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Research

Harnessing Neuroscientific Insights to Generate Alpha

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Building on evidence from neuroscience and psychology, we predict that prolonged exposure to high volatility causes market participants to subsequently underestimate volatility (and vice versa), leading to predictability in stock returns. We find VIX distortions consistent with this prediction and construct a trading strategy that exploits it. Applied to SPY ETFs and VIX futures contracts, the strategy significantly outperforms a buy-and-hold index portfolio, with higher annualized performance, lower volatility, and alphas exceeding 4%.

Keywords: Neurofinance; trading strategy; VIX

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Introduction

It is well established in neuroscience and psychology that prolonged exposure to a given stimulus systematically creates the illusion of an opposite stimulus—a phenomenon that has been referred to as "*after-effect*." For example, after looking at the downward flow of a waterfall, the static rocks to the side appear to ooze upward (Barlow and Hill 1963). Likewise, after viewing a red square, a gray square appears greenish (Hurvich and Jameson 1957). And after prolonged viewing of a male face, androgyne's faces appear more feminine than they normally would (Webster, Kaping, Mizokami, and Duhamel 2004).

In this study, we make the prediction that a similar after-effect may occur for the perception of volatility in financial markets after prolonged periods of persistently extreme volatility. Namely, after prolonged exposure to high volatility, market participants perceive moderate volatility as lower than the actual level (and vice versa). This could cause the Market Volatility Index (VIX), which embeds investor forecasts of future volatility, to be distorted. Indeed, when making their forecasts, investors use current and past realized volatility *as they perceive it*. In Section Anomaly of the paper, we propose a simple model showing how VIX will be distorted if investor perception of volatility is systematically biased by the after-effect. In empirical tests, we find evidence for the distortion predicted by the model; its magnitude is approximately the same as the impact of a 1% change in the S&P 500 index (the strongest predictor of changes in VIX).

In Section Trading Strategy, we construct a market timing strategy for the entry into, and exit from the market, based on identifying when an affect-effect occurs in the market. Applied to SPY ETF, front-month VIX futures contracts, and a combination of the two instruments, our strategy appears to significantly outperform a buy-and-hold index portfolio, with higher annualized performance, lower volatility, and alphas exceeding 4%.

Our study contributes to the large behavioral finance literature that documents price distortions caused by behavioral anomalies.[1] There is ample evidence of "context effects" in the perception of value.[2] Here we focus on the perception of volatility instead and document a market anomaly that can be linked to an after-effect in trader perception of volatility. We think the after-effect phenomenon is particularly interesting for financial investors because the VIX distortions created by the after-effect run in the opposite direction to the classical behavioral finance explanations including adaptive expectations (e.g., Greenwood and Shleifer 2014; Barberis, Greenwood, Jin, and Shleifer 2015), anchoring, and neglected risks (e.g., Gennaioli, Shleifer, and Vishny 2012; Goetzmann, Kim and Shiller 2016).[3]

Perhaps most importantly, we show that the after-effect is tradable. The outperformance of our after-effect index portfolio reflects both its effectiveness in avoiding periods of high volatility and substantial market drawdowns, and its ability to exploit the after-effect taking place when the market's transition from high volatility to medium volatility.

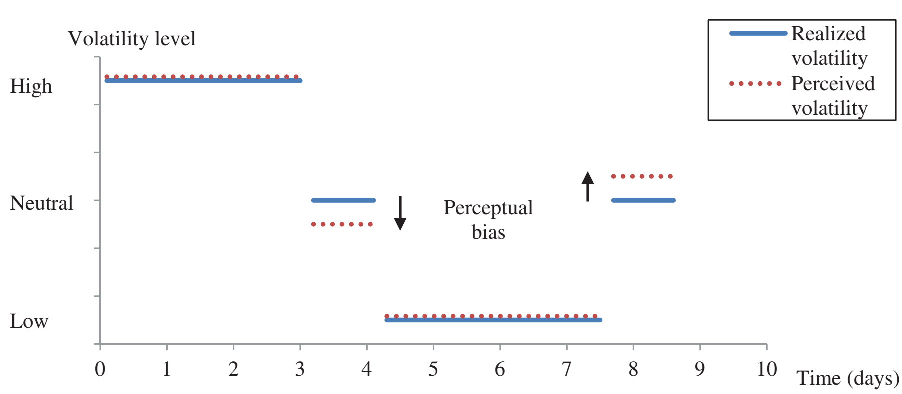
As such, our findings have implications for practitioners, especially in the volatility space. The Variance Risk Premium (VRP) has been a driving motivator for many short volatility strategies. Taking advantage of selling volatility, especially after significant volatility shocks, is not uncommon. We find it interesting that the after-effect can reduce, and even negate, the potential profitability of selling volatility, even in very high volatility environments. The higher the after-effect, the greater the distortion in the perceived VRP. As such, the after-effect phenomenon provides one explanation for why the profitability from selling volatility is not always proportional to the level of volatility.

Anomaly

After-Effect in Trader Perception of Volatility. Recent advancements in neuroscience point to the after-effect occurring not only for simple stimuli (e.g., color and motion) but also for highly abstract properties such as the perceived numerosity of dots in patches (Burr and Ross 2008), the value of an economic option (Khaw, Glimcher, and Louie 2017), and the perceived volatility of a financial index in a laboratory setting (Payzan-LeNestour, Pradier, and Putnins 2022; Payzan-LeNestour, Balleine et al. 2016; Payzan-LeNestour, Pradier et al. 2021). This body of neuroscientific evidence suggests that when experiencing medium ("neutral") volatility levels after prolonged exposure to high volatility, traders underestimate volatility, and vice versa. This effect is illustrated in Figure 1. The horizontal axis measures the passing of time, while the vertical axis shows realized volatility levels and how those levels are perceived. In the illustration, volatility is high for the first three days, then at $t = 3$ drops to a neutral level, at which point the aftereffect causes a downward bias in perceived volatility. The next three days have very low volatility, followed by an increase back to a neutral level at $t = 8$, at which point the aftereffect causes an upward bias in perceived volatility.

Evidence of the after-effect building up both with stimulus strength and with stimulus duration (e.g., Hershenson 1989; Leopold et al. 2005) suggests that the more extreme the volatility during the exposure period and the longer the exposure period, the larger the after-effect biasing trader perception of neutral volatility when the market transitions from extreme (very high or very low) volatility to the neutral level.

Figure 1. Volatility Regimes and the After-Effect



This figure illustrates how the after-effect phenomenon biases investor perception of realized volatility. After prolonged exposure to high (low) realized volatility, perceived volatility is lower (higher) than actual realized volatility.

Identification of the Volatility Regimes that May Induce Biased Volatility Perceptions. An after-effect occurs when transitioning from a prolonged very low or very high volatility level to a neutral volatility level (neither high nor low). To pin down how the after-effect may translate into VIX distortions, we use data on the S&P 500 index and VIX index values for the period January 2, 1996 to December 31, 2020 (the VIX measures implied volatility in the S&P 500 index). Details on the data and the methods we use to estimate realized volatility can be found in the Internet Appendix.[4] Denote the log S&P 500 index value by p. A daily interval $[t-1,\ t]$ consists of N tick-by-tick observations $\{t_0, t_1, \ldots t_N\}$. We first compute the realized variance at the optimal sampling frequency K as $RV_t^2 = \frac{1}{K}\sum_{i=0}^{N-K}\left[p(t_{i+K}) - p(t_i)\right]^2$. The realized volatility for the daily interval $[t-1,\ t]$ is computed by taking the square root of RV_t^2 and annualizing using a year of 252 business days: $RV_t = \sqrt{RV_t^2 \times 252}$.

To identify volatility regimes in our data, we must first identify very high, very low, and neutral volatility states. We use the approximate normality of the log realized volatility to create volatility bins.[6] We compute the mean and standard deviation of the distribution of the daily log realized volatility, during a rolling three-month (63 business days) window. We then define a very high (*VH*) volatility level as one that is more than x standard deviations above the mean, and a very low (*VL*) volatility level as one that is more than x standard deviations below the mean. A medium or neutral volatility level (*M*) is one that falls within y standard deviations of the mean.[7] Our results are robust to different choices of the look-back window (see Internet Appendix A.5.7).

We then create a volatility regime indicator variable, $VolReg_t$, which is defined over a four-day period. Specifically, $VolReg_t$ takes a value of $+1$ if we observe very high volatility levels in the three preceding days ("high volatility state") and a neutral volatility level on day t. $VolReg_t$ takes the value -1 if we observe very low volatility levels in the three preceding days ("low volatility state") and a neutral volatility level on day t. $VolReg_t$ is zero in all other instances. Formally:

$$VolReg_t = \begin{cases} +1 \ \textit{if} \ \{LnRV_{t-3},\ LnRV_{t-2},\ LnRV_{t-1}, LnRV_t\} \\ \qquad = \{VH,\ VH, VH, M\} \\ -1 \ \textit{if} \ \{LnRV_{t-3},\ LnRV_{t-2},\ LnRV_{t-1}, LnRV_t\} \\ \qquad = \{VL,\ VL, VL, M\} \\ 0 \ \textit{otherwise} \end{cases}, \tag{1}$$

where $LnRV_t$ is log realized volatility on day t.[8]

The higher we set x and the lower we set y the larger the differences between the stimulus in the adaptation phase (the very high or very low volatility) and the neutral volatility in the transition phase and therefore the stronger the expected after-effect. The downside of setting a very high x and low y is that we have fewer transitions in the data—fewer opportunities to test for an after-effect. In our empirical tests, we balance these competing considerations. In doing so, we discard choices of x and y that do not yield a sufficiently large number of regimes (from a statistical viewpoint). We show that our results are robust to different choices of x and y and in fact we exploit different combinations of x and y to test how the strength of the after-effect varies with the strength of the stimulus.

After removing the first three months of the sample used in the rolling window that determines high/low/neutral levels, we are left with 6,195 daily observations. When $x = y = 1,$ there are 240 volatility regimes (transitions from very high or very low volatility states to the neutral state) over the whole sample 1996–2020.[9]

The reader will find basic summary statistics related to realized volatility and VIX levels in the Appendix. Table 1 Panel A reports the number of regimes for a range of x and y between 1.00 and 1.75 standard deviations. Table 1 Panel B reports the average absolute difference between the log realized volatility in neutral states and the log realized volatility in very-high and very-low states for volatility regimes. The absolute difference in volatility levels increases with the threshold that defines an extreme volatility level (x) and it decreases with the threshold that defines a neutral volatility level (y). The average jump from either a very high or very low volatility state to a neutral volatility state is 0.42 in log terms (about 40% in realized volatility terms).

Structural Model. We use a structural model to derive the empirical measures that are able to isolate the changes in perceived volatility from the VIX. In the baseline version of this model, without loss of generality, we assume rational expectations (assuming adaptive expectations instead strengthens our main conclusions, more on this below).

The structural model begins by expressing VIX squared (which is the price of a synthetic variance swap)[10] as the sum of expected realized variance and a variance risk premium (like in Carr and Wu (2006)

Table 1. Number and Strength of Volatility Regimes for Different Threshold Values

	x			
y	1.00	1.25	1.50	1.75
Panel A: Number of regimes				
1.00	240	112	48	15
1.25	.	162	74	31
1.50	.	.	101	43
1.75	.	.	.	55
Panel B: Volatility differences between extreme and neutral states				
1.00	0.32	0.36	0.40	0.48
1.25	.	0.32	0.37	0.42
1.50	.	.	0.32	0.38
1.75	.	.	.	0.35

Panel A reports the number of realized volatility "regimes" (including both very-high-to-neutral ($VolReg_t = +1$) and very-low-to-neutral ($VolReg_t = -1$) transitions) for different threshold values. Panel B reports the average absolute difference between the log realized volatility in neutral states and the log realized volatility in very-high and very-low states for volatility regimes. Columns report different values of the threshold that defines very high and very low volatility states (volatility that is greater than *x* standard deviation from the mean). Rows report different values of the threshold that defines the neutral volatility state (volatility that is within *y* standard deviations from the mean).

and Bollerslev, Tauchen, and Zhou (2009)):

$$VIX_t^2 = \mathbb{E}_t\left[RV_{t,t+22}^2\right] + VRP_t, \qquad (2)$$

where $\mathbb{E}_t$ is the expectation under the statistical probability measure and VRP_t is the variance risk premium.[11] As noted by Carr and Wu (2006), VIX is a discretized approximation of the variance. The approximation is exact in the absence of jumps in the underlying. When the underlying index exhibits jump, the approximation error is negligible (Carr and Wu 2009; Jiang and Tian 2007).[12]

By differencing (2), we obtain:

$$\begin{aligned}\Delta VIX_t^2 &= VIX_t^2 - VIX_{t-1}^2 \\ &= \mathbb{E}_t\left[RV_{t,t+22}^2\right] - \mathbb{E}_{t-1}\left[RV_{t-1,t+21}^2\right] + \Delta VRP_t.\end{aligned} \qquad (3)$$

Daily changes in expected future volatility are driven by changes in daily realized volatility. We demonstrate this in Appendix A, Section A.1, but the intuition is simply as follows. Forecasts of future volatility are based on current and past realized volatility. So as we move from one day to the next, traders adjust their forecasts of future volatility using the new information that they have, which is that day's realized volatility. Therefore, (3) becomes:

$$\Delta VIX_t^2 \approx \beta_D\ \Delta RV_t^2 + \Delta VRP_t. \qquad (4)$$

If traders' perceptions of volatility are distorted due to after-effects by a perception error, PE, then we have the following (using subscript π for perceived volatility):

$$RV_{\pi,t}^2 = \begin{cases} RV_t^2 - PE, & \text{after a prolonged period of high volatility} \\ RV_t^2 + PE, & \text{after a prolonged period of low volatility} \\ RV_t^2, & \text{otherwise.}\end{cases}$$
$$= RV_t^2 - PE.VolReg_t \qquad (5)$$

Taking first differences gives:

$$\Delta RV_{\pi,t}^2 = \Delta RV_t^2 - PE.\Delta VolReg_t. \qquad (6)$$

Allowing for perception error in (4) by replacing the change in realized volatility with the perceived change in volatility (6), we get:

$$\Delta VIX_t^2 \approx \beta_D\ \Delta RV_t^2 - \beta_D PE.VolReg_t + \Delta VRP_t. \qquad (7)$$

At daily frequencies, changes in the variance risk premium are negligible. As Merton (1980) and Bollerslev, Gibson, and Zhou (2011) highlight, the variance risk premium is slow-moving, highly persistent and varies with the business cycle, rather than day to day. Therefore, the equation above shows that daily changes in VIX are primarily driven by daily changes in realized volatility, as well as distortion due to errors in volatility perception.

Regressions Showing the Impact of a Volatility Regime on VIX. The structural model above implies that the presence of after-effects in volatility perceptions can be identified by testing whether $VolReg_t$ explains changes in VIX. If after-effects are present and volatility perceptions are distorted ($PE > 0$) then in a regression of ΔVIX_t^2 on the $VolReg_t$ variable and control variables, the coefficient on the $VolReg_t$ the variable should be negative and statistically significant. If there is no distortion of volatility perceptions ($PE = 0$), then the coefficient on the $VolReg_t$ a variable should be zero.

Here we use a log specification of (7) for consistency with the definition of the variable $VolReg_t$.[13] The log specification is not pivotal for our results and in robustness tests, we find similar results, in some cases even stronger, under alternative specifications including specifications that are not in logs. The benchmark form of our regression is thus:[14]

$$\Delta LnVIX_t = \alpha + \beta \ VolReg_t + \gamma \ \Delta LnRV_t + \varepsilon_t. \tag{8}$$

The main coefficient of interest is β: if the after-effect distorts VIX as described by our structural model, β should be significantly negative.

Note that our benchmark regression assumes the ΔVRP_t term in (7) is negligible following Merton (1980) and Bollerslev, Gibson, and Zhou (2011). To ensure that such neglect of ΔVRP_t is not pivotal for our findings, we augment the baseline Regression (8) with variables that control for ΔVRP_t. For instance, we control for the first lag of changes in realized volatility (the results are robust to adding more lags), in line with Baele et al. (2019), whose findings suggest that volatility is the main predictor of variations in the variance risk premium. We also include the market return during the transition period (r_t) as a further proxy for changes in the variance risk premium, as well as negative market returns ($r_t^- = \min(r_t, 0)$) to account for possible leverage effects. To account for any possible auto-correlation of changes in VIX, we include the first lag of changes in VIX. This first lag accounts for any short-term reversals in VIX, like the short-term reversals, often seen in equity returns due to illiquidity. Finally, we include dummy variables for the "day-of-the-week effect" in VIX (Fleming, Ostdiek, and Whaley 1995). The regression with the complete set of control variables is thus:

$$\Delta LnVIX_t = \alpha + \beta \ VolReg_t + \gamma_0 \ \Delta LnRV_t + \gamma_1 \ \Delta LnRV_{t-1} + \delta \ r_t + \delta^- \ r_t^- + \rho_1 \ \Delta LnVIX_{t-1} + \sum_{i=2}^{5} \theta_i D_{it} + \varepsilon_t, \tag{9}$$

where $\{D_{it}\}_{i=2,3,4,5}$ are dummy variables for Tuesday to Friday (Monday is the base case).

Table 2 Column (1) reports estimates from the baseline Regression (8). The impact of $VolReg_t$ on changes in VIX has a negative sign, which is consistent with the presence of a volatility after-effect, and it is statistically significant. The economic impact of $VolReg_t$ is large: a transition from a very high or very low volatility state to neutral volatility changes VIX by about 2.73%.

We augment the baseline regression with a number of control variables. The coefficient of the key variable, $VolReg_t$, is hardly affected by the additional control variables. Column (2) reports the results of the regression with S&P 500 returns and negative returns added as control variables for changes in the variance risk premium and potential leverage effects. In Column (3) the regression includes lagged VIX difference and lagged realized volatility differences. Finally, Column (4) reports the results of the regression that includes day-of-the-week dummies (Regression (9)). The coefficient of $VolReg_t$ is remarkably stable across all four regressions.

To assess the statistical significance of the positive relationship between volatility level in the VH/VL periods and after-effect magnitude, we augment our baseline regression with an interaction $VolReg_t.x_t$, where x_t measures how extreme (in terms of a number of standard deviations from the mean) realized volatility has been on average during the past three-day adaptation phase. We also control for the level of x_t as a standalone term:

$$\Delta LnVIX_t = \alpha + \beta_1 VolReg_t + \beta_2 \ VolReg_t.x_t + \beta_3 x_t + \gamma_0 \ \Delta LnRV_t + \gamma_1 \ \Delta LnRV_{t-1} + \delta \ r_t + \delta^- \ r_t^- + \rho_1 \ \Delta LnVIX_{t-1} + \sum_{i=2}^{5} \theta_i D_{it} + \varepsilon_t. \tag{10}$$

Table 2 Column (5) reports the results from Regression (10). The main coefficient of interest, β_2, is significantly negative, indicating a statistically significant positive relation between volatility level in the VH/VL periods and after-effect magnitude.

Likewise, to assess the statistical significance of the relation between duration of the VH/VL period and after-effect magnitude, we augment our baseline regression with the interaction term $VolReg_t.z_t$, where z_t is the duration of the adaptation phase, measured by the number of days the phase lasts,

Table 2. VIX Distortions after Volatility Regimes

	(1) $\Delta LnVIX_t$	(2) $\Delta LnVIX_t$	(3) $\Delta LnVIX_t$	(4) $\Delta LnVIX_t$	(5) $\Delta LnVIX_t$	(6) $\Delta LnVIX_t$
$VolReg_t$	−3.304**	−2.800**	−2.727**	−2.603**	0.188	−1.292**
	(−3.14)	(−3.44)	(−3.42)	(−3.26)	(0.34)	(−4.62)
$VolReg_t.x_t$					−2.439**	
					(−2.80)	
x_t					−0.257*	
					(−1.98)	
$VolReg_t.z_t$						−0.643**
						(−4.15)
$\Delta LnRV_t$	0.075**	0.030**	0.039**	0.043**	0.041**	0.042**
	(19.32)	(11.33)	(11.60)	(11.92)	(11.24)	(11.52)
$\Delta LnRV_{t-1}$			0.017**	0.020**	0.019**	0.020**
			(5.37)	(6.13)	(5.82)	(5.95)
r_t		−3.513**	−3.419**	−3.429**	−3.406**	−3.409**
		(−18.75)	(−18.37)	(−18.61)	(−18.67)	(−18.76)
r_t^-		1.019**	1.027**	0.968**	1.017**	0.997**
		(3.22)	(3.28)	(3.11)	(3.29)	(3.21)
$\Delta LnVIX_{t-1}$			−0.116**	−0.115**	−0.114**	−0.115**
			(−4.72)	(−4.66)	(−4.67)	(−4.69)
D_{2t}				−1.340**	−1.372**	−1.401**
				(−6.21)	(−6.39)	(−6.51)
D_{3t}				−1.855**	−1.872***	−1.911***
				(−8.40)	(−8.53)	(−8.67)
D_{4t}				−1.402**	−1.430***	−1.451**
				(−6.44)	(−6.60)	(−6.70)
D_{5t}				−2.273**	−2.301**	−2.315**
				(−10.73)	(−10.87)	(−10.96)
α	0.019	−0.285*	−0.290*	1.125**	1.305**	1.171**
	(0.22)	(−2.44)	(−2.50)	(6.00)	(5.95)	(6.26)
R^2	9.08%	55.43%	56.63%	57.72%	57.83%	57.84%
Observations	6,195	6,195	6,195	6,195	6,195	6,192

This table reports coefficient estimates from Regressions (8–11). Negative values of the coefficient of $VolReg_t$ in Columns (1–4) are consistent with VIX distortions caused by the after-effect phenomenon. Negative values of the coefficients of $VolReg_t.x_t$ (Column (5)) and $VolReg_t.z_t$ (Column (6)) are consistent with a positive relationship between respectively stimulus strength and after-effect magnitude, and stimulus duration and after-effect magnitude (see also Figures 5,6). The other coefficients are the coefficients of the control variables. All the regressions use the threshold parameters $x = 1.75$ and $y = 1.50$ except for Column (5) & (6) which uses threshold parameters $x = 1.00$ and $y = 1.00$ (because it tests the effects of stimulus strength and duration from a weak to strong level). t-statistics (in parenthesis) are calculated with heteroskedasticity robust standard deviations. ** and * denote coefficients significant at the 1% and 5% levels respectively.

minus three. Recall that three days is the minimum length for the adaptation phases in our tests and thus z_t is zero for regimes with three-day adaptation phases and increases by one for every additional day of extreme volatility in the adaptation phase.

$$\Delta LnVIX_t = \alpha + \beta_1 VolReg_t + \beta_2 \; VolReg_t.z_t + \gamma_0 \; \Delta LnRV_t + \gamma_1 \; \Delta LnRV_{t-1} + \delta \; r_t + \delta^- \; r_t^- + \rho_1 \; \Delta LnVIX_{t-1} + \sum_{i=2}^{5} \theta_i D_{it} + \varepsilon_t. \quad (11)$$

Table 2 Column (6) reports the results from Regression (11). The main coefficient of interest, β_2, is significantly negative, indicating a statistically significant positive relationship between duration of the VH/VL period and after-effect magnitude.

In the foregoing regressions, we use threshold parameters $x = 1.75$ and $y = 1.50$ (recall x determines the volatility level during the adaptation phase and y determines the volatility level in the neutral state). This particular parameter choice for x and y is to ensure both a sufficiently large difference between the volatility states and a sufficiently large

Table 3. Strength of the VIX Distortions for Different Volatility State Thresholds

	x			
y	1.00	1.25	1.50	1.75
1.00	-1.255^{**}	-1.787^{**}	-3.033^{**}	-2.875^{**}
	(-4.40)	(-4.13)	(-3.96)	(-3.02)
1.25	.	-1.629^{**}	-2.934^{**}	-3.273^{**}
		(-4.42)	(-5.11)	(-4.79)
1.50	.	.	-1.716^{*}	-2.603^{**}
			(-2.78)	(-3.26)
1.75	.	.	.	-2.362^{**}
				(-3.43)

This table reports the coefficient of $VolReg_t$ variable in Regression (9) for different volatility state thresholds. The columns report different values of the threshold that defines very high and very low volatility states (volatility that is greater than x standard deviation from the mean). The rows report different values of the threshold that defines the neutral volatility state (volatility that is within y standard deviations from the mean). Negative values of the coefficient of $VolReg_t$ are consistent with VIX distortions caused by the after-effect. Larger magnitude coefficients suggest a stronger after-effect. t-statistics (in parenthesis) are calculated with heteroskedasticity-robust standard errors. ** and * denote coefficients significant at the 1% and 5% levels respectively.

number of regimes. Importantly, our results are robust to using different parameter choices for x and y. Table 3 reports the estimated coefficients and significance of $VolReg_t$ in Regression (9) for different values of both parameters. In all cases the estimated coefficient of $VolReg_t$ is negative and statistically significant.[15] The largest coefficient is 3.572, which implies that the impact of the after-effect on VIX is about the same as the impact of a 1% change in the S&P 500.

We test whether the VIX distortions persist beyond the day that the after-effect is triggered. To do this, we time to shift the left-hand side of Regression (9) so that the impact on VIX is measured at time $t+1$ rather than time t. We find that about one-third (approximately 33%) of the distortion attributable to the after-effect is reversed the following day. Thus, some of the distortions persists beyond one day.

We also examine whether the strength of the after-effect is diminished when the VH/VL period of the volatility regime spans a weekend. We do this by adding an interaction of the $VolReg_t$ variable with a dummy variable for whether the VH/VL period spans a weekend. We find that the after-effect is about 23% stronger if the period does not include a weekend. Therefore, our main results that use volatility

Table 4. Volatility Expectation Errors

	(1) $[LnRV^2_{t,t+22} - LnVIX^2_t]$.	(2) $[LnRV^2_{t,t+22} - LnVIX^2_t]$.
$VolReg_t$	0.319^{**}	0.313^{**}
	(2.86)	(2.81)
$\Delta LnRV_t$	0.000	0.000
	(0.40)	(0.59)
$\Delta LnRV_{t-1}$		0.000
		(0.61)
r_t		0.020
		(1.07)
r_t^-		0.030
		(0.90)
$\Delta LnVIX_{t-1}$		-0.002
		(-0.90)
D_{2t}		0.014
		(0.43)
D_{3t}		0.011
		(0.32)
D_{4t}		0.004
		(0.13)
D_{5t}		0.023
		(0.72)
α	-1.312	-1.335^{**}
	(-133.46)	(-51.71)
R^2	0.13%	0.19%
Observations	6,173	6,173

This table reports coefficient estimates from Regression (12), in which the dependent variable is a measure of ex-post expectation error, $[LnRV^2_{t,t+22} - LnVIX^2_t]$. Positive values of the coefficient of $VolReg_t$ in Columns (1–2) are consistent with the expectation errors predicted by the after-effect phenomenon. $VolReg_t$ are $+1$ following very-high-to-neutral volatility regimes, -1 following very-low-to-neutral volatility regimes, and zero otherwise. $\Delta LnRV_t$ is the change in the log realized volatility on day t. r_t is the market return and $r_t^- = \min(r_t, 0)$. $\Delta LnVIX_{t-1}$ is the change in the log VIX on day $t-1$. $\{D_{it}\}_{i=2,3,4,5}$ are day-of-the-week dummy variables (Tuesday to Friday). α is a constant. All the regressions use the threshold parameters $x = 1.75$ and $y = 1.50$. t-statistics (in parenthesis) are calculated with heteroskedasticity robust standard deviations. ** and * denote coefficients significant at the 1% and 5% levels respectively.

regimes that include and do not include weekends in the VH/VL period, tend to understate the magnitudes of the after-effect that arises following three continuous days of high or low volatility exposure.

Regressions Showing the VIX Distortions Are Due to Expectation Errors. To directly test for the presence of systematic expectation *errors* following volatility regimes that are expected to induce the after-effect, we replace the dependent variable in the previous regressions with a measure of the ex-post expectation error reflected in VIX, $[LnRV^2_{t,t+22} - LnVIX^2_t]$. To control for the variance risk premium that also contributes to the difference between realized volatility and the VIX, we include an intercept in the regression to absorb the mean-variance risk premium and several control variables that can capture changes in the variance risk premium, including changes in realized volatility, lagged changes in realized volatility, market returns, downside market returns, and lagged changes in VIX. The regression that we estimate is, therefore:

$$\left[LnRV^2_{t,t+22} - LnVIX^2_t\right] = \alpha + \beta\ VolReg_t + \gamma_0\ \Delta LnRV_t + \gamma_1\ \Delta LnRV_{t-1} + \delta\ r_t + \delta^-\ r_t^- + \rho_1\ \Delta LnVIX_{t-1} + \sum_{i=2}^{5} \theta_i D_{it} + \varepsilon_t. \tag{12}$$

The results in Table 4 show that, as predicted by the theory, significant expectation errors are observed in VIX following volatility regimes that induce after-effects. The positive and statistically significant coefficients on the $VolReg_t$ variable in both regression models in Table 4 (with and without control variables) indicate that future realized volatility is higher than implied by VIX (after controlling for the variance risk premium) following volatility regimes in which volatility switches from extremely high levels to moderate levels, and vice versa. This evidence suggests that volatility expectations are downward biased following regimes in which after-effects are expected to create a downward bias in perceived volatility.

Asymmetry in the Volatility Perception Bias. Finally, to investigate whether the risk after-effect is as strong when transitioning from a very high volatility state to a neutral state ("post-high") as it is when transitioning from a very low volatility state to a neutral state ("post-low"), we decompose our volatility regime variable $VolReg_t$ into the following two variables:

$$VolReg_t^+ = \begin{cases} +1\ if\ \{LnRV_{t-3},\ LnRV_{t-2},\ LnRV_{t-1}, LnRV_t\} \\ \qquad = \{VH,\ VH, VH, M\} \\ 0\ otherwise \end{cases}, \tag{15}$$

$$VolReg_t^- = \begin{cases} -1\ if\ \{LnRV_{t-3},\ LnRV_{t-2},\ LnRV_{t-1}, LnRV_t\} \\ \qquad = \{VL,\ VL, VL, M\} \\ 0\ otherwise \end{cases}. \tag{16}$$

Table 5 Panel A reports the numbers of transitions from VH to M for a range of x and y between 1.00 and 1.75 standard deviations. Panel B reports the numbers of transitions from VL to M. It is interesting to note that there are more VL to M transitions when $x = y = 1$, but as y increases, the ratio of transitions from VH to M steady increases relative to the VL to M transitions. This highlights the natural asymmetry in stock market volatility since higher volatility states are more observable and not bounded by lower bounds like lower volatility states. We can test how important this asymmetry is on the results. Table 6 reports the estimated coefficients of $VolReg_t^+$ and $VolReg_t^-$ when they are used as replacements for $VolReg_t$ in Regression (9). The coefficients of $VolReg_t^+$ are even larger than the coefficients of $VolReg_t$ in Table 3. In contrast, the coefficient of $VolReg_t^-$ is not statistically distinguishable from zero. The implications here are important since this suggests the meaningful and potentially tradable information is contained in the VH to M transitions. This is not to say that VL to M transitions is not important; rather, it means that because stock market volatility can't get "low enough" to properly enter into the VL to M regimes, there are few meaningful low volatility transitions. The trading strategy proposed next accounts for such asymmetry.

To summarize, we document a market anomaly that can be linked to the after-effect. Its magnitude appears to be significant. The phenomenon further appears to be robust: the main conclusion related to the presence of VIX distortions caused by the after-effect presents itself consistently across an extensive set of robustness checks that we ran (see the Internet Appendix).

Trading Strategy

In this section, we construct three simple market timing strategies that exploit the after-effect identified in Section Anomaly. Given the anomaly in VIX reported in the previous section, perhaps the simplest and most direct of the strategies we propose exploits VIX futures contracts to take positions when VIX is expected to be distorted. However, given the negative correlation between volatility levels and market returns, the anomaly also suggests it may be possible to construct a profitable trading strategy using the market portfolio, for which we use the most liquid S&P500 index ETF, the SPY. Finally, we also consider a combined strategy.

Starting with the strategy that exploits the market portfolio, the strategy involves making buy and sell decisions based on identifying entries into very high

Table 5. The Number of Transitions from Very High and Very Low to Neutral Volatility

y	*x* 1.00	1.25	1.50	1.75
Panel A: Transitions from *VH* to *M*				
1.00	105	52	25	10
1.25	.	78	44	24
1.50	.	.	59	35
1.75	.	.	.	40
Panel B: Transitions from *VL* to *M*				
1.00	135	60	23	5
1.25	.	84	30	7
1.50	.	.	42	8
1.75	.	.	.	15

This table reports the number of realized volatility transitions from the very high (*VH*) state to the neutral state (Panel A) and from the very low (*VL*) state to the neutral state (Panel B) for different threshold values. Columns report different values of the threshold that defines very high and very low volatility states (volatility that is more than *x* standard deviation from the mean). Rows report different values of the threshold that defines the neutral volatility state (volatility that is within *y* standard deviations from the mean).

(VH) volatility states and transitions from VH to M: upon observing an entry into a VH state at time t, the portfolio goes to cash in period $t+1$ and stays in cash until the market exits the VH state at $t+n$, where n is the number of days in the VH state. If at $t+n$ the market transitions from VH to M, triggering an after-effect, we go long the index portfolio in period $t+n+1$. If no after-effect is triggered, then the portfolio stays in cash an extra day, then goes long the index portfolio as long as a new VH state is not observed.

The strategy can be in cash for one day or n days, depending on the length of the VH state (the longest period in our sample is 18 days). Ideally, under perfect foresight, one would stay in the market during short (1 or 2 days) VH states and would exit the market one day before the market transitions to M. Such a perfect-foresight portfolio generates annualized returns of over 30% per year. It is however not viable and our portfolio is immune to the "look-ahead bias"—the fact that one cannot trade today on tomorrow's information.

Instead of going long when the market exits the VH state, the strategy could be modified to systematically go long after observing the 3rd day of VH. However, that strategy loses when the VH period

Table 6. Asymmetry of the After-Effect in the VIX Data

y	*x* 1.00	1.25	1.50	1.75
Panel A: Transitions from *VH* to *M*				
1.00	−2.493**	−3.203**	−4.315**	−2.953*
	(−5.34)	(−4.88)	(−3.90)	(−2.23)
1.25	.	−2.920**	−4.122**	−3.413**
		(−5.03)	(−5.51)	(−4.04)
1.50	.	.	−2.483**	−2.628**
			(−2.68)	(−2.72)
1.75	.	.	.	−2.990**
				(−3.40)
Panel B: Transitions from *VL* to *M*				
1.00	−0.268	−0.536	−1.615	.
	(−0.82)	(−1.03)	(−1.67)	
1.25	.	−0.419	−1.173	.
		(−1.00)	(−1.49)	
1.50	.	.	−0.645	.
			(−0.97)	
1.75	.	.	.	−0.699
				(−0.91)

This table reports coefficient for the $VolReg_t^+$ (Panel A) and $VolReg_t^-$ (Panel B) variables, which measure very-high-to-neutral and very-low-to-neutral volatility transitions, respectively. The coefficient estimates are obtained from Regression (9), replacing $VolReg_t$ with $VolReg_t^+$ (Panel A) and $VolReg_t^-$ (Panel B). Columns report different values of the threshold that defines very high and very low volatility states (volatility that is greater than *x* standard deviation from the mean). Rows report different values of the threshold that defines the neutral volatility state (volatility that is within *y* standard deviations from the mean). t-statistics (in parenthesis) are calculated with heteroskedasticity-robust standard errors. ** and * denote coefficients significant at the 1% and 5% levels respectively.

extends beyond three days. In contrast, our strategy buys back into the market only when the after-effect takes place.

Our strategy exploits the persistence of the after-effect and the negative correlation between volatility and market returns—one wants to be out of the market when the volatility is high since contemporaneous increases in volatility are negatively correlated with returns.[16] Accordingly, the strategy both avoids high periods of volatility (except for the first day of the VH period, as this framework does not attempt to forecast when VH starts) and takes advantage of the after-effect in the aftermath of a VH state.[17]

We test this strategy on three portfolios. The first uses the SPY ETF from April 1996 to 2020. The second uses front month VIX futures contracts from

Table 7. Performance of the After-Effect Strategy Applied to SPY from 1996 to 2020

			After-Effect Portfolios x			
	SPY	y	1	1.25	1.5	1.75
Annual return	9.25%	1	5.93%	7.82%	10.58%	11.92%
Annual risk	19.75%		15.25%	16.00%	17.02%	17.54%
Max drawdown	−55.19%		−54.42%	−53.20%	−45.86%	−49.42%
Alpha			0.23%	1.56%	3.46%	4.33%
t(stat)			(0.11)	(0.78)	(1.88)	(2.51)*
Beta			0.59	0.65	0.73	0.78
Annual return		1.25		8.34%	10.83%	12.08%
Annual risk				16.12%	17.08%	17.60%
Max drawdown				−52.09%	−46.64%	−48.83%
Alpha				1.97%	3.66%	4.44%
t(stat)				(1.00)	(1.99)*	(2.59)**
Beta				0.65	0.74	0.78
Annual return		1.5			10.81%	11.99%
Annual risk					17.12%	17.63%
Max drawdown					−48.51%	−48.83%
Alpha					3.62%	4.34%
t(stat)					(1.98)*	(2.54)*
Beta						0.78
Annual return		1.75				11.92%
Annual risk						17.66%
Max drawdown						−48.06%
Alpha						4.26%
t(stat)						(2.51)*
Beta						0.79

This table compares the returns of a buy and holds SPY portfolio vs. after-effect portfolios from April 1996 to 2020. For the after-effect portfolios, the columns report different values of the threshold that defines very high volatility states (volatility that is greater than *x* standard deviation from the mean). Rows report different values of the threshold that defines the neutral volatility state (volatility that is within *y* standard deviations from the mean). The after-effect portfolios go to cash in VH states at $t+1$ and stay in cash until the market exits the VH state at $t+n,$ where *n* is the number of days in VH. If the market transitions from VH to the M state at $t+n$ triggering an after-effect, the portfolio goes long the market portfolio in period at $t+n+1$. The after-effect portfolio will remain long from $t+n+1$ until VH is observed again. Annual return is calculated as $\left(\frac{portfolio\ \ value\ \ on\ \ Dec\ \ 31,\ \ 2020}{portfolio\ \ value\ \ on\ \ Apr\ \ 1,\ \ 1996}\right)^{\frac{1}{24.75}} - 1$. Annual Risk is daily returned standard deviation times the square root of 252. Max Drawdown is the peak to trough return. Alpha is Jensen's alpha. Beta is the beta of the portfolio to the SPY. *t*-statistics (in parenthesis) are calculated with heteroskedasticity robust standard errors. ** and * denote coefficients significant at the 1% and 5% levels respectively.

May 2004[18] to 2020. The third uses a combination of the SPY and front-month VIX futures contracts.[19]

Table 7 shows the returns of applying the strategy to SPY only for different values of *x* and *y* between 1 and 1.75 to identify the volatility regimes. Consistent with the pattern documented in Table 3, the performance of our after-effect portfolio increases with *x* (the threshold to define VH). For example, a move from $x = 1$ to $x = 1.75$ leads to an increase in annualized return from 5.93% to 11.92% and an increase in alpha from 0.23% to 4.33%. This reflects the fact that a higher value for VH identification means fewer periods in cash (when $x = 1$ the beta of the portfolio is 0.58 vs. it is 0.78 when $x = 1.75$). Further, note the improved max drawdown figure and lower volatility of the after-effect portfolio over the buy and hold portfolio, which suggests that identifying VH periods improves performance by avoiding large negative days without missing many positive days.

Also consistent with the pattern documented in Table 3, when $x = 1.5$ or $1.75,$ and *y* is slightly below the level of $x,$ the annualized performance, alphas, and drawdowns of our after-effect portfolio improve. The best performance is achieved for $x = 1.75$ and $y = 1.25 - 1.5,$ i.e., when there is a distinct drop in realized volatility when transitioning from VH to M. This suggests that it is good to be restrictive in the identification of the volatility regimes (to isolate instances of strong after-effects) but not so restrictive that there are few identified instances of after-effects (when $x = 1.75$ and $y = 1$ for example, it seems we are losing information).[20]

Next, we apply the second strategy, which exploits front month VIX futures contracts. After that, we consider a combined strategy that uses both SPY and VIX futures. Applied to front-month VIX futures only, the strategy consists of going long the VIX futures at time $t + 1$ when VH is first observed at time $t,$ and holding that long position through $t + n$ when the market transitions out of the VH state. If an after-effect is triggered at $t + n$ by the market transitioning to the M state, the strategy switches to a short position in the VIX futures at time $t + n + 1,$ otherwise, the position stays long. At $t + n + 2,$ the VIX position is removed and put back into cash. For the combined portfolio, when a VIX position is taken, the portfolio uses 3% allocation to the VIX futures, and 97% to the SPY. If the SPY is in cash at the time, then the 97% allocation to SPY goes into cash.[21]

The performance of both portfolios is shown in Table 8. For the VIX futures-only portfolio, the annualized performance is positive for almost all values of x and $y,$ and increases with levels of x. In contrast, a buy and hold VIX futures position consistently loses value. This highlights the value of identifying VH volatility periods and the after-effect.[22] Finally, the combined portfolio, which captures both the benefit of the equity price and volatility reactions to the after-effect, produces the highest returns, alphas, and risk reductions. When $x = 1.75$ and $y = 1.5,$ the portfolio returns 16.84% annually, with a max draw-down close to 12% better than just a buy and hold combined portfolio.[23]

It is clear from the above that correct identification of the start of the VH periods is an important aspect of the performance of our portfolio, as that tells us when to exit the market. But it is equally clear that there is more to it: it also matters to isolate the after-effect when it takes place, as that tells us what day to buy back in. To highlight the tradable impact of the after-effect, we compare the performance of our portfolio, which goes long only if an after-effect is identified, to the performance of a portfolio that always goes long after the VH period ends. We find that the annualized portfolio returns are lower when we always buy the SPY (or short the VIX) after the end of the VH period. When $x = 1.75$ and $y = 1.5,$ the annualized returns fall approximately 50 basis points for the SPY and 2% for the VIX standalone portfolios. For the combined portfolio this means almost 70 basis points of annualized return relative underperformance.

Figure 2 shows the long-term performance of applying our after-effect strategy to SPY and VIX combined. Note in particular the significant outperformance of the after-effect portfolio in the recent February/March 2020 period. The 37% returns difference over the SPY reflects the ability of our strategy to avoid the significant market shock and re-renter the market at the right time.[24]

Conclusion

To summarize, it appears that the after-effect is tradable. We show how to exploit it through a simple market timing tool that improves overall returns and reduces risk relative to an index only or an index plus volatility portfolio. The current evidence that the after-effect constitutes an exploitable arbitrage opportunity, especially in the last ten years, was not a foregone conclusion. Indeed, at first glance, one could expect the prevalence of the after-effect to diminish through time with the increasing automation of trading. This is not what practitioner reports of the trading process and recent evidence on manipulation of the VIX (Griffin and Shams 2018) suggest though: Although the process of trade execution and market maker quoting is largely automated, the trading decisions that ultimately determine price levels are still driven by humans. This is true of many markets including the S&P500 options market that underpins the VIX. Automation has become widespread in the *mechanical* aspects of trading, such as market-making algorithms that quote prices based on the prices of other assets and the market maker's inventory, trade execution algorithms that take an order (from a human) and optimally slice it up and execute it strategically to minimize costs and arbitrage algorithms that seek out and exploit relative mispricing. But in contrast, humans continue to control tasks that involve *judgement*, such as key trading decisions, forecasting future prices anticipating the actions of other traders, and gauging whether price levels are correct. These judgement tasks, which are susceptible to distortions from perceptual errors such as after-effects, are ultimately what determine price levels.[25] We hope the present study will inspire more work aimed to construct new trading strategies through harnessing neuroscientific insights into human perception.

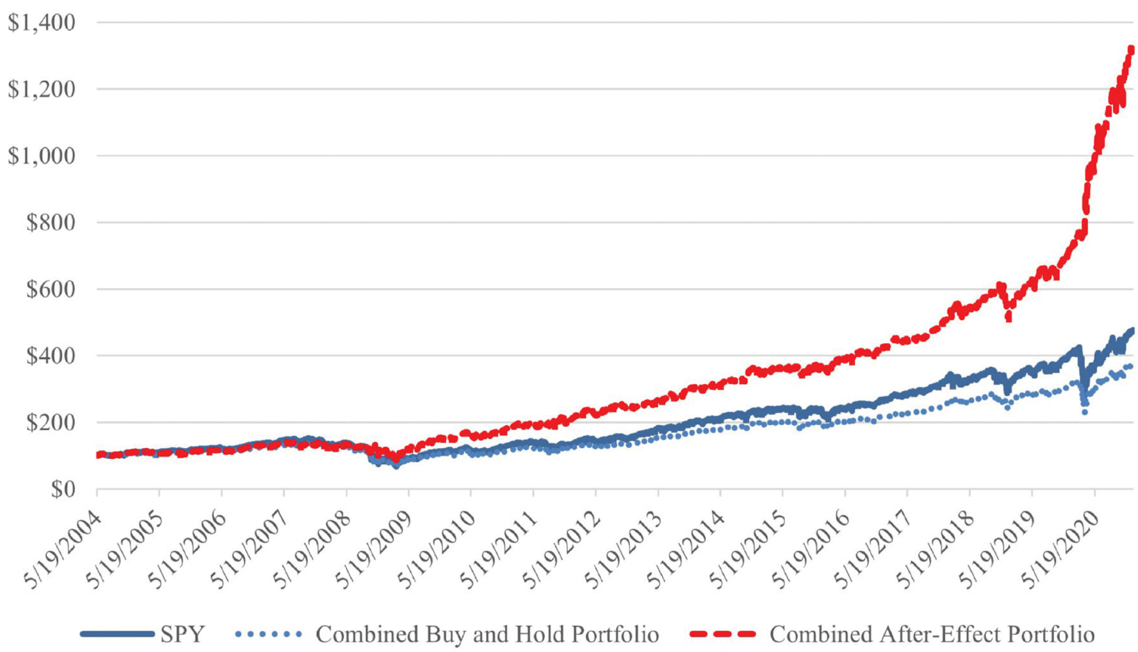
Table 8. Performance of the After-Effect Strategy Applied to SPY, VIX, and a Combination of the Two Instruments, from 2004 to 2020

	Buy and Hold Portfolios				After-Effect Portfolios											
					$x=1$			$x=1.25$			$x=1.5$			$x=1.75$		
	SPY	VIX	Combined		SPY	VIX	Combined	SPY	VIX	Combined	SPY	VIX	Combined	SPY	VIX	Combined
Annual return	9.85%	−55.94%	8.29%	$y=1$	7.26%	−6.87%	7.47%	9.47%	5.84%	10.01%	13.44%	13.64%	14.21%	15.70%	18.88%	16.58%
Annual risk	19.36%	82.77%	17.10%		13.76%	55.18%	13.89%	14.45%	51.05%	14.54%	15.72%	47.63%	15.78%	16.34%	44.23%	16.39%
Max drawdown	−55.19%		−51.26%		−59.58%		−45.92%	−63.24%		−47.19%	−48.23%		−43.66%	−41.35%		−38.65%
Alpha			−0.48%		2.28%		2.91%	3.83%		4.71%	6.43%		7.42%	7.91%		8.93%
t(stat)			(1.11)		(0.96)		(1.12)	(1.62)		(1.84)	(2.86)**		(3.04)**	(3.68)**		(3.83)**
Beta			0.88		0.50		0.47	0.56		0.52	0.66		0.63	0.71		0.69
Annual return				$y=1.25$				9.96%	11.13%	10.66%	13.79%	19.70%	14.72%	15.90%	22.49%	16.88%
Annual risk								14.53%	51.04%	14.64%	15.74%	47.62%	15.81%	16.35%	44.22%	16.41%
Max drawdown								−61.83%		−48.16%	−48.01%		−44.49%	−41.36%		−39.55%
Alpha								4.22%		5.21%	6.72%		7.85%	8.06%		9.16%
t(stat)								(1.79)		(2.04)*	(2.99)**		(3.22)**	(3.76)**		(3.94)**
Beta								0.56		0.53	0.66		0.64	0.71		0.69
Annual return				$y=1.5$							13.82%	19.49%	14.75%	15.82%	23.82%	16.84%
Annual risk											15.79%	47.62%	15.87%	16.40%	44.22%	16.47%
Max drawdown											−50.88%		−45.37%	−44.61%		−39.44%
Alpha											6.70%		7.82%	7.95%		9.08%
t(stat)											(2.99)***		(3.21)**	(3.73)**		(3.92)**
Beta											0.67		0.64	0.72		0.70
Annual return				$y=1.75$										15.48%	24.79%	16.53%
Annual risk														16.44%	44.21%	16.50%
Max drawdown														−43.78%		−39.44%
Alpha														7.63%		8.79%
t(stat)														(3.59)**		(3.8)**
Beta														0.72		0.70

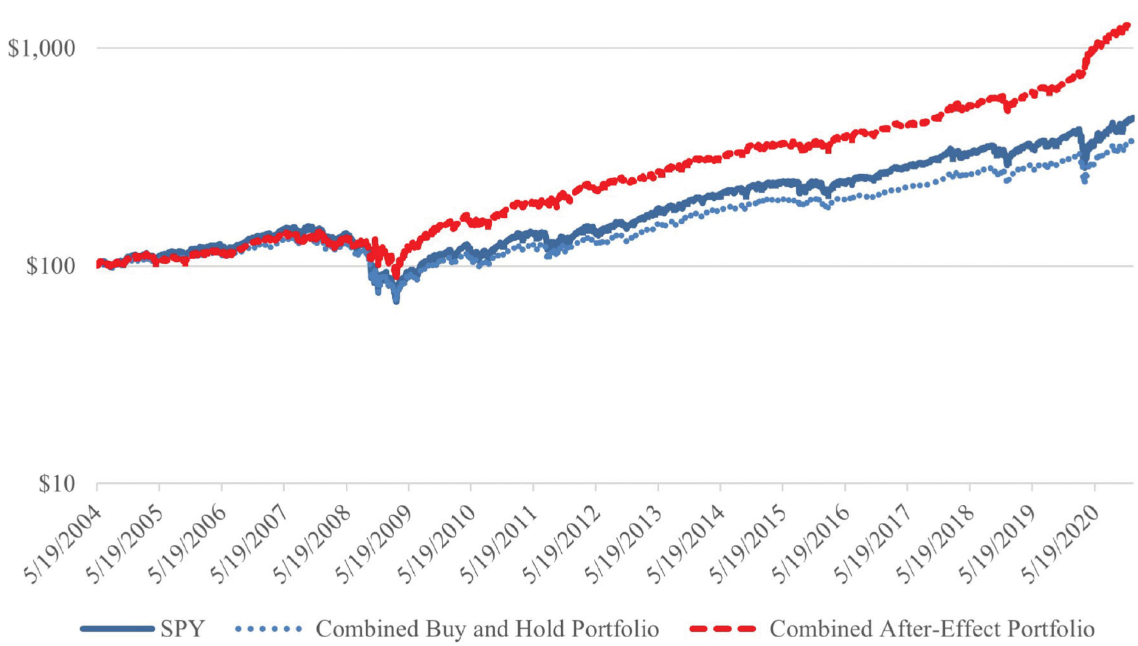
This table compares the returns of a buy and holds SPY, VIX only, and combined portfolios vs. after-effect portfolios from May 19, 2004 to 2020. The combined portfolio holds 97% in SPY and 3% in VIX front-month futures. For the after-effect portfolios, the columns report different values of the threshold that defines very high volatility states (volatility that is greater than x standard deviation from the mean). Rows report different values of the threshold that defines the neutral volatility state (volatility that is within y standard deviations from the mean). The after-effect portfolios for the SPY go to cash in VH states at $t+1$ and stay in cash until the market exits the VH state at $t+n$, where n is the number of days in VH. If the market transitions from VH to the M state at $t+n$ triggering an after-effect, the portfolio goes long the market portfolio in period at $t+n+1$. The after-effect portfolio will remain long from $t+n+1$ until VH is observed again. For front month VIX futures only, the strategy consists of going long the VIX futures at time $t+1$ when VH is first observed at time t, and holding that position through $t+n$ when the market transitions out of state VH. If the after-effect is triggered at $t+n$ in a transition from VH to M, a short position in VIX futures is taken at time $t+n+1$, otherwise, the position stays long. At $t+n+2$, the VIX position is removed and put back into cash. Annual return is calculated as $\left(\frac{portfolio\ value\ on\ Dec\ 31,\ 2020}{portfolio\ value\ on\ May\ 19,\ 2004}\right)^{\frac{1}{16.63}}-1$. Annual Risk is daily returned standard deviation times the square root of 252. Max Drawdown is the peak to trough return. Alpha is Jensen's alpha. Beta is beta of the portfolio to the SPY. t-statistics (in parenthesis) are calculated with heteroskedasticity robust standard errors. ** and * denote coefficients significant at the 1% and 5% levels respectively.

Figure 2. Long-Term Cumulative Performance of the After-Effect Combined Portfolio

Panel A: Linear scale



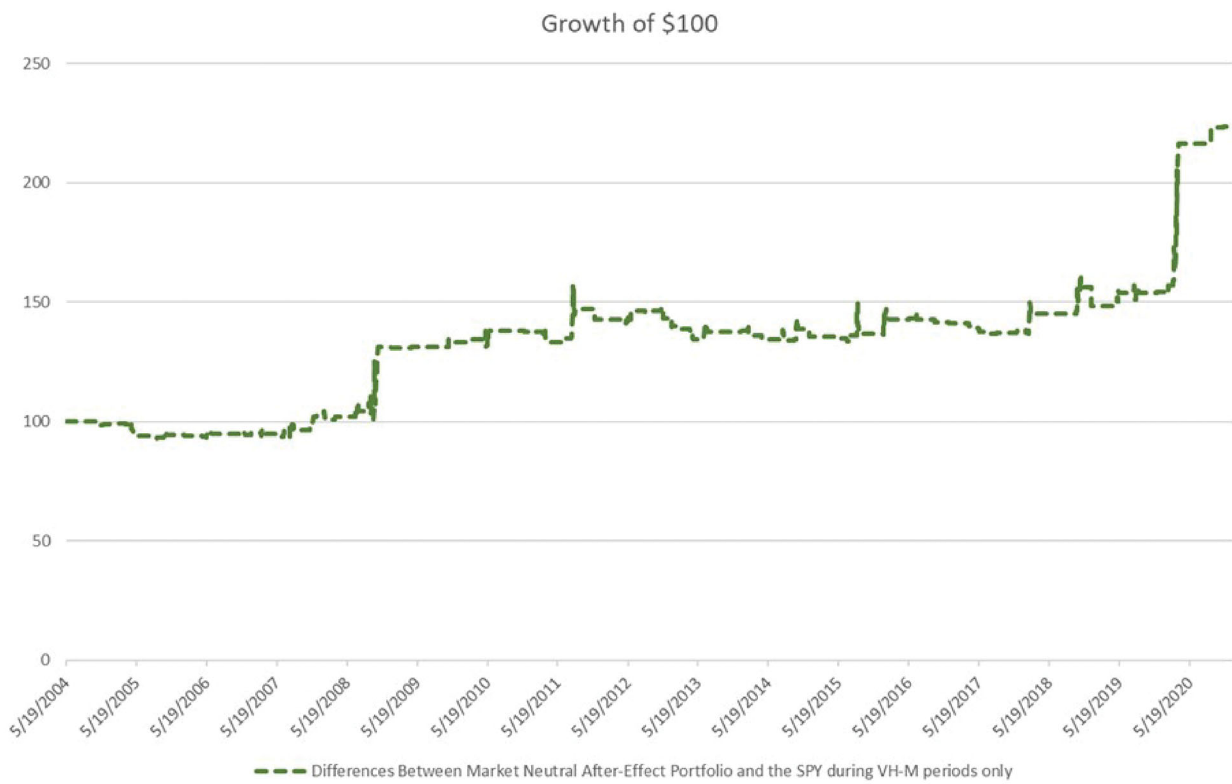
Panel B: Log scale



This figure plots the growth of $100 invested in the buy-and-hold SPY, the combined portfolios, and the after-effect portfolio for $x = 1.75$ and $y = 1.5$, from May 19, 2004 to December 31, 2020. All portfolios are normalized to $100 at the start of the sample.

Appendix A. Summary Statistics for Volatility and VIX Levels

Figure A1. Long-Term Cumulative Performance of the Market-Neutral After-Effect Combined Portfolio



This figure plots the growth of $100 invested in the market-neutral after-effect combined portfolio minus the SPY during VH to M periods for $x = 1.75$ and $y = 1.25$, and cash in all other periods, from May 19, 2004 to December 31, 2020. The portfolio value is normalized to $100 at the start of the sample.

Table A1. Descriptive Statistics and Unit Root Tests for Volatility Level Series

	RVol	Ln(Rvol)	VIX
Panel A: Descriptive statistics			
Mean	11.40	2.24	20.93
Std Dev	8.41	0.60	8.98
Maximum	145.85	4.98	82.69
P99	45.68	3.82	54.23
P95	25.71	3.25	37.64
P90	20.30	3.01	31.71
P75	14.21	2.65	24.84
P50	9.22	2.22	19.12
P25	5.97	1.79	14.22
P10	4.29	1.46	12.14
P5	3.82	1.34	11.28
P1	3.22	1.17	9.98
Minimum	2.25	0.81	9.14
Skewness	3.37	0.36	1.83
Kurtosis	26.24	2.92	8.60
Panel B: Unit root tests			
ADF	−22.78	−22.53	−7.06
P-value	0.0000	0.0000	0.0000

Table A2. Descriptive Statistics and Unit Root Tests

	VIX Differences	RVol Differences
Panel A: Descriptive statistics		
Mean	−0.0006	−0.0008
Std Dev	1.89	4.77
Maximum	26.95	78.68
Minimum	−23.72	−99.78
Skewness	1.44	−0.09
Kurtosis	32.73	63.49
Panel B: Unit root tests		
ADF	−80.81	−22.78
P-value	0.0000	0.0000

First difference series.

Editor's Note

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Table A3. Average Realized Volatility in the Very High and Very Low Volatility States

	x			
y	1.00	1.25	1.50	1.75
Panel A: Transitions from *VH* to *M*				
1.00	18.90	18.78	22.69	23.40
1.25	.	19.81	22.92	24.07
1.50	.	.	23.97	25.27
1.75	.	.	.	24.53
Panel B: Transitions from *VL* to *M*				
1.00	7.33	6.75	5.92	.
1.25	.	7.07	6.90	.
1.50	.	.	7.42	.
1.75	.	.	.	7.35

This table reports the average realized volatility in the very high (Panel A) and very low (Panel B) volatility states for different threshold values. Columns report different values of the threshold that defines very high and very low volatility states (volatility that is more than x standard deviation from the mean). Rows report different values of the threshold that defines the neutral volatility state (volatility that is within y standard deviations from the mean).

Notes

1. For example, De Long et al. (1990), Shleifer and Vishny (1997), and Lamont and Thaler (2003).
2. For example, Khaw, Glimcher, and Louie (2017) provide laboratory evidence that the valuation of a snack food item depends on the history of recently experienced food: a recent history of low value increases, and high-value decreases, how people value subsequent options. Hartzmark and Shue (2018) provide evidence that investors mistakenly perceive earnings news today as more impressive if yesterday's earnings surprise was bad and less impressive if yesterday's surprise was good.
3. For details, see Payzan-LeNestour, Pradier, and Putnins (2022).
4. The Internet Appendix that accompanies this paper can be found at https://tinyurl.com/y7ttyw4q
6. An additional reason for working with log realized volatility is that its volatility shows little persistence (Corsi et al. 2008).
7. We choose to use symmetrical intervals because the distribution is approximately symmetrical (see the Internet Appendix). We use five buckets to avoid threshold effects happening when volatility has been in the highest or lowest bucket and a small change brings it into the adjacent middle bucket. Setting $x = y$ collapses the five buckets into three adjacent ones.

8. Note that volatility regimes ($VolReg_t = \pm 1$) can involve very high or very low realized volatility that persists for more than three days before transitioning to the neutral level. Below we investigate the impact of the length of the stimuli on effect size.

9. The relatively low number of regime change is not surprising: our regime indicator is defined over four days and we have 6,195 days in the sample. So we have a maximum of 1,548 non-zero values. To get a non-zero value, realized volatility has to stay in the tail of the distribution for three days in a row before jumping. This is an unlikely path (albeit it is possible given the persistent nature of realized volatility and the presence of jumps).

10. VIX is quoted as an annualized standard deviation (volatility), so VIX squared is annualized variance. VIX squared corresponds to variance over the following 30 calendar days, which for expositional ease, we denote as 22 business days to avoid introducing a second measure of time.

11. Carr and Wu (2006) find that VIX is on average around five percentage points higher than realized volatility as a result of the variance risk premium. The variance risk premium implies that investors require compensation for bearing variance risk (a position that incurs losses when variance is unexpectedly high, e.g., the short side of a variance swap). Equivalently, investors are willing to pay a positive premium (accept a negative expected return) to hedge variance risk with a contract that has a positive (negative) payoff when volatility is unexpectedly high (low). See the Internet Appendix for more details.

12. VIX also exhibits two numerical errors due to its construction methodology. The truncation error leads to a downward bias in the calculated variance and the discretization error leads to overestimation of variance (Jiang and Tian 2007). At high (low) volatility levels, the truncation (discretization) error dominates and leads to an underestimation (overestimation) of the true volatility. Taken together, these results mean that in both a transition from high volatility to medium volatility and a transition from low volatility to high volatility, the change in VIX will underestimate the true change in volatility. Taking into account these approximations will only strengthen our results.

13. We multiply the log difference by 100 to make it consistent with the definition of S&P 500 returns.

14. In logging the series, the squares become linear terms, with the factor of two being absorbed into the corresponding coefficients and regression intercept.

15. The coefficients of the control variables are virtually unchanged for the different values of x and y.

16. In our sample there is a -0.26 correlation between changes in volatility and market returns.

17. We similarly designed a strategy to exploit the after-effect in the aftermath of VL periods. The strategy consists of keeping the portfolio unchanged upon entering into a VL period and moving to cash for one day after identifying an after-effect. We do not test this strategy here given the low number of VL periods in our sample, see Section Anomaly.

18. May 19, 2004 was the first time VIX futures contracts were traded.

19. The transactions costs are quite minimal with a strategy like this. The bid/ask spreads in the SPY indeed average about \$.01 and SPX futures and VIX futures contracts are less than 1 tick. Additionally, since there are very few trades (see Tables 1 and 5), trading and commissions should have no significant impact on the results (even if we account for trading slippage on transaction days at the close).

20. We checked the foregoing findings regarding performance, alpha, and risk are almost identical in the 2004–2020 subsample and the full sample. See Table 8, “SPY only” lines.

21. If holding the VIX occurs during an expiry of the front month contract, the position is switched to the next month two days prior to expiry. Additionally, we ignore the impact of margin and assume that the VIX futures have full cash coverage.

22. Of note, tighter after-effect windows ($y < x$) do not necessarily help the performance of the VIX futures portfolio, suggesting that VIX futures have a slightly different response than spot VIX, consistent with recent findings (Payzan-LeNestour and Doran, in preparation).

23. We checked that this performance improvement is robust to different allocation of VIX and SPY, so having a 97% / 3% allocation to either is not important for our main conclusions here.

24. A market neutral strategy is further shown in the appendix (Figure A1) to highlight the benefit of being in cash versus the SPY during VH to M periods.

25. We thank a number of practitioners for providing insights about the trading process (James Doran, Shuo Song, David Rabinowitz, and Christian Daher). Their views consistently emphasized the important role of human decision making despite automation of parts of the trading process.

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