Stock Return Predictability of Realized-Implied Volatility Spread and Abnormal Turnover

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Abstract

The existence of a negative volatility risk premium in individual equity options and its predictive power for the cross-section of stock returns, as measured by realized-implied volatility spread (RVol-IVol), are documented in the literature. We show that the stock return predictability of RVol-IVol does not hold for stocks that experience abnormal turnover. While the option implied volatility remains stable for these stocks, the realized volatility rises (falls) with abnormally high (low) turnover and subsequently reverts. This causes realized volatility to deviate from long-term fundamental volatility and contaminates the predictive power of RVol-IVol for stock returns. Excluding stocks with abnormal turnover significantly improves the returns to trading strategies based on RVol-IVol. These findings provide evidence for the idea that option implied volatility filters out the temporary noise in realized volatility and that mainly fundamental volatility risk is priced in the cross-section of stock returns.

Keywords: Implied volatility, realized volatility, abnormal turnover

JEL classification: G12, G13, G14

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1 Introduction

Options markets are generally seen as markets for trading volatility risk. Literature documents the existence of a negative volatility risk premium, implying that investors are willing to pay extra or accept lower returns for securities like options whose values increase when volatility goes up. This explains why option implied volatilities exceed realized volatilities. While earlier studies mainly focus on the volatility risk premium in index options,[1] Duarte et al. (2022) show that, after accounting for data complications, the estimates of volatility risk premium in individual equity options are as large as those of S&P 500 index options. Moreover, Bollerslev et al. (2009, 2011) show that the difference between option implied variance and expected realized variance of the S&P 500 index predicts aggregate stock market returns as it captures economic uncertainty and investors' risk aversion. Similarly, Bali and Hovakimian (2009) find that volatility risk premium in individual equity options, measured by realized-implied volatility spread (*RVol-IVol*), predicts the cross-sectional variation in stock returns, suggesting that volatility risk is also priced in the cross-section of stocks.

Even though volatility risk premium serves as a useful predictor of stock returns and hence a valuable trading signal, it is not straightforward to measure since expected realized volatility is a priori unknown. Previous studies commonly use recent realized volatility as a proxy (such as realized volatility over the last month as in Bollerslev et al. (2009) or Bali and Hovakimian (2009)), assuming that it is a good forecast for realized volatility in the near future. Although this approach has the advantage of capturing the latest volatility dynamics, it ignores the long-term mean-reverting nature of volatility.[2] More importantly, recent volatility estimates may not be in line with the fundamental volatility of the underlying, which can contaminate the predictive power of volatility risk premium for stock returns.[3]

In line with this idea, Conrad and Loch (2015) propose a new realized variance measure for the S&P 500 index which incorporates a long-term component to capture fundamental uncertainty better. They show that using this realized variance measure significantly improves the predictive power of index volatility risk premium, suggesting that it is mainly the fundamental economic uncertainty that is priced in the aggregate stock returns. In this paper, we argue that it is also the fundamental volatility risk that is priced in the cross-section of stock returns. Specifically, we show that the predictive power of *RVol-IVol* as a measure of volatility risk premium in individual stocks does not hold when realized volatility is not in line with the long-term fundamental volatility of the stock, where we use abnormal stock turnover as a proxy for the

[1] See, e.g., Coval and Shumway (2001), Bakshi and Kapadia (2003a,b), Carr and Wu (2009) and Driessen et al. (2009)

[2] See, e.g., Granger and Poon (2003) and Andersen et al. (2006) for a review.

[3] Bollerslev et al. (2009) assume that conditional realized variance follows a martingale process so that recent realized variance can be used as the expected value of future realized variance. However, Bekaert and Hoerova (2014) note that this assumption is not supported in the data, implying that using recent realized variance might lead to biased volatility risk premium estimates.

misalignment of realized volatility with long-term fundamental volatility. We find that excluding stocks with abnormally high or low turnover when constructing trading strategies based on $RVol$-$IVol$ improves strategy returns significantly.

Abnormal stock turnover can be driven by factors such as hedging, liquidity, portfolio rebalancing needs, differences of opinion, and overconfidence. Chuang and Lee (2006) and Hong and Stein (2007) argue that hedging, liquidity, and portfolio rebalancing needs are too small to account for the large trading activity observed in the stock market. Hence, abnormal stock turnover is more likely attributable to differences of opinion and overconfidence (Glaser and Weber (2007, 2009)). Excess trading driven by these speculative factors introduces noise into stock prices and is associated with temporary increases in volatility, which are eventually reversed after the excess trading dissipates (Odean (1998), Chuang and Lee (2006)). Therefore, we expect stocks that experience a positive (negative) turnover shock to have abnormally high (low) recent volatility. This causes the realized volatility not to align with long-term fundamental volatility, leading to biased volatility risk premium estimates measured by $RVol$-$IVol$.

We follow Pan et al. (2016) to construct our abnormal turnover measure and focus on speculative trading after removing the effects of liquidity and other factors that affect trading volume. Specifically, we first regress the daily turnover ratio of individual stocks on the aggregate market turnover and a set of dummy variables that correspond to informative corporate events over the previous 12 months. We then use the coefficient estimates from this regression to calculate the predicted normal turnover ratio over the current month that captures trading driven by liquidity and market-wide or firm-specific information. The difference between actual and predicted turnover represents the abnormal turnover ratio (ATR) and captures speculative or noise trading.

We start with examining the characteristics of stocks that experience abnormal turnover. We find that stocks in the highest or lowest ATR quintiles (with abnormally high or low turnover) have smaller market capitalization, are more volatile, and have higher idiosyncratic risk. Moreover, a larger portion of their long-term return variance comes from noise, as measured by the variance decomposition model of Brogaard et al. (2022). Hence, these stocks are more likely to attract speculative retail trading with variable trading activity (see, e.g., Hvidkjaer (2008), Han and Kumar (2013), and Barinov (2015)).

Next, we examine how ATR affects recent realized volatility over the current month. Excess trading not driven by fundamental information typically causes the stock price to overreact and revert over the next day. This leads to a temporary spike in realized volatility. Accordingly, stocks in the highest ATR quintile experience a 7.78% increase in realized volatility, which completely reverses over the next month as the excess trading disappears. Similarly, stocks in the lowest ATR quintile experience a 4.95% decrease in realized volatility with a subsequent reversal. Furthermore, the temporary changes in realized volatility are stronger among illiquid stocks since illiquid stocks are more prone to price pressures (Avramov et al. (2006), Nagel (2012)). These results support our choice of using extreme ATR as a proxy for the misalignment of recent realized volatility with long-term fundamental volatility.

We also examine if ATR is associated with any significant changes in option implied volatility. Goncalves-Pinto et al. (2020) argue that option prices provide an anchor fundamental stock value that helps distinguish stock price movements due to price pressure versus news. When there is price pressure due to excessive trading in the stock market, the options market does not respond to the price pressure and signals the level to which the stock price will revert back. We find similar results for stock volatility; i.e. option implied volatility does not respond to the changes in realized volatility caused by abnormal turnover. This suggests that option traders recognize the transitory nature of these changes and filter them out in their estimation of future volatility.

After showing a temporary dislocation of $RVol$-$IVol$ among stocks that experience abnormal turnover solely caused by changes in realized volatility, we examine how ATR affects the stock return predictability of $RVol$-$IVol$. For this purpose, we create equally-weighted portfolios based on univariate sorts by $RVol - IVol$ and on double-sorts by ATR and $RVol - IVol$. We calculate raw or risk-adjusted returns of these portfolios over the next month. In univariate sorts, similar to Bali and Hovakimian (2009), we find that a trading strategy that longs the stocks in the lowest $RVol$-$IVol$ quintile and shorts the stocks in the highest $RVol$-$IVol$ quintile produces an average return of 49 to 51 basis points per month (with t-statistics of 2.89 to 3.01). In double sorts, on the other hand, the strategy return varies considerably across ATR quintiles. For stocks in the highest or lowest ATR quintiles (with abnormal turnover), the return differences between the lowest and highest $RVol$-$IVol$ quintiles decrease to insignificant levels of 22 to 34 basis points.In contrast, for the medium ATR quintiles (with normal turnover), the return differences are much larger, ranging from 57 to 72 basis points (with t-statistics of 3.06 to 3.91).

We also implement trading strategies based on $RVol$-$IVol$ among stocks with abnormal vs. normal turnover separately. We find that longing stocks in the lowest $RVol$-$IVol$ quintile and shorting stocks in the highest $RVol$-$IVol$ quintile produce a non-significant return of 32 to 34 basis points among stocks with abnormal turnover. On the other hand, the same strategy leads to a highly significant (t-statistic: 4.27 to 4.47) return of 66 to 67 basis points per month among stocks with normal turnover. This is, on average, 33% higher than the initial strategy returns of 49-51 basis points, which does not consider stock turnover.

We obtain qualitatively similar results when we use Fama and MacBeth (1973) regressions to control for various factors that affect the cross-section of stock returns, such as systematic risk, size, book-to-market ratio, momentum, short-term reversal, liquidity, implied volatility skew, and call-put volatility spread. After controlling for these factors, we find that $RVol$-$IVol$ is significantly related to next month's returns, providing further support that volatility risk is priced in the cross-section of equity returns. Again, this relationship does not hold among stocks that experience abnormal turnover but is economically and statistically significant for stocks with normal turnover.

Collectively, our results show that *RVol-IVol* does not serve as a good measure for volatility risk premium among stocks that experience abnormal turnover, since the realized volatility of these stocks is abnormally high or low compared to their long-term fundamental volatility, contaminating the predictive power of *RVol-IVol* for stock returns. Therefore, excluding these stocks when constructing trading strategies based on volatility risk premium in individual stocks improves the strategy returns significantly. This suggests that it is mainly the fundamental volatility risk that is priced in the cross-section of stocks returns.

In additional tests, we explore alternative ways to measure volatility risk premium. First, we show that our results are very similar when we use the model-free implied volatility of Jiang and Tian (2005) calculated with options of all available strikes instead of using at-the-money implied volatility. We next consider using historical realized volatility over the previous 12 months instead of one month. Despite being less prone to volatility spikes, using historical volatility reduces the overall predictive power of *RVol-IVol* as it is less effective in capturing the current volatility dynamics of the underlying stock. We also create value-weighted portfolios instead of equally-weighted ones. While forming value-weighted portfolios result in higher strategy returns, since they put less weight on small stocks that are more likely to face abnormal turnover, our results remain qualitatively similar with value-weighted portfolios. Finally, we find that the predictive power of *RVol-IVol* is stronger in the first subperiod of our sample (1996-2007) compared to the second subperiod (2008-2019), while the robust effect of abnormal turnover on this predictability is present in both subperiods.

Our paper contributes to the literature on the predictive power of volatility risk premium for stock returns. Bollerslev et al. (2009, 2011, 2013) and Drechsler and Yaron (2011), among others, show that volatility risk premium in index options captures time-varying economic uncertainty and investor's risk aversion, thereby affecting aggregate stock market returns. Subsequent studies such as Bekaert and Hoerova (2014), Conrad and Loch (2015), Bollerslev et al. (2016), and Li et al. (2020) address the measurement issues for volatility risk premium since expected realized variance should be estimated based on conditional variance of past returns. The overall consensus in these studies is that taking temporal variation in realized volatility into account and incorporating a long-term component significantly improve the predictive power of volatility risk premium.

Our paper differs from these studies as we focus on volatility risk premium embedded in individual equity options and its predictive power for the cross-section of stock returns, similar to Bali and Hovakimian (2009). We extend the results in Bali and Hovakimian (2009) and show that stock return predictability of volatility risk premium in individual equity options is stronger when realized volatility captures the long-term fundamental volatility of the stock rather than noise. Given that the realized volatilities of individual stocks are noisier than index volatility (see, e.g., Brogaard et al. (2022)), we use the abnormal turnover ratio as a simple method to detect stocks with volatility risk measurement issues.

Our paper also adds to the literature documenting the superiority of option implied volatility over historical realized volatility due to its forward-looking nature. Fleming (1998), Christensen and Prabhala (1998), Jiang and Tian (2005) and Kourtis et al. (2016) show that the implied volatilities of different indices outperform their realized volatilities in forecasting future volatility. Mayhew and Stivers (2003) and Dennis et al. (2006) find similar results for the implied volatilities of individual stocks. Our paper complements these studies by documenting that option implied volatility's ability to filter out the temporary changes in realized volatility due to market microstructure issues can drive its superior forecasting ability. Moreover, we show that option implied volatility provides an anchor for long-term fundamental stock volatility by filtering out the temporary changes in realized volatility, in line with the results in Goncalves-Pinto et al. (2020) that option prices provide an anchor for fundamental stock values by filtering out temporary price pressures.

The rest of our paper is organized as follows. Section 2 describes our data and methodology. Section 3 presents our empirical results, while Section 4 concludes.

2 Data and Methodology

We obtain options data from OptionMetrics, stock data from CRSP, and corporate accounting data from Compustat. We retain data only for ordinary common stocks with listed options. Since OptionMetrics data starts from 1996, our sample covers the period from January 1996 to December 2019.

We follow a similar approach to Pan et al. (2016) to compute abnormal stock turnover and isolate speculative or noise trading from liquidity and informed trading components of turnover. Specifically, for each stock i over the month m, we run the following regression using daily observations from month m-12 to month m-1:

$$DTR_{it} = a + b \cdot DMTR_t + \sum_{j=1}^{n} c_j \cdot Event(j)_{it} + \epsilon_{it} \tag{1}$$

where DTR_{it} is the daily stock turnover on day t calculated by dividing the trading volume by shares outstanding. $DMTR_t$ is the daily market turnover computed as the aggregated dollar volume divided by the market value of all stocks. $Event(j)_{it}$ is a dummy variable equal to 1 for three days surrounding an informative corporate event and zero otherwise. Similar to Pan et al. (2016), we include the following events: (1) announcements of quarterly, semi-annual, and annual earnings; (2) announcements of mergers and acquisitions and other major changes in ownership structure such as stock repurchases; (3) announcements of debt and equity issuance; (4) announcements of key managerial turnovers; and (5) announcements of regular or special cash dividends.[4] We use the coefficient estimates from this regression to compute the predicted (normal) and residual (abnormal) turnover for each day in month m. We then take the average daily abnormal turnover during the month as our final measure for the abnormal turnover ratio ATR.[5]

Realized-implied volatility spread (*RVol-IVol*) refers to the difference between realized and option implied volatility at the end of month m. Following Bali and Hovakimian (2009), we compute realized volatility as the annualized standard deviation of daily log stock returns during the month. It is common practice in the literature to measure implied volatility by focusing on at-the-money options with maturity of around 30 days since they are the most liquid option contracts (see, e.g., Bali and Hovakimian (2009) and An et al. (2014)). Hence, we calculate implied volatility as the average of the implied volatilities of a 30-day at-the-money put option with Δ=-0.50 and call option with Δ=0.50 measured at the end of the month, which are obtained directly from the implied volatility surfaces available in OptionMetrics.[6]

Our preliminary tests examine the characteristics of stocks with abnormal turnover. In particular, we analyze the main components of the variation of daily returns for these stocks over the past 12 months. First, we calculate the portion of idiosyncratic risk in return variation, as opposed to systematic risk, as 1-R^2 of the regression of daily stock excess returns on the four factors of Carhart (1997)'s model.[7] Then, we calculate the portion of noise in return variation, as opposed to fundamental information, using the decomposition model of Brogaard et al. (2022), which is estimated with a vector autoregression of how a stock's daily return responds to market returns, firm-specific order flow and other firm-specific shocks.[8]

Our main empirical tests examine how ATR affects $RVol$-$IVol$ and its stock return predictability as a proxy for volatility risk. To this end, we form portfolios of stocks sorted by $RVol$-$IVol$ and calculate their equally-weighted raw or risk-adjusted returns based on Carhart (1997)'s model over the next month. We also consider Fama and MacBeth (1973) regressions of next month's stock returns on $RVol - IVol$ while we control for other factors that affect the cross-section of equity returns.

Our first set of control variables includes beta, size, book-to-market ratio, and momentum (Fama and French (1992, 1993), Carhart (1997)). Beta is estimated as the slope coefficient of the regression of daily stock

[4]We obtain the dates of earnings announcements from Compustat, dividend announcements from CRSP, and key managerial turnover from Boardex. The announcement dates for share repurchases, merger and acquisitions, and equity and debt issuances are from Bloomberg.

[5]We obtain qualitatively similar results when we measure abnormal turnover simply as the difference between the average daily turnover in month m and the average daily turnover in months m-12 to m-1.

[6]In additional tests in section 3.4, we show that our results remain similar when we use the model-free implied volatility of Jiang and Tian (2005), which is calculated by integrating over options of all available strikes.

[7]Factor returns are kindly provided at Kenneth French's data library:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[8]See Brogaard et al. (2022) for further details.

excess returns on market excess returns over the previous 12 months. LogSize is the natural logarithm of the market value of equity in millions of dollars. The book-to-market ratio is the ratio of the book value of equity to the market value of equity. Momentum is defined as the cumulative return of the stock over the previous 12 months. Next, we account for market frictions by controlling for short-term return reversals and stock liquidity. Following Jegadeesh (1990), Lehmann (1990), and others, we define short-term reversal as the stock return over the previous month. We measure stock liquidity using the Amihud (2002) illiquidity measure, which is calculated as the average ratio of daily absolute stock return to dollar trading volume over the previous month. Our last two control variables come from the options market. Like Bali and Hovakimian (2009), we include call-put implied volatility spread in our regressions, defined as the difference between the implied volatility of a 30-day at-the-money call with Δ=0.50 and put with Δ=-0.50. Finally, we control for the implied volatility skew of Xing et al. (2010), measured as the difference between the implied volatility of a 30-day out-of-the-money put with Δ=-0.25 and at-the-money call with Δ=0.50.

Table 1 presents the summary statistics of the variables used in our study for a sample of 6,848 distinct optionable stocks with 583,669 stock-month observations. We require a stock to have non-missing volatility data in the current month and one month before and after. Hence, the final sample period is from February 1996 to November 2019 (286 months), with 2,041 stocks in an average month. The mean value for ATR is 0%, while it can amount to -0.19% or 0.13% for the lower or upper quartiles of stocks, which is sizable compared to an average normal daily turnover of 1.03%. The average stock in our sample has a realized volatility of 42.74% and an implied volatility of 47.09%, which results in a negative realized-implied volatility spread of -4.35%, in line with the negative volatility risk premium documented for individual equity options (see, e.g., Duarte et al. (2022)). The mean daily return variation is 0.11%. 71.47% of this variation comes from idiosyncratic risk, and 15.98% comes from noise, similar to the results in Brogaard et al. (2022) for larger optionable stocks in later time periods. Our sample stocks deliver an average 1% return over the next month with a beta of 1.14. The mean log size is 7.33, corresponding to a market capitalization of \$1.53 billion, and the mean book-to-market ratio is 0.52. The average momentum and short-term reversal are 17.74% and 1.04%, respectively, while the average value for Amihud (2002)'s illiquidity is 1.34%. In line with previous studies (see, e.g., Bali and Hovakimian (2009), Xing et al. (2010) An et al. (2014)) implied volatilities of out-of-the-money or at-the-money put options are higher than the implied volatility of at-the-money call options, resulting in mean values of -0.43% for $CVol$-$PVol$ and 4.79% for IV skew.

3 Empirical Results

3.1 Characteristics of Stocks with Abnormal Turnover

Our preliminary analysis shows that abnormal stock turnover captures the misalignment of recent realized volatility with long-term fundamental volatility. For this purpose, we first examine the characteristics of stocks with abnormal turnover.

Barinov (2015) shows that firms with higher turnover variability tend to be more financially distressed with smaller market capitalizations and have higher idiosyncratic risk. These features are common for stocks that attract speculative retail trading (Hvidkjaer (2008), Han and Kumar (2013)), which introduces noise into stock prices, increasing overall volatility with a greater noise component. Therefore, we expect stocks that experience abnormal turnover to have smaller market capitalizations with higher overall volatility and idiosyncratic risk. Moreover, more of their volatility will be driven by noise rather than fundamental information.

In Table 2, we sort stocks into five portfolios based on ATR at the end of each month and calculate each portfolio's equally weighted average of different characteristics. We then report the averages over all sample months. We observe that stocks in the first ATR quintile experience 0.68% less turnover than normal, while stocks in the last quintile experience 0.77% more. Given an average 1.03% daily normal turnover for our sample stocks, these numbers suggest significant abnormal turnover in the lowest and highest ATR quintiles, indicating large negative and positive turnover shocks, respectively.

The first four columns report the average stock beta, log size, book-to-market, and momentum for each ATR quintile and for stocks with abnormal vs. normal turnover (high or low vs. medium ATR quintiles). We find that stocks with abnormal turnover tend to be more volatile than the market with high betas and have significantly smaller market capitalizations, supporting our expectations. Additionally, stocks in the highest ATR quintile have higher momentum, while we do not see a significant difference in book-to-market ratio across different ATR quintiles.

The last three columns report the average of daily return variance measured over the previous 12 months, the percentage of return variation driven by idiosyncratic risk calculated using the 4-factor Carhart (1997) model, and the percentage of return variation driven by noise based on Brogaard et al. (2022)'s decomposition. We find that stocks with abnormal turnover have significantly greater return variance than those with normal turnover. Also, a greater portion of their return variation comes from idiosyncratic risk (75.03% vs. 69.65%). Moreover, their return variance contains more noise (17.32% vs. 14.49%), suggesting that these stocks attract speculative or noise trading, which drives the turnover shocks they face.

3.2 Effect of Abnormal Turnover on Realized vs. Implied Volatility

Next, in order to verify that abnormal turnover proxies for the misalignment of recent realized volatility with long-term fundamental volatility, we examine how abnormal turnover affects realized volatility vs. implied volatility. To that end, we again divide the stocks in our sample into five portfolios sorted by ATR at the end of each month and calculate their average realized and implied volatility over the three months before and after ATR is measured. The results of this exercise are plotted in Figure 1.

Panel A of Figure 1 shows that stocks that experience abnormally high or low turnover (in the highest or lowest ATR quintiles, respectively) exhibit higher levels of realized volatility throughout this period compared to stocks in the medium quintiles, in line with their higher return variance reported in Table 2. More importantly, stocks in the highest ATR quintile experience a sudden increase in realized volatility during the month when ATR is observed, while the stocks in the lowest ATR quintile experience a drop. Also, these changes are temporary and completely reversed over the next month as the trading shocks disappear.

Panel B of Figure 1 presents a different picture for option implied volatility. While the stocks in the highest or lowest ATR quintiles still have higher implied volatility levels similar to their higher historical volatility, we do not see any significant changes in implied volatility associated with abnormal stock turnover. This indicates that the options market does not react to temporary shocks in realized volatility due to price pressures since these shocks are temporary and reversed in the subsequent month. The options market continues to price options at unperturbed levels, suggesting that options traders can filter out the temporary noise in realized volatility in their estimation of future volatility, in line with the results in Goncalves-Pinto et al. (2020).

Panel C of Figure 1 reports how $RVol$-$IVol$ evolves around stock turnover shocks in different ATR quintiles. The average $RVol$-$IVol$ of stocks in the highest or lowest ATR quintiles is not significantly different from those of stocks in the medium ATR quintiles before or after the turnover shock. However, $RVol$-$IVol$s of these stocks are distorted during the turnover shocks, while these distortions are solely caused by the temporary changes in their realized volatilities due to price pressures. This result supports our choice of ATR as a proxy for the misalignment of recent realized volatility with long-term fundamental volatility and motivates us to analyse if this contaminates the predictive power of $RVol$-$IVol$.

We also report the changes in realized and implied volatility associated with abnormal turnover in Panel A of Table 3. The first column shows that the change in realized volatility during the month of the turnover shock increases monotonically as we move from the lowest to the highest ATR quintile. Stocks in the lowest ATR quintile experience a 4.95% decrease in their realized volatility, while stocks in the highest

ATR quintile experience a 7.78% increase. The difference between the change in realized volatilities in the high and low quintiles is 12.76%, highly significant with a t-statistic of 15.58. Moreover, since ATR captures excess trading in a stock that is unrelated to fundamental information, the excess trading subsides in the next month. Accordingly, we see subsequent reversals in realized volatility in the second column.

The following two columns show the effect of ATR on implied volatility. During the portfolio formation month, the change in implied volatility increases slightly as we move from the lowest to the highest ATR quintile. Nevertheless, the difference between the change in implied volatilities in the high and low ATR quintiles is 1.04%, which is not statistically significant. Similarly, there is no significant reversal in implied volatility in the next month. These results show that a stock's realized volatility is affected by ATR, while implied volatility does not react to abnormal trading in a stock. Consequently, in the last two columns, we see that as we move from the lowest to the highest ATR quintile, the change in *RVol-IVol* spread increases from -4.29% to 7.40%, entirely driven by the changes in realized volatility. Finally, these changes again reverse over the next month, indicating that the effect of ATR on *RVol-IVol* is transitory.

Avramov et al. (2006) and Nagel (2012) show that illiquid stocks are more prone to price pressures. Therefore, we expect that excessive trading in a stock that is not driven by fundamental information increases the stock's realized volatility more if it is less liquid. To understand the effect of stock liquidity in our results, we separate stocks into two groups based on Amihud (2002)'s illiquidity and repeat our analysis. These results are presented in Panels B and C of Table 3.

Comparing Panel B with Panel C in Table 3, we see that, even though liquid stocks have higher turnover by definition, the variation in abnormal turnover across different ATR quintiles is comparable between liquid and illiquid stocks (from -0.56% to 0.87% for liquid stocks and from -0.77% to 0.66% for illiquid stocks). This implies that ATR removes liquidity and other components of trading volume and mostly captures speculative or noise trading, as Pan et al. (2016) suggest. More importantly, while the effect of ATR on realized volatility is highly significant among both groups, it is stronger for illiquid stocks compared to liquid stocks, in line with our expectations. The difference in the change in realized volatility between the high and low ATR quintile is 15.52% (t-stat: 17.95) for illiquid stocks, while the same difference is 10.27% (t-stat: 13.22) for liquid stocks.

Collectively, the results in this section show that stocks that experience a positive (negative) turnover shock have abnormally high (low) recent volatility due to price pressures. This causes their realized volatility not to be in sync with their long-term fundamental volatility, which can lead to biased volatility risk-premium estimates measured by $RVol$-$IVol$ and decrease its predictive power for future stock returns.

3.3 Effect of Abnormal Turnover on Stock Return Predictability of Realized-Implied Volatility Spread

Bali and Hovakimian (2009) show that *RVol-IVol* predicts stock returns as a proxy for volatility risk. Stocks with a higher forward-looking option implied volatility compared to their recently realized volatility deliver higher returns to compensate investors for their higher volatility risk. This finding implicitly assumes that the stocks' realized volatility in the near future would be similar to its recently realized volatility so that *RVol-IVol* captures the volatility risk premium embedded in individual equity options. However, as shown in the previous section, for stocks that experience abnormal turnover, recent realized volatility is distorted and abnormally high or low compared to long-term volatility. Hence, it can not be a good forecast for realized volatility in the near future, making *RVol-IVol* a biased estimator of volatility risk premium. We expect this to contaminate the predictive power of *RVol-IVol* for stock returns. Therefore, we analyze how ATR affects the stock return predictability of *RVol-IVol* using classical asset pricing tests such as portfolio sorts and Fama and MacBeth (1973) regressions.

3.3.1 Portfolio Sorts

In this subsection, we examine how ATR affects the stock return predictability of *RVol-IVol* using univariate portfolio sorts by $RVol\text{-}IVol$ vs. double-sorts by ATR and $RVol\text{-}IVol$.

We first form univariate sorts by $RVol\text{-}IVol$, similar to Bali and Hovakimian (2009). At the end of each month, we assign stocks into $RVol\text{-}IVol$ quintile portfolios and calculate their equally-weighted raw or risk-adjusted returns over the next month.[9] Panel A of Table 4 reports the average monthly return for each quintile portfolio over the sample months. We find that the lowest $RVol\text{-}IVol$ quintile portfolio generates a raw return of 1.29%, while the highest quintile portfolio generates 0.80%. Constructing an arbitrage portfolio that longs the stocks in the lowest RVol-IVol quintile and shorts the stocks in the highest quintile produces a significant average return of 0.49% per month (t-stat: 2.89). In the next row, we obtain similar results when we risk-adjust portfolio returns based on the four-factor Carhart (1997) model. The lowest $RVol\text{-}IVol$ quintile portfolio generates a 4-factor alpha of 0.37%, while the highest quintile portfolio generates -0.14%. The same "low-high" arbitrage portfolio earns a 4-factor alpha of 0.51% (t-stat: 3.01). These findings are comparable to Bali and Hovakimian (2009)'s results and confirm that volatility risk is still priced in the cross-section of equity returns in our extended sample period.[10]

In order to examine how ATR affects the stock return predicatability of *RVol-IVol*, we next form double-

[9] In additional tests in section 3.4, we also consider forming value-weighted portfolios.

[10] In subperiod tests in section 3.4, we find that arbitrage portfolio returns are higher in the first subperiod of our sample covering 1996-2007, even closer to the estimates in Bali and Hovakimian (2009) covering 1996-2004.

sorts. At the end of each month, we sort stocks into quintiles based on ATR. Then within each ATR quintile, we further sort stocks into *RVol*-$IVol$ quintile portfolios and calculate their equally-weighted raw or risk-adjusted returns over the next month. In Panel B of Table 4, we present the average monthly raw return for each quintile portfolio and the arbitrage portfolio returns generated by longing the stocks in the lowest *RVol*-$IVol$ quintile and shorting the stocks in the highest *RVol*-$IVol$ quintile within each ATR quintile. Arbitrage portfolio returns based on *RVol*-$IVol$ vary considerably among different ATR quintiles. For stocks in the lowest and highest ATR quintiles (with abnormal turnover), arbitrage returns decrease to 0.22% and 0.34%, which are not statistically significant. On the other hand, for medium ATR quintiles (with normal turnover), arbitrage returns are much higher ranging from 0.60% to 0.70% with t-statistics ranging from 3.06 to 3.71. In the last two rows, we separately implement the arbitrage strategy for the two groups of stocks with abnormal vs. normal turnover. We find an insignificant arbitrage return of 0.32% among stocks with abnormal turnover and a highly significant arbitrage return of 0.67% (t-stat: 4.27) among stocks with normal turnover.

In Panel C, we repeat our double sorts with risk-adjusted portfolio returns based on Carhart (1997)'s four-factor model instead of raw returns. We obtain very similar results. The 4-factor alpha of the arbitrage portfolios based on *RVol-IVol* is insignificant for stocks in the high or low ATR quintiles ranging from 0.23% to 0.34%. In contrast, it is highly significant for stocks in the medium ATR quintiles ranging from 0.57% to 0.72%. Similarly, the arbitrage return in the subgroup of stocks with abnormal turnover is only 0.34%, while it is 0.66% in the subgroup of stocks with normal turnover. These results show that the predictive power of *RVol-IVol* does not work for stocks that experience abnormal turnover since the *RVol-IVol* of these stocks is distorted due to transitory changes in realized volatility. Hence, excluding these stocks when constructing arbitrage trading strategies based on *RVol-IVol* improves strategy returns by 33% on average compared to the initial strategy returns without taking stock turnover into account (0.67% vs. 0.49% based on raw returns and 0.66% vs. 0.51% based on 4-factor alpha).

3.3.2 Fama-Macbeth Regressions

We next employ Fama and MacBeth (1973) regressions to examine whether our result regarding the effect of ATR on stock return predictability of *RVol-IVol* persists after controlling for well-known determinants of cross-sectional variation in stock returns. Besides beta, log size, book-to-market ratio, and momentum (Fama and French (1992, 1993), Carhart (1997)), here we also control for illiquidity (Amihud (2002)) and short-term return reversals (Jegadeesh (1990), Lehmann (1990)) in the stock market as well as call-put implied volatility spread (Bali and Hovakimian (2009)) and implied volatility skew (Xing et al. (2010)) in the options market.

Column (1) of Table 5 shows the results of regressing next month's stock return on *RVol-IVol* for all stocks in our sample. Similar to our univariate sorts in the previous section, we find that one unit increase in *RVol-IVol* results in 0.5% lower returns next month (t-stat: 2.10). In columns (2) and (3), we see a similar effect after controlling for various variables from the stock or options markets with even higher t-statistics. These results confirm that volatility risk is priced in the cross-section of equity returns after controlling for other factors, as documented in Bali and Hovakimian (2009).

In columns (4)-(6), we repeat the same regressions for the subsample of stocks that experienced abnormally high or low stock turnover over the last month. In line with our double-sorts in the previous section, we find that one unit increase in *RVol-IVol* results only in 0.2% lower returns next month for these stocks, which is not statistically significant. On the other hand, columns (7)-(9) show that the same increase leads to a 1.0-1.1% decrease in next month's returns for the subsample of stocks with normal turnover (medium ATR quintiles) with t-statistics ranging from 3.28 to 4.11. Collectively, these results confirm that, even after controlling for various cross-sectional effects, the stock return predictability of *RVol-IVol* is concentrated among stocks with normal turnover where realized volatility reflects the long-term fundamental volatility of the stock.

3.4 Additional Tests

In this section, we examine the robustness of our results to alternative ways to measure the volatility risk premium embedded in individual equity options, form value-weighted instead of equally-weighted portfolios, and conduct subperiod tests.

Duarte et al. (2022) argue that using only at-the-money options to calculate implied volatility can underestimate the volatility risk premium in individual equity options. Moreover, at-the-money implied volatilities used in our main empirical tests are sourced directly from OptionMetrics and calculated based on a binomial model. In order to see if our choice of implied volatility affects our results, we repeat our calculations with the model-free implied volatility of Jiang and Tian (2005) calculated by integrating over out-of-the-money options of all available strikes.[11] As shown in Panel A of Table 6, forming an arbitrage portfolio by longing the stocks in the lowest and shorting the stocks in the highest quintile of *RVol-IVol* calculated with model-free implied volatility creates a significant average return of 0.47%, very similar to the results in Panel A of Table 4 with at-the-money implied volatility. Moreover, we again find that the average arbitrage portfolio return is only 0.31% and insignificant among the subgroup of stocks with abnormal turnover. In comparison, it is 0.63% and highly significant for stocks with normal turnover. This confirms

[11] Similar to Jiang and Tian (2005), we estimate implied volatility as a function of strike price using the implied volatilities of all out-of-the-money puts and calls available on OptionMetrics. We interpolate implied volatilities between available strikes and extrapolate outside of the available range to get a series of option prices to calculate the integrand $2\int_0^\infty \frac{C(K)-max(S-K,0)}{K^2}\,dK$

that our results are robust to alternative ways to measure implied volatility.

Our results show that using realized volatility over the past month can overestimate or underestimate the realized volatility for next month due to temporary abnormal trading in the stock and hence can distort the stock return predictability of *RVol-IVol* as a biased estimator of volatility risk premium. Therefore, it is natural to consider using historical realized volatility over the past 12 months since it will be less prone to temporary spikes in volatility due to abnormal turnover. Nevertheless, historical volatility will also be less effective in capturing the latest volatility dynamics of the stock. Accordingly, we find that the stock return predictability of *RVol-IVol* is reduced when we use historical realized volatility in our univariate portfolio sorts, as shown in Panel B of Table 6. The arbitrage portfolio created based on *RVol-IVol* with historical realized volatility creates an average return of 0.39%, less than the 0.49% return generated with recent realized volatility as in Panel A of Table 4. More importantly, even though the difference in arbitrage portfolio returns between the subgroup of stocks with abnormal vs. normal turnover is reduced (0.30% vs. 0.46%), the predictive power of *RVol-IVol* is still concentrated among the stocks with normal turnover when we use historical volatility, in line with our main results.

In section 3.1, we show that stocks that experience abnormally high or low turnover tend to have smaller market capitalizations. This implies that forming value-weighted portfolios, instead of equally-weighted ones as in our main tests, indirectly puts lower weights into stocks with abnormal turnover, thereby improving the arbitrage portfolio returns based on *RVol-IVol*. As shown in Panel C of Table 6, arbitrage portfolio return increases to 0.53% when we use value-weighting compared to 0.49% with equal-weighting in Panel A of Table 4. However, our main result about the superior predictive power of *RVol-IVol* among stocks with normal turnover (0.62%) compared to stocks with abnormal turnover (0.42%) still holds when we form value-weighted portfolios as well, even though the difference between the two groups slightly decreases.

Bali and Hovakimian (2009) show the predictive power of *RVol-IVol* for next month's stock returns for the sample period of 1996-2004, while our study covers the extended period of 1996-2019. In order to examine how the stock return predictability of *RVol-IVol* changes over time and if this change can affect our results, we perform subperiod tests. Panel D of Table 6 repeats the main portfolio sorts for the two subperiods of 1996-2007 and 2008-2019 in our sample. In line with the idea that stock return predictability of a variable reduces after it is published in academic research (Mclean and Pontiff (2016)), we find that the stock return predictability of *RVol-IVol* decreases over time. Forming an arbitrage portfolio by longing the stocks in the lowest and shorting the stocks in the highest quintile of *RVol-IVol* produces a return of 0.40% in the second subperiod compared to a return of 0.59% in the first subperiod. However, our result that the stock return predictability of *RVol-IVol* holds only among stocks with normal turnover is robust in both subperiods. The arbitrage portfolio focusing only on stocks in the medium ATR quintiles produces significant returns of 0.75% and 0.59% per month in the two subperiods.

4 Conclusion

Literature documents the existence of a negative volatility risk premium in individual equity options and its predictive power for the cross-section of stock returns as measured by realized-implied volatility spread. Our study extends this line of research by demonstrating that the stock return predictability of the realized-implied volatility spread does not hold for stocks that experience abnormal turnover since abnormal turnover indicates misalignment of recent realized volatility with long-term fundamental volatility, making realized-implied volatility spread a biased estimate of volatility risk premium.

We use an abnormal turnover measure that mostly captures speculative trading. We find that stocks with abnormally high (low) turnover in a month exhibit a sudden increase (decrease) in their realized volatility due to price pressures, which completely reverses over the next month as the excess trading dissipates. Option implied volatility does not respond to these changes, implying that option traders filter out the temporary noise in realized volatility in their estimation of future volatility. Since recent realized volatility is not a good forecast for future realized volatility for stocks with abnormal turnover, realized-implied volatility spread cannot serve as a reasonable volatility risk premium estimate for for these stocks. Hence, the predictive power of realized-implied volatility is concentrated among stocks with normal turnover, where realized volatility is in line with long-term fundamental volatility. Overall, our results suggest that mainly fundamental volatility risk is priced in the cross-section of equity returns.

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Table 1: Summary Statistics

Variables	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
ATR	0.00%	0.81%	-0.19%	-0.03%	0.13%
$RVol$	42.74%	29.70%	23.85%	34.95%	52.62%
$IVol$	47.09%	25.09%	29.45%	40.89%	58.30%
$RVol$-$IVol$	-4.35%	22.37%	-12.51%	-4.74%	2.85%
$RetVar$	0.11%	0.20%	0.03%	0.06%	0.13%
$Idiosyn(\%)$	71.47%	17.29%	60.35%	74.38%	85.17%
$Noise(\%)$	15.98%	9.85%	10.48%	14.10%	19.46%
$Return$	1.00%	14.43%	-5.92%	0.75%	7.25%
$Beta$	1.14	0.52	0.79	1.08	1.43
$LogSize$	7.33	1.62	6.16	7.19	8.33
BtM	0.54	0.59	0.24	0.42	0.68
Mom	17.74%	98.83%	-16.84%	8.36%	34.97%
Rev	1.04%	14.43%	-5.93%	0.76%	7.30%
$Illiq$	1.34%	5.38%	0.04%	0.17%	0.71%
$CIVol$-$PIVol$	-0.43%	12.67%	-2.41%	-0.25%	1.62%
$IVSkew$	4.79%	13.85%	0.86%	3.46%	7.39%

Table 1 reports the summary statistics of the main variables used in this study. The sample consists of 6,848 distinct optionable stocks over 1996-2019 with 583,669 stock-month observations. We require a stock to have non-missing volatility data in the current month as well as one month before and after. Hence, the final sample period is from February 1996 to November 2019 (286 months) with 2,041 stocks in an average month. Abnormal turnover ratio ATR is calculated as the difference between the actual average daily stock turnover in a month and the predicted turnover estimated as in Pan et al. (2016): We regress the daily turnover ratio of individual stocks on the aggregate market turnover and a set of dummy variables that correspond to informative corporate events over the previous 12 months (Equation (1)). We then use the coefficient estimates from this regression to calculate the predicted or normal turnover ratio over the current month. *RVol* is the realized volatility measured as the standard deviation of daily stock log-returns in a month. $IVol$ is the average implied volatility of a 30-day ATM put option with Δ=-0.50 and ATM call option with Δ=0.50 measured at the end of the month. $RVol - IVol$ is the realized-implied volatility spread. *RetVar* is the variance of daily stock returns over the past 12 months. $Idiosyn(\%)$ is the portion of return variance due to firm-specific (idiosyncratic) risk, estimated as 1-R^2 of regressing daily stock excess return on the four factors of Carhart (1997) model. $Noise(\%)$ is the portion of return variance due to noise, estimated using a vector autoregression of how a stock's daily return responds market returns, firm-specific order flow and other firm-specific shocks as in Brogaard et al. (2022). *Return* is the next month's stock return. *Beta* is estimated by regressing daily stock excess returns on the market excess return over the previous 12 months. *LogSize* is the natural logarithm of the market value of equity in million dollars. *BtM* is the ratio of book value of equity to market value of equity measured at the end of a month. *Mom* is the momentum defined as the cumulative return of the stock over the previous 12 months. *Rev* is the short-term return reversal defined as the stock return over the previous month (similar to Jegadeesh (1990) or Lehmann (1990)). *Illiq* is Amihud (2002)'s stock illiquidity measure calculated as the average ratio of daily absolute stock return to dollar trading volume in a month. Similar to Bali and Hovakimian (2009), $CIVol$-$PIVol$ is the difference between the implied volatility of a 30-day ATM call with Δ=0.50 and ATM put with Δ=-0.50. $IVSkew$ is defined as the difference between the implied volatility of a 30-day OTM put with Δ=-0.25 and ATM call with Δ=0.50 as in Xing et al. (2010). Besides *Return* over the next month, all the variables are measured at the end of the current month.

Table 2: Characteristics of Portfolios Sorted on Abnormal Turnover Ratio

Quintile	*ATR*	*Beta*	*LogSize*	*BtM*	*Mom*	*RetVar*	*Idiosyn%*	*Noise%*
1-Low	-0.68%	1.33	6.77	0.57	11.39%	0.18%	75.86%	17.21%
2	-0.16%	1.09	7.29	0.55	12.73%	0.09%	71.54%	14.46%
3	-0.04%	1.01	7.71	0.54	14.32%	0.07%	68.35%	14.02%
4	0.09%	1.04	7.66	0.53	17.25%	0.08%	69.05%	14.77%
5-High	0.77%	1.24	7.16	0.53	34.25%	0.14%	74.21%	17.44%
High or Low ATR		1.29	6.96	0.55	22.82%	0.16%	75.03%	17.32%
Medium ATR		1.05	7.55	0.54	14.77%	0.08%	69.65%	14.49%
Difference		0.24***	-0.59***	0.01	8.05%**	0.08%***	5.38%***	2.83%***
t-stat		(7.44)	(5.95)	(0.82)	(2.14)	(7.99)	(7.63)	(8.02)

Table 2 reports the average characteristics of stocks sorted into portfolios based on abnormal turnover ratio (ATR). At the end of each month, we first sort stocks into five portfolios and calculate their different characteristics with equal-weighting. We then report the average characterictics over months. Abnormal turnover ratio (ATR) is calculated as the difference between the actual average daily stock turnover in a month and the predicted turnover estimated as in Pan et al. (2016). *Beta* is estimated by regressing daily stock excess returns on the market excess return over the previous 12 months. *LogSize* is the natural logarithm of the market value of equity in million dollars. *BtM* is the ratio of book value of equity to market value of equity measured at the end of a month. *Mom* is the momentum defined as the cumulative return of the stock over the previous 12 months. *RetVar* is the variance of daily stock returns over the past 12 months. $Idiosyn(\%)$ is the portion of return variance due to firm-specific (idiosyncratic) risk, estimated as 1-R^2 of regressing daily stock excess return on the four factors of Carhart (1997) model. $Noise(\%)$ is the portion of return variance due to noise, estimated using a vector autoregression of how a stock's daily return responds market returns, firm-specific order flow and other firm-specific shocks as in Brogaard et al. (2022). T-statistics for the differences in characteristics of stocks with abnormal turnover (ATR quintiles 1 and 5) vs. normal turnover (ATR quintiles 2, 3, 4) are calculated with robust Newey and West (1987) standard errors. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Table 3: Realized vs. Implied Volatility Changes of Portfolios Sorted on Abnormal Turnover Ratio

Panel A: All Stocks

Quintile	*ATR*	$\Delta RVol$	$\Delta RVol_{t+1}$	$\Delta IVol$	$\Delta IVol_{t+1}$	$\Delta RVol\text{-}IVol$	$\Delta RVol\text{-}IVol_{t+1}$
1-Low	-0.68%	-4.95%	4.92%	-0.66%	0.04%	-4.29%	4.89%
2	-0.16%	-2.37%	3.00%	-0.18%	0.05%	-2.19%	2.96%
3	-0.04%	-1.24%	1.55%	-0.11%	0.11%	-1.13%	1.44%
4	0.09%	0.15%	-0.27%	0.11%	0.02%	0.03%	-0.29%
5-High	0.77%	7.78%	-9.72%	0.39%	-0.45%	7.40%	-9.27%
5-1		12.74%***	-14.65%***	1.04%	-0.49%	11.69%***	-14.16%***
t-stat		(15.58)	(-15.60)	(1.59)	(-0.95)	(19.99)	(-21.13)

Panel B: Liquid Stocks

Quintile	*ATR*	$\Delta RVol$	$\Delta RVol_{t+1}$	$\Delta IVol$	$\Delta IVol_{t+1}$	$\Delta RVol\text{-}IVol$	$\Delta RVol\text{-}IVol_{t+1}$
1-Low	-0.56%	-4.49%	4.42%	-0.65%	0.19%	-3.85%	4.23%
2	-0.11%	-2.05%	2.35%	-0.21%	0.11%	-1.84%	2.24%
3	-0.01%	-1.07%	1.25%	-0.08%	0.10%	-0.98%	1.15%
4	0.12%	0.01%	-0.20%	0.14%	0.06%	-0.13%	-0.26%
5-High	0.87%	5.77%	-7.59%	0.30%	-0.31%	5.48%	-7.28%
5-1		10.27%***	-12.01%***	0.94%	-0.50%	9.33%***	-11.51%***
t-stat		(13.22)	(-14.02)	(1.24)	(-0.89)	(15.23)	(-16.89)

Panel C: Illiquid Stocks

Quintile	*ATR*	$\Delta RVol$	$\Delta RVol_{t+1}$	$\Delta IVol$	$\Delta IVol_{t+1}$	$\Delta RVol\text{-}IVol$	$\Delta RVol\text{-}IVol_{t+1}$
1-Low	-0.77%	-5.40%	5.43%	-0.73%	-0.07%	-4.67%	5.50%
2	-0.21%	-2.81%	3.55%	-0.15%	0.01%	-2.66%	3.55%
3	-0.07%	-1.45%	1.97%	-0.14%	0.07%	-1.31%	1.90%
4	0.05%	0.13%	-0.16%	0.05%	-0.02%	0.08%	-0.14%
5-High	0.66%	10.12%	-12.08%	0.59%	-0.63%	9.53%	-11.45%
5-1		15.52%***	-17.51%***	1.32%*	-0.56%	14.20%***	-16.95%***
t-stat		(17.95)	(18.23)	(1.75)	(-1.14)	(23.07)	(-24.72)

Panel A of Table 3 reports the changes in realized volatility, implied volatility, and realized-implied volatility spread of stocks sorted into portfolios based on abnormal turnover ratio (ATR). At the end of each month, we first sort stocks into five portfolios and calculate their volatility changes during the current month and the next month with equal-weighting. We then report the average changes over months. Abnormal turnover ratio (ATR) is calculated as the difference between the actual average daily stock turnover in a month and the predicted turnover estimated as in Pan et al. (2016). *RVol* is the realized volatility measured as the standard deviation of daily stock log-returns in a month. $IVol$ is the average implied volatility of a 30-day ATM put option with Δ=-0.50 and ATM call option with Δ=0.50 measured at the end of the month. *RVol-IVol* is the realized-implied volatility spread. Panel B and C report the results of the same exercise for liquid and illiquid stocks seperately. We consider a stock as illiquid (liquid) if its Amihud (2002) illiquidity is above (below) the median for the current month. T-statistics for the differences of changes in ATR quintiles 5 vs. 1 are calculated with robust Newey and West (1987) standard errors. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Table 4: Returns of Portfolios Sorted on Realized-Implied Volatility Spread and Abnormal Turnover Ratio

Panel A: Raw Return and 4F Alpha for Single-Sorts on RVol-IVol

	RVol-IVol Quintiles						
	1	2	3	4	5	5-1	t-stat
Return	1.29%	1.08%	0.92%	0.93%	0.80%	-0.49%	-2.89
4F Alpha	0.37%	0.14%	0.02%	0.03%	-0.14%	-0.51%	-3.01

Panel B: Raw Return for Double-Sorts on ATR and RVol-IVol

	RVol-IVol Quintiles						
ATR Quintiles	1	2	3	4	5	5-1	t-stat
1-Low	0.95%	0.95%	0.81%	0.73%	0.74%	-0.22%	-0.96
2	1.40%	1.11%	0.91%	0.85%	0.70%	-0.70%	-3.62
3	1.56%	1.07%	0.87%	1.00%	0.90%	-0.66%	-3.71
4	1.45%	1.10%	1.07%	0.98%	0.85%	-0.60%	-3.06
5-High	1.34%	1.02%	0.93%	0.78%	1.01%	-0.34%	-1.35
High or Low ATR	1.15%	0.91%	0.87%	0.88%	0.83%	-0.32%	-1.55
Medium ATR	1.46%	1.11%	0.94%	0.96%	0.80%	-0.67%	-4.27

Panel C: 4F Alpha for Double-Sorts on ATR and RVol-IVol

	RVol-IVol Quintiles						
ATR Quintiles	1	2	3	4	5	5-1	t-stat
1-Low	0.01%	-0.01%	-0.20%	-0.24%	-0.22%	-0.23%	-1.02
2	0.52%	0.19%	0.01%	-0.06%	-0.21%	-0.72%	-3.84
3	0.70%	0.21%	0.03%	0.17%	0.04%	-0.65%	-3.91
4	0.54%	0.22%	0.25%	0.12%	-0.03%	-0.57%	-3.11
5-High	0.34%	-0.01%	-0.06%	-0.20%	0.00%	-0.34%	-1.47
High or Low ATR	0.18%	-0.09%	-0.12%	-0.11%	-0.15%	-0.34%	-1.66
Medium ATR	0.58%	0.22%	0.09%	0.10%	-0.08%	-0.66%	-4.42

Panel A of Table 4 presents the raw returns and Carhart (1997)'s 4-factor alphas of portfolios formed based on univariate sorts by realized-implied volatility spread (*RVol-IVol*). At the end of each month, we sort stocks into five portfolios and calculate their equally-weighted portfolio returns or alphas over the next month. We report the average equally-weighted return or alpha across all months. Panel B and C report the results for double-sorts where we first sorts stocks by abnormal turnover ratio (*ATR*) into quintiles and then by *RVol-IVol* within each *ATR* quintile. We also form groups of stocks with abnormal turnover (*ATR* quintiles 1 and 5) vs. normal turnover (*ATR* quintiles 2, 3, 4) and then sort stocks by *RVol-IVol* within each group. Abnormal turnover ratio (*ATR*) is calculated as the difference between the actual average daily stock turnover in a month and the predicted turnover estimated as in Pan et al. (2016). *RVol* is the realized volatility measured as the standard deviation of daily stock log-returns in a month. *IVol* is the average implied volatility of a 30-day ATM put option with Δ=-0.50 and ATM call option with Δ=0.50 measured at the end of the month. T-statistics for the return or alpha of arbitrage portfolios with a long position in the 5th *RVol-IVol* portfolio and short position in the 1st portfolio are calculated with robust Newey and West (1987) standard errors.

Table 5: Fama-Macbeth Regressions of Returns on Realized-Implied Volatility Spread: High or Low vs. Medium Abnormal Turnover Ratio

	Return								
	All			High or Low ATR			Medium ATR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$RVol - IVol$	-0.005**	-0.005***	-0.005***	-0.002	-0.002	-0.002	-0.011***	-0.010***	-0.010***
	(-2.10)	(-2.84)	(-2.90)	(-0.70)	(-0.76)	(-0.96)	(-3.28)	(-3.96)	(-4.11)
$Beta$		-0.001	-0.001		-0.002	-0.002		-0.001	-0.001
		(-0.49)	(-0.43)		(-0.58)	(-0.54)		(-0.22)	(-0.19)
$LogSize$		-0.001	-0.001		-0.001	-0.001		-0.001	-0.001
		(-1.01)	(-1.02)		(-1.02)	(-1.07)		(-0.95)	(-0.91)
BtM		0.002*	0.002*		0.002	0.002		0.002**	0.002*
		(1.73)	(1.74)		(1.23)	(1.31)		(2.02)	(1.91)
Mom		-0.000	-0.000		-0.000	-0.000		0.000	0.000
		(-0.13)	(-0.09)		(-0.21)	(-0.17)		(0.17)	(0.18)
Rev		-0.017***	-0.015***		-0.010**	-0.008*		-0.029***	-0.027***
		(-3.48)	(-3.10)		(-2.16)	(-1.75)		(-5.34)	(-4.99)
$Illiq$		0.023*	0.021*		0.047**	0.042*		0.018	0.017
		(1.87)	(1.75)		(2.05)	(1.84)		(1.29)	(1.26)
$CIVol\text{-}PIVol$			0.028***			0.031***			0.026***
			(6.37)			(4.40)			(5.37)
$IVSkew$			-0.015***			-0.020***			-0.013***
			(-4.02)			(-3.12)			(-3.07)
$Intercept$	0.010***	0.013**	0.014**	0.009**	0.014**	0.016**	0.010***	0.012**	0.012**
	(2.86)	(2.33)	(2.46)	(2.14)	(1.99)	(2.19)	(3.33)	(2.36)	(2.45)
Adj Rsq	0.003	0.069	0.071	0.003	0.064	0.066	0.005	0.071	0.073
Obs	583,669	583,669	583,669	233,476	233,476	233,476	350,193	350,193	350,193

Columns (1)-(3) of Table 5 shows the results from Fama and MacBeth (1973) regressions of next month's stock returns on realized implied volatility spread ($RVol - IVol$) and various control variables for all stocks in our sample. Columns (4)-(6) and (7)-(9) repeat the same regressions for the subsample of stocks with abnormal turnover (ATR quintiles 1 and 5) vs. normal turnover (ATR quintiles 2, 3, 4). Abnormal turnover ratio (ATR) is calculated as the difference between the actual average daily stock turnover in a month and the predicted turnover estimated as in Pan et al. (2016). $RVol$ is the realized volatility measured as the standard deviation of daily stock log-returns in a month. $IVol$ is the average implied volatility of a 30-day ATM put option with Δ=-0.50 and ATM call option with Δ=0.50 measured at the end of the month. The definitions of control variables are as in Table 1. T-statistics in parentheses are calculated using robust Newey and West (1987) standard errors. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Table 6: Additional Tests

Panel A: Using model-free IVol

	RVol-IVol Quintiles						
	1	2	3	4	5	5-1	t-stat
All	1.28%	1.09%	0.94%	0.94%	0.81%	-0.47%	-2.74
High or Low ATR	1.14%	0.93%	0.90%	0.87%	0.82%	-0.31%	-1.49
Medium ATR	1.44%	1.12%	0.96%	0.97%	0.81%	-0.63%	-3.99
Panel B: Using historical RVol							
All	1.23%	1.10%	1.00%	0.89%	0.84%	-0.39%	-2.02
High or Low	1.10%	1.05%	0.93%	0.84%	0.80%	-0.30%	-1.52
Medium	1.32%	1.15%	1.03%	0.91%	0.86%	-0.46%	-2.68
Panel C: Value-weighted Portfolios							
All	1.21%	1.03%	0.95%	0.89%	0.68%	-0.53%	-3.05
High or Low	1.07%	0.83%	0.90%	0.84%	0.65%	-0.42%	-2.11
Medium	1.35%	1.10%	0.96%	0.92%	0.72%	-0.62%	-3.87
Panel D: Subperiods							
1996-2007							
All	1.30%	1.08%	0.93%	0.82%	0.71%	-0.59%	-2.14
High or Low	1.20%	0.80%	0.82%	0.82%	0.73%	-0.47%	-1.42
Medium	1.46%	1.14%	0.94%	0.90%	0.71%	-0.75%	-3.28
2008-2019							
All	1.28%	1.09%	0.92%	1.03%	0.88%	-0.40%	-1.97
High or Low	1.10%	1.01%	0.92%	0.94%	0.93%	-0.17%	-0.69
Medium	1.47%	1.08%	0.96%	1.02%	0.88%	-0.59%	-2.73

Table 6 repeats the univariate sorts by realized implied volatility spread (*RVol-IVol*) vs. double-sorts by abnormal turnover ratio (ATR) and *RVol-IVol*) for raw returns as in Table 4 under alternative specifications. In Panel A, we use the model-free implied volatility of Jiang and Tian (2005) instead of ATM implied volatility when calculating *RVol-IVol*. Panel B replaces realized volatility over the last one month with historical realized volatility over the last 12 months. In Panel C, we form value-weighted portfolios instead of equally-weighted ones. Panel D repeats the portfolio sorts for the two equal subperiods of 1996-2007 and 2008-2019 separately. T-statistics for the return of arbitrage portfolios with a long position in the 5th *RVol-IVol* portfolio and short position in the 1st portfolio are calculated with robust Newey and West (1987) standard errors.

Figure 1: Effect of Abnormal Stock Turnover Ratio on Realized vs. Implied Volatility

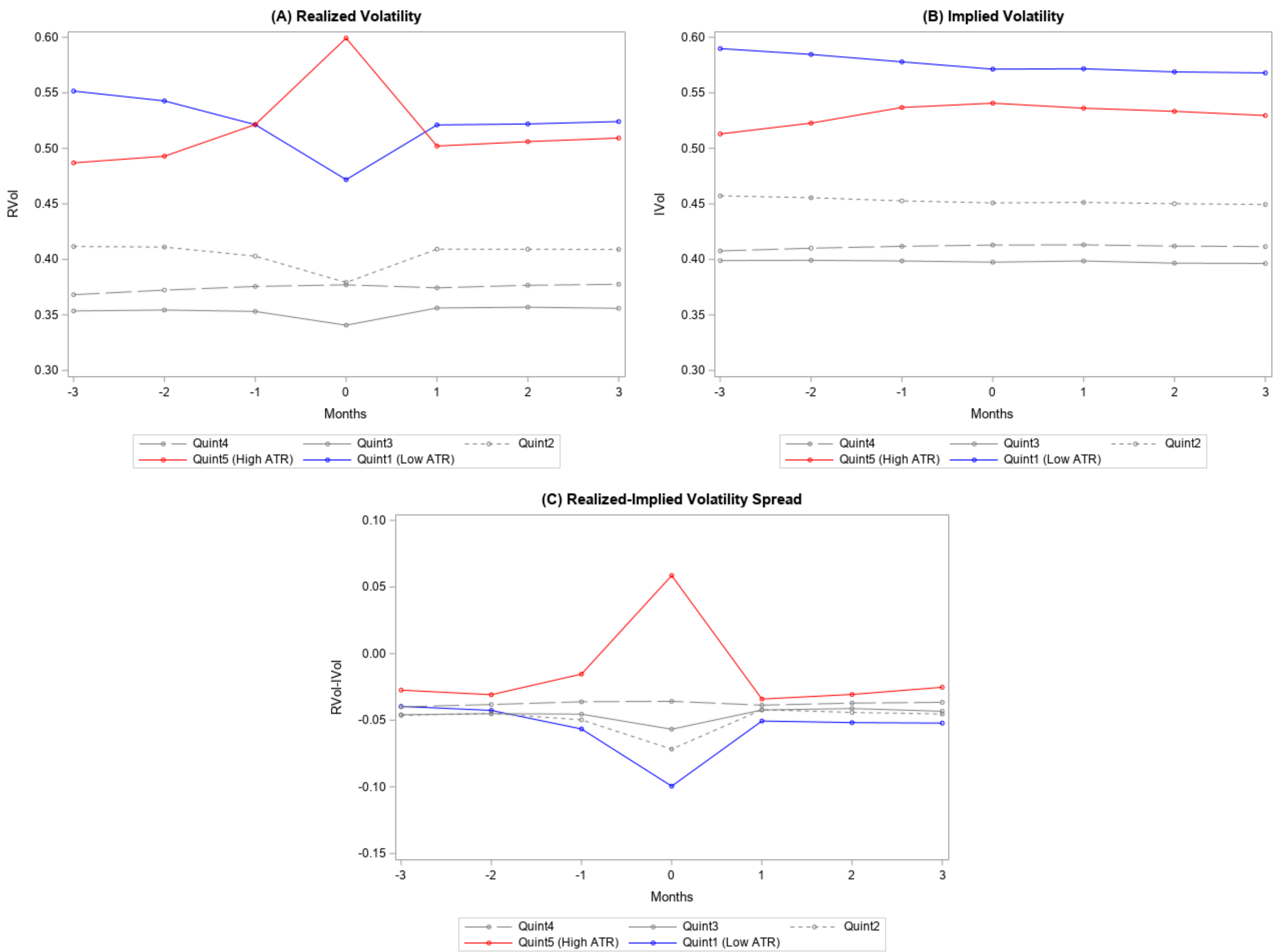

Figure 1 plots the realized volatility (RVol), implied volatility (IVol) and realized-implied volatility spread (RVol-IVol) of stocks in different quintile portfolios sorted by abnormal turnover ratio (ATR) for 3 months before and 3 months after ATR is measured. For each month, we first calculate the equal-weighted averages of volatilities and then report the averages over months. Abnormal turnover ratio (ATR) is calculated as the difference between the actual average daily stock turnover in a month and the predicted turnover estimated as in Pan et al. (2016). $RVol$ is the realized volatility measured as the standard deviation of daily stock log-returns in a month. $IVol$ is the average implied volatility of a 30-day ATM put option with Δ=-0.50 and ATM call option with Δ=0.50 measured at the end of the month.