	(1.417)
$\theta_{\sigma_{MIDAS}}$	-4.793	-3.909	-4.992	-3.873
Std. Err.	(1.292)	(1.013)	(1.146)	(0.917)
κ_1			-0.0642	-0.0528
κ_2			0.0002	-0.0003

Panel B: In-Sample Results

CE(r)	0.295	0.279	0.306	0.301
$\bar{r}$	0.519	0.483	0.553	0.539
$\sigma(r)$	0.306	0.292	0.321	0.316
SR	1.652	1.611	1.679	1.663
$\sum \lvert w_i - w_i^h \rvert$	24.011	23.045	30.505	31.472
$\sum w_i I(w_i < 0)$	-2.676	-2.576	-2.649	-2.694

Panel C: Out-of-Sample Results

CE(r)	0.291	0.227	0.182	0.232
$\bar{r}$	0.652	0.554	0.648	0.644
$\sigma(r)$	0.421	0.404	0.462	0.442
SR	1.550	1.371	1.401	1.457
$\sum \lvert w_i - w_i^h \rvert$	24.326	24.117	36.575	33.425
$\sum w_i I(w_i < 0)$	-3.412	-3.349	-3.587	-3.568

Table A.9: MIDAS Volatility Timing. This table reports the in-sample and out-of-sample portfolio performance of the MIDAS volatility timing strategy under 0 bps of transaction costs.

Volatility Timing with Additional Characteristics

	BAB			(IL)LIQ			INV		
	BASE	$RV(252)$	$AV(252)$	BASE	$RV(252)$	$AV(252)$	BASE	$RV(252)$	$AV(252)$
Panel A: Portfolio Policies									
θ_{ME}	-0.613	-6.413	-7.459	1.186	-4.484	-4.011	-0.352	-6.448	-6.090
Std. Err.	(1.077)	(2.213)	(2.668)	(1.009)	(1.787)	(1.815)	(1.051)	(1.740)	(1.691)
θ_{BTM}	6.044	4.952	5.006	4.014	5.221	4.921	2.608	4.031	4.373
Std. Err.	(1.549)	(1.636)	(1.615)	(1.465)	(1.548)	(1.507)	(1.462)	(1.496)	(1.508)
θ_{MOM}	3.505	3.148	3.727	3.652	3.670	3.642	4.149	3.760	4.207
Std. Err.	(1.321)	(1.375)	(1.364)	(1.275)	(1.338)	(1.292)	(1.323)	(1.330)	(1.306)
θ_{BAB}	-3.372	-0.780	0.388						
Std. Err.	(0.821)	(1.198)	(1.561)						
$\theta_{(IL)LIQ}$				10.778	7.821	7.042			
Std. Err.				(2.065)	(2.140)	(2.184)			
θ_{INV}							-11.671	-9.008	-8.651
Std. Err.							(2.509)	(2.561)	(2.545)
θ_{σ}		-6.363	-6.551		-6.015	-4.434		-7.027	-5.512
Std. Err.		(2.057)	(2.248)		(1.491)	(1.282)		(1.461)	(1.218)
Panel B: In-Sample Portfolio Results									
CE(r)	0.226	0.297	0.284	0.273	0.389	0.352	0.252	0.365	0.391
$\bar{r}$	0.391	0.507	0.478	0.564	0.697	0.608	0.500	0.631	0.684
$\sigma(r)$	0.275	0.294	0.279	0.393	0.381	0.347	0.349	0.347	0.366
SR	1.377	1.680	1.662	1.405	1.798	1.714	1.396	1.781	1.833
$\sum \lvert w_i - w_i^h \rvert$	18.557	20.296	20.902	19.406	23.265	21.008	26.130	26.824	27.606
$\sum w_i I(w_i < 0)$	-2.213	-2.605	-2.606	-1.844	-2.601	-2.296	-2.587	-3.106	-3.299
Panel C: Out-of-Sample Portfolio Results									
CE(r)	0.115	0.208	0.173	0.110	0.315	0.231	0.183	0.362	0.279
$\bar{r}$	0.369	0.579	0.507	0.511	0.705	0.593	0.450	0.775	0.631
$\sigma(r)$	0.377	0.421	0.397	0.525	0.483	0.463	0.384	0.454	0.418
SR	0.980	1.374	1.277	0.972	1.459	1.279	1.171	1.704	1.508
$\sum \lvert w_i - w_i^h \rvert$	19.255	21.612	22.924	20.443	23.211	23.446	23.869	27.366	26.853
$\sum w_i I(w_i < 0)$	-2.798	-3.235	-3.420	-2.491	-3.024	-3.038	-2.812	-3.762	-3.632

Table A.10: Volatility Timing with Multiple Characteristics. This table reports the results of the volatility timing strategy when additional characteristics are included in the portfolio construction. All characteristics are sourced from Jensen et al. (2023) and are at firm level. BAB refers to the Betting Against Beta of Frazzini and Pedersen (2014); $(IL)LIQ$ refers to the Amihud illiquity measure; INV refers to a measure of firm-asset growth. BASE refers to the portfolio constructed using the three baseline characteristics and adding the individual additional characteristic. The results reported are for 10 bps of transaction costs.

Firm-level Asymmetry								
	N	Mean	Median	Std.	Min	Max	$Frac^{group} > 0$	$Frac^{tot} > 0$
All stocks	5058	0.157	0.147	0.29	-1.554	4.676	73.329	100
$b_i \neq 0$	2319	0.294	0.291	0.332	-1.476	2.023	85.813	45.848
$b_i > 0$	1990	0.393	0.32	0.237	0.08	2.023	100	39.344
$b_i < 0$	329	-0.305	-0.276	0.146	-1.476	-0.081	0	6.505
$b_i = 0$	2739	0.041	0.049	0.181	-1.554	4.676	62.76	54.152

Table A.11: Summary Statistics: Firm-Level Asymmetry Parameter. This table reports the summary statistics of the firm-level asymmetry parameter. We refer to the description of Figure A.1 for details on the computations.

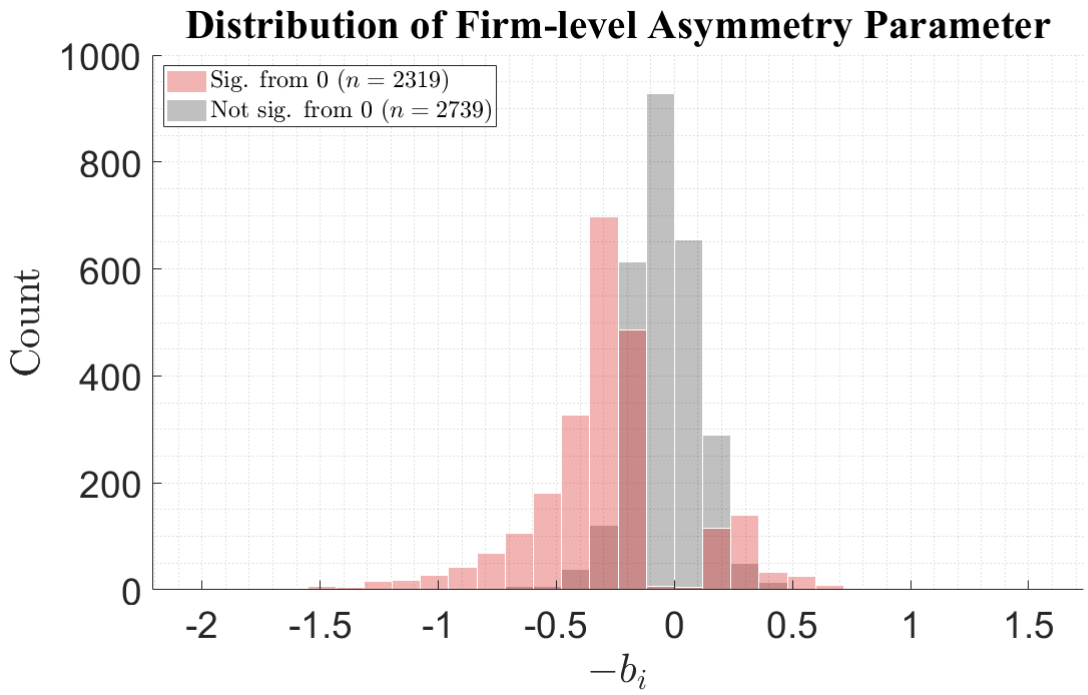


Figure A.1: Firm-Level Asymmetry Parameter. This figure plots the firm-level estimates of the asymmetry parameter (scaled by -1) from the following time-series regressions: $RV_{i,t} = c_i + a_i RV^+_{i,t-1} + (a_i + b_i) RV^-_{i,t-1} + \epsilon_{i,t},\ i = 1, \ldots, N$. We consider stocks traded for at least 60 consecutive months, to obtain reliable estimates, and we test the null of no asymmetry $H_0 : b_i = 0$ at the 10% level using HAC-robust standard errors computed with a Bartlett kernel and the automated lag-length selection of Newey and West (1994).