Understanding Volatility-Managed Portfolios*

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Contrary to the intuition that the standard risk-return tradeoff should lead to underperformance of a portfolio that scales down exposure during volatile periods a recent paper by Moreira and Muir (2017) actually shows that volatility-managed portfolios produce robust and significant alphas. The present paper investigates the mechanisms that lead to the outperformance of volatility management. By implementing timing regressions and relating returns of a volatility-managed portfolio to discount-rate, cash-flow and expected volatility news we provide evidence that volatility management outperforms by levering up good times without increasing downside exposure to fundamental risk drivers. On the contrary, during the most severe cumulative news shocks (either to cash flows, discount rates or expected volatility) the scaling strategy suffers less than the buy-and-hold portfolio and, thus, increases investor utility.

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1 Introduction

A large body of literature in the field of asset pricing tries to identify variables that correlate with conditional expected returns in equity markets in order to provide tools for active portfolio management. While many papers have succeeded in finding a factor structure in the cross-section of equity returns that can be exploited to generate alpha relative to a market portfolio (including the well-known papers by Fama and French (1993), Carhart (1997) and Fama and French (2015)) the evidence on time series predictability of the overall equity market is weak (Welch and Goyal, 2008). However, a recent paper by Moreira and Muir (2017) highlights that a simple scaling strategy based on last month's market volatility substantially outperforms a pure buy-and-hold investment in the market. Due to its surprising robustness and very narrow set on market data required for implementation the paper has received a lot of attention, both in academia and the practice of investment management. Contrary to the intuition that the standard risk-return trade off should lead to underperformance of a portfolio that scales down exposure during volatile periods it can actually be shown that such a strategy produces significant alpha. The strategy seems to work as it turns out that on the one hand volatility is sticky and, thus, scaling by past volatility also reduces future volatility and on the other hand times of increased volatility do not appear to be compensated by substantially higher conditional expected returns (Moreira and Muir, 2019).

In the present paper we investigate the mechanisms that lead to the outperformance of volatility management. Most importantly, we analyze if volatility management alters fundamental risk drivers as compared to the corresponding passive factor. By implementing timing regressions that account for non-linearities we show that volatility management levers up positive returns while levering down negative ones and, especially very negative ones. The scaling underperforms very high positive returns, however, this is a state of low marginal utility. We move on to relate volatility-managed returns to cash-flow, discount-rate and expected volatility news. Our results suggest that the risk exposures of managed and unmanaged factors are statistically the same during negative innovations of the three news terms, while the managed strategy tends to outperform statistically significantly during cumulative periods of positive (joint) news realizations. While the returns of the managed and unmanaged strategies are on average statistically indistinguishable during down states, volatility management outperforms in almost all of the biggest drawdowns as measured by cumulative negative cash-flow, discount-rate and expected volatility news. In conclusion, our results show that volatility management levers up good times, does not alter the composition of risk drivers in down states and outperforms by levering down in the most severe cumulative news shocks.

The remainder of the paper is organized as follows: section 2 presents the literature related to this project, while section 3 describes the data used throughout the paper. Section 4 contains the main analyses and results. Finally, section 5 concludes.

2 Related Literature

Black (1976) discovered that volatility and returns are negatively correlated. Hence, in times of high volatility equity returns tend to be negative. Therefore, a strategy that manages its exposure inversely to past realized volatility tends to have a positive impact on investment performance (Lo, 2019).

Several recent academic papers investigate the properties of volatility-managed portfolios: Moreira and Muir (2017) find that alphas generated by volatility management are not spanned by their underlying original factors. Highlighting some shortcomings of the Moreira and Muir (2017) paper (such as a scaling parameter that is estimated in-sample and methodological issues related to spanning tests) Cederburg et al. (2019) argue that volatility management does not systematically outperform the original, unmanaged, portfolios. Still, they acknowledge that the strategy is able to generate statistically significant outperformance in terms of Sharpe ratios that are of comparable in magnitude to momentum-based strategies. Moreover, Harvey et al. (2018) show that volatility management produces large alphas for risk-assets that exhibit a *leverage effect* and thereby force momentum on the underlying strategy.

Barroso and Detzel (2018) find that limits to arbitrage (LTA) do not explain the benefits of volatility-managed portfolios and that utility gains from volatility managing low-LTA stocks are consistently higher than for high-LTA stocks, which is in contrast to the common finding that anomaly returns are lower in low-LTA segments, i.e. liquid stocks. The authors confirm the established finding that rational asset pricing models do not explain the alphas and utility gains generated by volatility management.

Arguing in favor of volatility management, recent work by Israelov (2018) shows that put options are bad drawdown protection tools. Instead, reducing the overall equity exposure is superior to protective puts.

Volatility management is also applied in practice, most prominently shown by the dynamic approach towards exposure management used by Scalable Capital[1].

With respect to systematic risk factors the seminal work by Campbell and Vuolteenaho (2004) shows that market beta can be split into sensitivities to discount-rate news and cash-flow news. Campbell et al. (2013) provide an update and specifically focus on the relevance of bad times for asset prices. Campbell et al. (2018) extend these models by allowing for heteroscedastic returns and thus augment the return decomposition to include a news term related to expected market volatility.

3 Data

This section elaborates on the data used for our analyses. To compute the returns of volatility-managed portfolios we use daily and monthly Fama-French factors from 1929 to 2019 as well as daily and monthly returns on the CRSP value-weighted stock index. For constructing cash-flow and discount-rate news, we use the same time series as in Campbell et al. (2013). Similar to their original study Campbell and Vuolteenaho

[1] see Scalable Capital (2018)

(2004) we use monthly data from December 1928 to December 2019 on the following variables:

- the log market excess return is computed using the CRSP value-weighted stock index and Treasury bills of approximately three months maturity as the risk free rate. Both time series are obtained from CRSP.
- the log P/E ratio (PE) from Robert Shiller's website, calculated as the price of the S&P 500 index divided by a ten-year trailing moving average of aggregate earnings.
- the term yield spread (TY) is constructed using data from Global Financial Data. We subtract the yield on the 3-month U.S. Treasury bill (ITSUSA3D) from the yield on the 10-year U.S. constant maturity bond (IGUSA10D).
- the small-stock value spread (VS) is constructed from data obtained from Kenneth French's website.
- the default spread (DEF) is defined as the difference in yield on Moody's BAA and AA rated bonds. The data is obtained from the Federal Reserve Bank of St. Louis.

Table 17 in the appendix contains summary statistics on the VAR state variables.
In order to relate the returns of volatility-managed portfolios also to news on expected volatility risk as defined in the heteroscedastic model of Campbell et al. (2018), we directly use the quarterly time-series of risk news as provided by the authors of the original paper (see Figure 2 in Campbell et al. (2018) for an illustration of the dynamics of this variable).

4 Empirical Analyses

4.1 Volatility-Managed Portfolios

4.1.1 Replication of Established Facts

We lay the foundation for our analyses by replicating established facts about volatility-managed portfolios. We describe how we construct the time-series, provide summary statistics and key observations and implement spanning regression tests. First, we follow Moreira and Muir (2017) and define the volatility- managed portfolio as

$$f^{\sigma}_{t+1} = \frac{c}{\hat{\sigma}^2_t(f)} f_{t+1} \tag{1}$$

where f is the buy-and-hold excess return of any given asset, $\hat{\sigma}^2_t(f)$ is a measure of the asset's volatility and the constant c scales the average exposure such that the managed strategy has the same unconditional volatility as its unmanaged counterpart.

In our base setting we use monthly standard deviations instead of variances, since scaling by variance leads to very high levels of leverage in the resulting strategy, as

Figure 1 shows, while the performance of portfolios scaled by either measure is similar. Consequently, applying a volatility-managed strategy in a real world setting is more easily feasible than a variance managed strategy, due to lower levels of average and maximum leverage.

[Figure 1 about here.]

We define the following specific portfolios for subsequent analyses:

$$\text{ftm} = f_t^{\sigma} \tag{2}$$

$$\text{ft} = f_t \tag{3}$$

$$\text{fo} = \text{ftm - ft} = f_t^{\sigma} - f_t \tag{4}$$

which correspond to the volatility-managed CRSP value-weighted excess return from 1929 to 2019, the unmanaged CRSP returns and the outperformance generated by volatility management. The resulting managed portfolio of CRSP value-weighted excess returns from 1929 to 2019 outperforms its unmanaged counterpart, as Figure 2 and Table 1 show.

[Table 1 about here.]

While Table 1 shows that the minimum return in a single period (month) and the monthly return skewness was lower for the volatility-managed strategy the opposite is true for cumulative drawdowns. The most severe drawdown of the vol-managed CRSP strategy was -63% from September 1929 to June 1932 (see Table 2a), while the original (unmanaged) CRSP value-weighted index lost as much as 85% on an excess return basis (see Table 2b).

[Table 2 about here.]

[Figure 2 about here.]

The returns of both time-series are distributed similarly as Figure 3 shows. However, while volatility-management leads to less density on very large positive return months (more than 22%), which most likely come from reversals after months with higher volatility and therefore less exposure in the strategy, it leads to more density in months with positive returns when compared to the baseline strategy. That is, volatility-management tends to scale up positive months while having less density in months with small returns around 0.

[Figure 3 about here.]

Volatility-managed portfolios are often not spanned by the original portfolios (see (Moreira and Muir, 2017)). To confirm this effect for CRSP value-weighted excess returns, as well as Fama-French 3 and 5 factors, we fit the following regressions.

$$f_t^\sigma = \alpha + \beta f_t \tag{5}$$

$$f_t^\sigma = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t \tag{6}$$

$$f_t^\sigma = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t \tag{7}$$

Tables 3 to 6 report on the results. The strategy produces economically significant outperformance of around 300 bps per year, when applied to CRSP value-weighted returns and the Fama-French market factor. It also outperforms its unmanaged counterpart when applied to the HML factor, while there is no outperformance in the SMB factor in the full sample period from 1929 to 2019, as the intercepts in Table 3 show. In a shorter sample ranging from August 1963 to December 2019, we regress the strategy on the CRSP index and Fama-French 5 factors and find an annual outperformance of at least 100 bps in the the market factor and the CRSP index, HML and RMW, while there are only limited gains to volatility-managing the SMB and CMA factors as can be seen in Table 4. Note however, that alphas are insignificant in the shorter sample except for RMW.

[Table 3 about here.]

[Table 4 about here.]

The results in Table 5 and 6 confirm that the managed portfolios that led to a strong outperformance in the longer and shorter sample period, respectively, i.e. the CRSP value-weighted index, the Fama-French market factor, HML and RMW, are not spanned by the Fama-French 3 and 5 factors in the sample period from 1929 to 2019 and the shorter sample period from August 1963 to 2019. Note however, that the managed market factor is actually spanned by the Fama-French factors in the shorter sample period.

[Table 5 about here.]

[Table 6 about here.]

In short, we broadly confirm the previous findings of Moreira and Muir (2017) and continue to investigate the ability of volatility-management to time the market.

4.1.2 Timing Regressions

As a first step towards gaining knowledge on the structure of volatility-managed portfolios we analyze the leverage dynamics implied by such a scaling strategy. In terms of methods we follow Lan and Wermers (2017) and fit Treynor-Mazuy (1966) and Henriksson-Merton (1981) market timing regressions. In addition, we implement specifications that split beta into up and down-market betas using squared positive and negative market returns as additional controls. Remember that we define f_t^σ

as the volatility-managed CRSP value-weighted excess return. The Treynor-Mazuy (TM) timing measure is defined as the estimated coefficient β_2 in the regression $f_t^\sigma = \alpha + \beta_1 f_t + \beta_2 f_t^2$, while the Henriksson-Merton timing measure is the estimated coefficient of β_2 in the regression $f_t^\sigma = \alpha + \beta_1 f_t + \beta_2 \max(0, f_t)$. Additionally, we fit regressions of the form:

$$f_t^\sigma = \alpha + \beta_1 \min(0, f_t) + \beta_2 \max(0, f_t) + \beta_3(-\min(0, f_t)^2) + \beta_4 \max(0, f_t)^2 \tag{8}$$

$$f_t^\sigma = \alpha + \beta_1 \min(0, f_t) + \beta_2 \max(0, f_t) + \beta_4 \max(0, f_t)^2 \tag{9}$$

to analyze the empirical relationship of f_t^σ to large positive and negative returns of the underlying factor.

Table 7 reports on the regression results. According to the Treynor-Mazuy measure volatility-management has a market beta < 1, while the strategy's returns are negatively associated with big moves, as the coefficient of -0.937 for squared market excess returns shows. The Henriksson-Merton measure indicates, that the strategy has a downside beta close to 1 and an upside beta < 1. Since both models are extensions of the basic CAPM that measure squared and positive returns separately, we would need to see positive values on the betas for f_t^2 and $\max(0, f_t)$ in order to find evidence for market timing ability.

[Table 7 about here.]

However, since rare but large moves in the underlying market have an outsized impact on the cumulative return since start of the portfolio, regressions (8) and (9) look at up and downside betas as well as the effect of squared directional returns. The resulting betas for regression (8) show that the strategy leads to betas that are bigger than 1 in the up- and downside returns, but the strategy strongly reacts to large returns, as indicated by the coefficients for $-\min(0, f_t)^2$ and $\max(0, f_t)^2$ with values of -2.3 and -2.7. Regression (9) reports an upside beta of 1.3, a downside beta of 0.8 and a negative coefficient of -3.02 for squared positive returns. Figure 4 provides a visual impression of the regressions fits.

Comparing all specifications of the timing regressions it turns out that the model with the best fit according to adjusted R^2 and $RMSE$ (and the ability to drive out significant alpha) is specification (8), which has a sinusoidal shape. Hence, according to this specification volatility-management leads to smaller downside returns than the original factor, while having bigger upside returns. Still, there is a turning point for positive and negative returns at roughly 20% per month, as the plot in the third quadrant shows. We suspect that the strong positive returns might occur after months with very high volatility and therefore the volatility-managed factor is not able to capture them due to less exposure in these months. Thus, as a first contribution, the results of the best fitting timing regression specification suggests that the outperformance of volatility-managed portfolios stems from a return asymmetry induced by the leverage dynamics , i.e. (substantial) negative returns tend to be reduced due to less leverage and frequently occurring positive returns (except for very high returns when marginal utility is lowest anyways) are boosted by high leverage. The outperformance of volatility-managed portfolios can, thus, be partially explained by the avoidance of large negative returns, while levering up good times.

[Figure 4 about here.]

4.1.3 Relation to Volatility Levels

In order to investigate the characteristics of periods in which the volatility-managed strategy outperforms, we try to relate outperformance and volatility levels. A simple linear regression shows no clear relationship between outperformance and volatility in the underlying factor, as can be seen in Table 8.

[Table 8 about here.]

However, once volatility exceeds a certain threshold, the volatility-managed portfolio always outperformed the unmanaged strategy. This threshold corresponds to an annualized realized volatility of about 68%. In all five of the most volatile months, the strategy outperformed the unmanaged index. In case of the most volatile month, October 2008, the outperformance was as high as 13.78%.

[Figure 5 about here.]

It is important to mention that in previous work Moreira and Muir found that the average returns in months following months with low, medium or high volatility are almost equal, so that the return-variance tradeoff following calmer months is superior (see Moreira and Muir (2017)). Therefore, a mean-variance optimizing investor who can vary his exposure ought to be invested more heavily in tranquil periods. Our regression on volatility levels augments this finding by showing that the outperformance of volatility management is not confined to a certain level of past realized volatility.

4.2 Relation to Cash-Flow and Discount-rate News

In a series of papers Campbell and Shiller (1988), Campbell (1991) and Campbell and Vuolteenaho (2004) show that unexpected excess stock returns can be split into innovations (news) in cash flows and innovations in discount rates:

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} = N_{CF,t+1} - N_{DR,t+1}$$

where d are dividends and ρ is the log-linearization constant.

Thus, as the next logical step toward understanding the characteristics of volatility-managed strategies, we focus on this established decomposition and relate strategy returns to the two essential news items. To get empirical proxies of cash-flow and discount-rate news, we fit the same models as in Campbell and Vuolteenaho (2004) using the market-excess return, PE, TY and VS as the state variables (i.e. leaving out DEF for now):

$$z_{t+1} = a + \Gamma z_t + u_{t+1} \tag{10}$$

where z_{t+1} is m-by-1 state vector with r_{t+1} as its first element. a and Γ are a m-by-1 vector and a m-by-m matrix of constant parameters. u_{t+1} is an i.i.d. m-by-1 vector of shocks. Given that z_{t+1} is the data-generating process, cash-flow and discount-rate news are defined as:

$$N_{CF,t+1} = (e1' + e1'\lambda)u_{t+1} \tag{11}$$

$$N_{DR,t+1} = e1'\lambda u_{t+1} \tag{12}$$

VAR shocks are mapped to news by $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$ and $\rho \equiv 0.95^{\left(\frac{1}{12}\right)}$. The interpretation of news is as follows: positive values of cash-flow news are good news, i.e. higher expected cash-flows in the future are associated with higher expected returns. Discount-rate news are defined to be positive when expected future returns increase, hence a higher value has a negative effect on the current return. That is why $-DR \equiv -N_{DR,t+1}$ is used in many regression settings, since then the interpretation for both news terms is the same (positive values are good, negative values are bad).
For ease of interpretation, we define the following types of news:

$$\text{cf} = N_{CF} \tag{13}$$

$$\text{dr} = N_{DR} \tag{14}$$

$$\text{mdr} = -N_{DR} \tag{15}$$

$$\text{cf6m} = \sum_{t-5}^{t} N_{CF,t} \tag{16}$$

$$\text{mdr6m} = \sum_{t-5}^{t} -N_{DR,t} \tag{17}$$

which correspond to cash-flow, discount-rate, negative discount-rate news and cumulative cash-flow and discount-rate news over the past 6 months.

We decompose the return variance and covariance as follows in order to attribute strategy return variance to the two news terms:

$$\text{Var}(f_t) = \text{Cov}\,(f_t, \text{mdr}) + \text{Cov}\,(f_t, \text{cf}) \tag{18}$$

$$\text{Cov}(f_t^\sigma, f_t) = \text{Cov}\,(f_t^\sigma, \text{mdr}) + \text{Cov}\,(f_t^\sigma, \text{cf}) \tag{19}$$

This decomposition shows, that the returns of both series are mostly driven by discount-rate news, with a contribution of about two thirds, while cash-flow news cause only about 31% of the movements in variance and covariance, respectively (see table 9). For the market factor itself this is consistent with common findings in the literature, as Campbell et al. (2018) find that discount-rate news are nearly twice as volatile as cash-flow news, confirming empirical results by Campbell (1991) and Campbell and

Vuolteenaho (2004) who find that discount-rate news cause more variation than cash-flow news. Our results show, that volatility management does not alter this fact as the return variance of the managed factor has virtually the same variance decomposition coefficients.[2]

[Table 9 about here.]

In order to estimate the relative importance of cash-flow and discount-rate news for the outperformance generated by volatility-management, we regress ft, ftm and fo on the two news terms. Table 10 reports on the results. While the managed strategy has positive betas to cash-flow and negative discount-rate news of 0.82 and 0.87, the outperformance seems to be negatively related to both news terms, although we can only explain 6% of the variation in the returns in excess of the unmanaged factor and only the coefficient of -0.12 on negative discount-rate news is significant. Still, this first relationship indicates a reduction in discount-rate news exposure. However, the regression specification does not account for varying amounts of leverage and the news direction.

[Table 10 about here.]

As a next step, we distinguish positive and negative news by running dummy regressions concerning the news direction to check if there are any asymmetries in the sensitivities to the news terms and their direction. Again, the outperformance of volatility management does not have any exposure to cash-flow news. The marginal exposure to discount-rate news mentioned above comes entirely from positive discount-rate shocks, while there is no clear relation to negative discount-rate shocks.

[Table 11 about here.]

In the appendix we show a clear indication of both time-varying cash-flow and discount-rate betas (see Figure 7 in the appendix).
Moreover, a volatility-managed strategy has, by definition, a time-varying exposure to the underlying factor. Figure 6 shows the amount of leverage for month $t+1$, which is influenced by the previous month's volatility, and cash-flow and discount-rate news for month $t+1$. Volatility management tends to avoid both, very positive and very negative movements in cash-flow and discount-rate news, by reducing the overall exposure.

[Figure 6 about here.]

[2] Our variance decompositions do not sum to 100 due to rounding and the fact that the news series come from a VAR that uses log-excess-returns with a different risk-free rate than the geometric CRSP-excess returns. However, the variance terms explain 97.91% and 99.48% of $\mathrm{Var}(f_t)$ and $\mathrm{Cov}(f_t^{\sigma}, f_t)$, respectively and the relative contributions are in line with previous findings for $\mathrm{Var}(f_t)$.

As shown by Campbell and Vuolteenaho (2004) and Celiker et al. (2016), news terms can be very erratic in a single period. Thus, in order to relate returns to cumulative shocks to cash flows or discount rates of relevant size, we aggregate both news terms over rolling windows of 1, 3, 6, 9, 12, and 24 months and continue to analyze the performance of the managed strategy depending on news-states, i.e. if cumulative news are positive or negative in the investigated months.

The subtables on the left of Table 12 report summary statistics of conditional returns depending on whether cumulative cash-flow or discount-rate news were positive in a certain month. They also show t-statistics for the outperformance fo (see (4)) versus H_0 that the returns are not different from zero. Independent of the cumulating period, we show that volatility-management is significantly outperforming an unmanaged portfolio in up-states. That is, there is strong statistical evidence for volatility-management to produce excess returns over an unmanaged benchmark in upstates (as measured by cash-flow and discount-rate news) that are significantly different from zero, as the t-values in the subtables of Table 12 show. The lowest t-value when either cumulative cash-flow or discount-rate news are positive, including the current month, is 1.9075 for cash-flow news and a cumulating period of 9 months. All other t-values are larger in "good" states, i.e. when either cash-flow or discount-rate news are up. The biggest annualized outperformance was found for a cumulating period of 6 months and a positive sum of negative discount-rates with an annual geometric outperformance of 4.93%. However we don't find a significant difference in returns in non-disjoint down-states. Despite the lack of significant outperformance in months when cash-flow or discount-rates are down, this is a remarkable feature, since it implies that a volatility-managed CRSP index is able to to do better than the underlying benchmark, when cash-flow or negative discount-rates are positive, i.e. the overall market is doing well over the past 1 to 24 months. At the same time the strategy is able to not perform significantly worse, when cash-flow and discount-rates are down over cumulating periods of 1 to 24 months. Hence, a volatility-managed market portfolio seems to be able to lever up the good times, while reducing risk when its appropriate and thereby performing not worse than its benchmark in bad times and better than the benchmark overall.

The subtables on the right side of Table 12 slice the strategy's returns in disjoint states, that is, either both, cumulative cash-flow and discount-rates are bigger than zero, both are smaller, or either one of them is up and the other is down and vice versa. We run the same t-tests as in the tables on the left side with cumulating periods of 1 to 24 months and find that our volatility-managed CRSP excess return index produces significant outperformance only in months in which both, cash-flow and discount-rate news, are up, producing t-values as high as 4.11 in case of a 3-month cumulating period. We do not find significant t-values for months when the market is down.

We can interpret the states in which both kinds of cumulative news are bigger than zero as periods in which the market has gained positive momentum and therefore had a positive cumulative return in that period. Whereas periods in which both cumulative news are smaller than zero represent states, in which the market has negative momentum and is down over that period. This finding links our results to Celiker et al. (2016) who find that the momentum effect is stronger following positive cash-flow news.

[Table 12 about here.]

4.2.1 The Best and Worst Periods for News and Outperformance

We continue to investigate the periods with the most extreme moves in our cumulative news time series and factor outperformance. Table 13 reports on the results.

When looking at cash-flow news, our volatility-managed portfolio outperformed in all of the 10 worst periods as Table 13a shows. In the period spanning the biggest 6 month cumulative cash-flow shock from September 2008 to February 2009 the unmanaged index returned -43%, while the volatility-managed strategy dropped only by 17.1%. The volatility-managed strategy underperformed in some of the best periods according to cumulative cash-flow news, especially in the best two of them. While the unmanaged index gained about 100%, the managed strategy returned only 21.96%. However, the volatility-managed strategy managed to partly avoid the severe drawdown before that period and never touched the lows reached by the unmanaged index before the underperformance from March 1933 to August 1933 (see Figure 2). Therefore, the strategy still outperformed the underlying index at that point in time, although it was not able to capture the strong recovery due to almost no leverage during that time (see Figure 1 due to high amounts of volatility).

As in the case of the worst cash-flow periods, a volatility-managed portfolio tends to perform better in periods with strongly negative minus discount-rate news, as table 13c shows. The biggest outperformance was generated from from December 1931 to May 1932. While the unmanaged index lost 48% on an excess-return basis, the managed strategy dropped only 21.4%. There are only two occasions with a minor underperformance in 1941 to 1942 and 1962, that are easily compensated by the reduction in drawdowns in the remaining periods. In the best periods according to minus discount-rate news the strategy's results are rather mixed. The best period from March 1933 to August 1933 covers the same recovery already mentioned above. The strategy also didn't benefit as much from the recovery after the global financial crisis from April 2009 to September 2009.

Tables 13e and 13f report on the worst and best months in terms of pure outperformance generated by volatility-management. The biggest underperformance is generated in periods of a recovery after severe and volatile drawdowns such as March 1933 to August 1933 or March 2009 to August 2009. The periods with the biggest outperformance of volatility-management contain both, times when the aggregate market was up and down. They don't contain any of the best periods for minus discount-rate news and overlap only one of the best periods for cash-flow news (October 1942 to March 1943). Therefore, we conclude that volatility-management tends to underperform in the very best periods after a recovery while it is able to partly avoid the most severe shocks to cash-flow and discount-rate news.

[Table 13 about here.]

4.3 Relation to Risk News

In a follow-up paper on their previous work Campbell et al. (2018) allow for heteroscedasticity in returns and, thus, introduce a third kind of news term (in addition to cash-flow and discount-rate news), namely risk or expected volatility news (N_V). More formally, in the model of Campbell et al. (2018) innovations to the stochastic discount factor (m_{t+1}) can be written in terms of the market return and innovations to future variables:

$$m_{t+1} - E_t m_{t+1} = -\gamma \left[r_{t+1} - E_t r_{t+1}\right] - (\gamma - 1) N_{DR,t+1} + \frac{1}{2} N_{V,t+1}$$

or equivalently, by splitting up the market return into cash-flow news and discount-rate news :

$$m_{t+1} - E_t m_{t+1} = -\gamma N_{CF,t+1} - \left[N_{DR,t+1}\right] + \frac{1}{2} N_{V,t+1}$$

where γ is the price of risk. Similar to the empirical VAR estimation of cash-flow news and discount-rate news, news about expected volatility can also be estimated in an extended VAR (for details we refer to section 3.1.3 of Campbell et al. (2018)).

Analogous to the analysis above, we investigate the relationship between risk news and volatility management by running regressions of the quarterly returns of the volatility-managed portfolio, the market return and the outperformance on all three news terms. We also investigate the strategy's returns in the quarters with the highest expected volatility news and run a regression of the outperformance on quarterly cash-flow, discount-rate and volatility news from 1929 to 2011. Finally we report t-statistics of the cumulative returns of the market, volatility-managed returns and the outperformance conditional on the state of the three news terms.

Table 14 reports on the regression results. The returns of a volatility-managed portfolio are positively associated with higher volatility news (the same holds true for the outperformance (fo), while the unmanaged portfolio (ft) has an insignificant beta of -0.15.

These results are not surprising, as the quarterly N_V time series is heavily influenced by the expected return variance on the market portfolio (see Campbell et al. (2018)). Since current volatility tends to forecast future volatility well, the resulting quarterly time series tends to correlate with the volatility measure used for scaling the unmanaged portfolio. In combination with the expected return versus risk tradeoff described by Moreira and Muir (2017), that is, the expected Sharpe ratio tends to be better after calmer months, we would expect to see a positive relationship between quarterly returns on both, the managed portfolio and the generated outperformance, and volatility news.

[Table 14 about here.]

Similar to our analysis above, we look at the quarterly performance with the highest value for volatility news. Table 15 shows that in most of these quarters the unmanaged portfolio (ft) generated negative returns and a volatility-managed portfolio performed better in all but 3 quarters from 1929 to 2011.

[Table 15 about here.]

Again, we investigate the average performance of the three strategies ft, ftm and fo depending on the news states. The cumulating periods are 1,2,3,4 and 8 quarters and always include the concurrent period. We find that volatility-management tends to statistically significantly outperform when we look at shorter cumulating periods of 1 to 2 quarters and volatility or discount-rate news (in case of a 2 quarter cumulating period) are up. Table 16 reports on the results. Volatility-management produces an average annualized geometric outperformance of 6% in the quarters that have positive volatility news. This number amounts to 4.1% when the sum of minus discount-rate news are positive in the previous and current quarter. We do not find statistically significant evidence for outperformance in the other states with cumulating periods of less than 8 quarters. If we look at longer cumulating periods then volatility-management outperforms with about 2.3% on an averaged annualized basis in the states when the sum of volatility news over the past 8 quarters is less than zero. This is consistent with the construction of volatility-managed portfolios, as they increase leverage in calmer periods.

In sum, we find a positive relation between the returns of our volatility-managed CRSP excess return portfolio and the new kind of volatility news introduced by Campbell et al. (2018). At the same time our other observations regarding the connection between cash-flow and discount-rate news and volatility-management remain intact.

[Table 16 about here.]

5 Conclusion

Timing regressions that account for non-linearities reveal that volatility management leads to a positive return asymmetry where positive returns are scaled up, except for very high returns occurring during reversals, while negative returns are scaled down. The most severe negative returns are especially scaled down, thereby increasing investor utility. We find that volatility management does not alter the overall risk profile with regards to the contribution of cash-flow risk, discount-rate risk and expected volatility risk. In line with the findings of the timing regressions, we find that good times are levered up, where good times are defined as cumulative periods in which both cash-flow news and discount-rate news are positive. During these positive momentum periods the strategy produces most of its alpha by outperforming between 2.8% to 7.7% in monthly returns, depending on the cumulating period. However, the performance of both managed and unmanaged factors is statistically indistinguishable in other news states. In almost all of the most severe cumulative shocks to cash-flow news, discount-rate news or expected volatility news, though, the volatility-managed portfolio outperformed the passive buy-and-hold portfolio.

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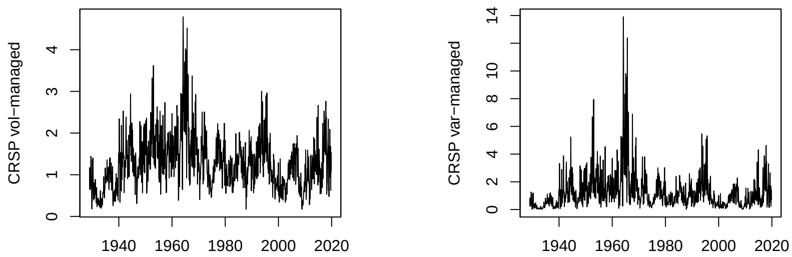

Figure 1: Leverage comparison for CRSP value-weighted excess returns managed by standard deviation (left) and variance (right) from 1929 to 2019.

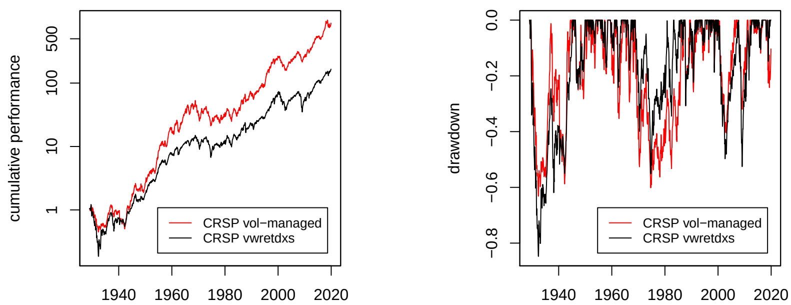

Figure 2: Cumulative performance and drawdowns for monthly CRSP value-weighted excess returns managed by standard deviation from 1929 to 2019.

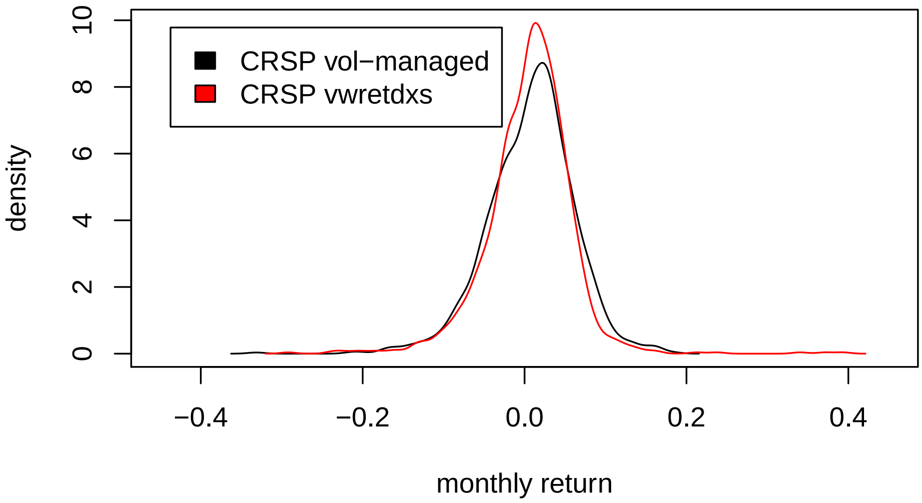

Figure 3: Density plot of monthly CRSP value-weighted excess returns managed by standard deviation and unmanaged returns from 1929 to 2019.

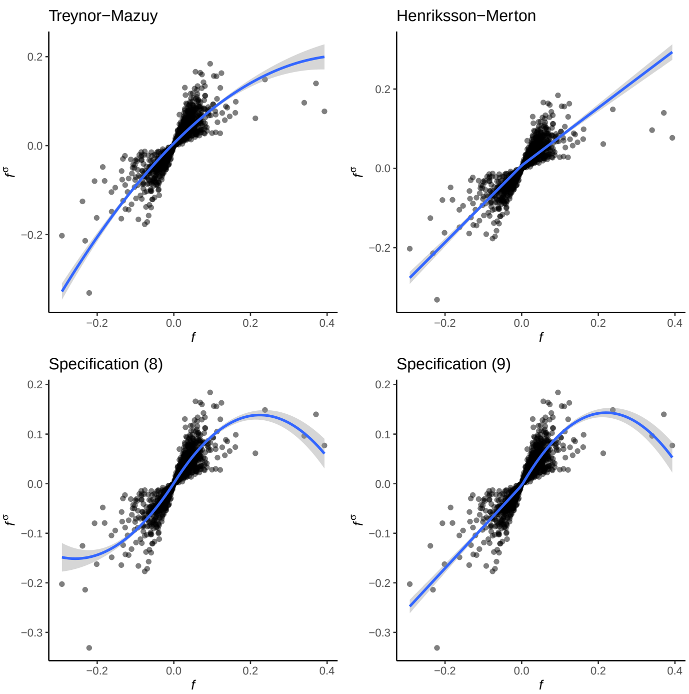

Figure 4: Regression plots of market timing regressions using monthly returns from 1929 to 2019. Unmanaged CRSP value-weighted excess returns are shown on the x-axis, while the y-axis shows managed excess returns.

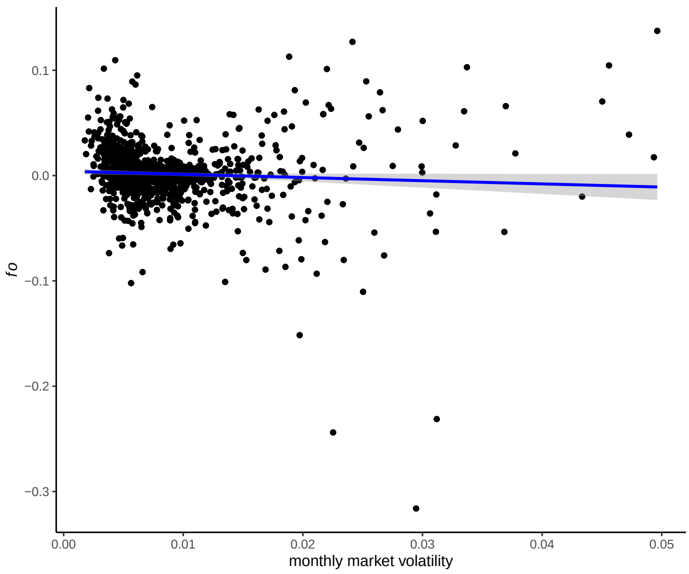

Figure 5: Factor outperformance versus volatility.

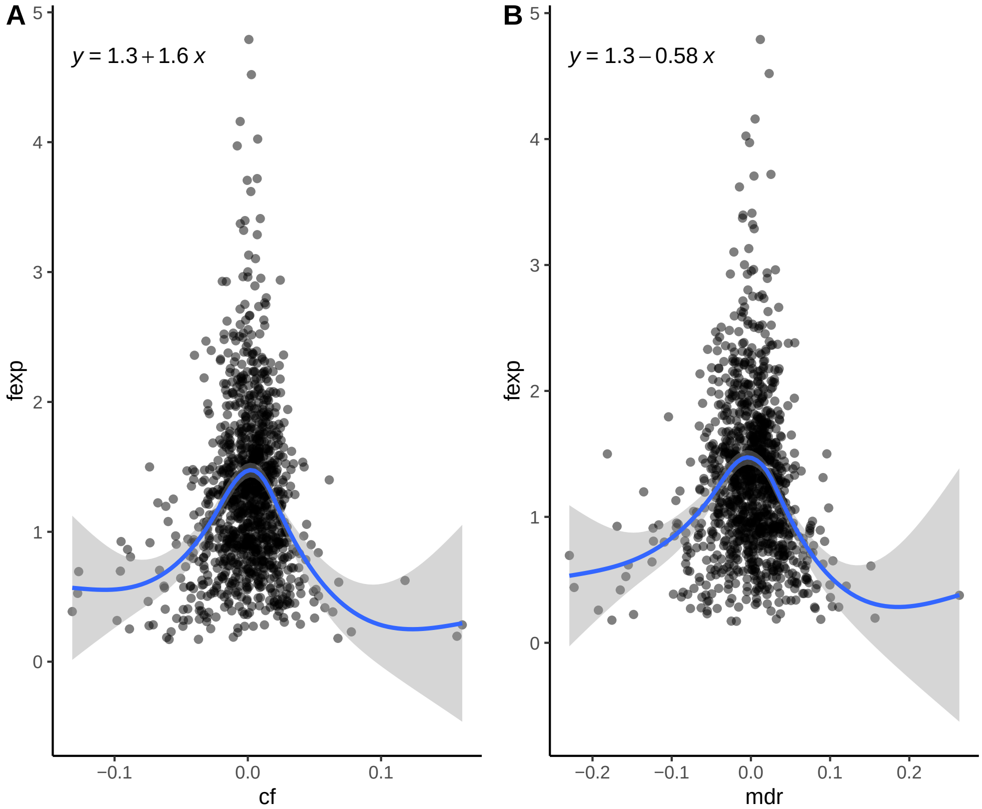

Figure 6: This figure shows the volatility-managed strategy's leverage (fexp for factor exposure) versus cash-flow and minus discount-rate news in the same month from 1929 to 2019.

	ftm	ft
Annualized Return	0.0774	0.0578
Annualized Std Dev	0.1855	0.1855
Annualized Sharpe Ratio	0.4171	0.3113
Observations	1092	1092
NAs	0	0
Minimum	-0.3313	-0.2920
Quartile 1	-0.0233	-0.0208
Median	0.0122	0.0099
Arithmetic Mean	0.0077	0.0061
Geometric Mean	0.0062	0.0047
Quartile 3	0.0397	0.0357
Maximum	0.1841	0.3931
SE Mean	0.0016	0.0016
LCL Mean (0.95)	0.0045	0.0029
UCL Mean (0.95)	0.0109	0.0093
Variance	0.0029	0.0029
Stdev	0.0536	0.0536
Skewness	-0.5405	0.1879
Kurtosis	2.2100	8.0384

Table 1: Performance statistics of the volatility-managed CRSP excess return index and the unmanaged CRSP index from 1929 to 2019.

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1929-09-01	1932-06-01	1944-06-01	-0.6316	178	34	144
2	1968-12-01	1974-09-01	1986-05-01	-0.6015	210	70	140
3	2000-01-01	2003-02-01	2006-04-01	-0.4045	76	38	38
4	1961-12-01	1962-10-01	1964-02-01	-0.3530	27	11	16
5	2007-06-01	2009-02-01	2011-01-01	-0.3199	44	21	23

(a) Volatility-managed portfolio

	From	Trough	To	Depth	Length	To Trough	Recovery
1	1929-09-01	1932-06-01	1945-04-01	-0.8476	188	34	154
2	1968-12-01	1974-09-01	1983-04-01	-0.5514	173	70	103
3	2007-11-01	2009-02-01	2012-09-01	-0.5255	59	16	43
4	2000-04-01	2002-09-01	2007-10-01	-0.4974	91	30	61
5	1987-09-01	1987-11-01	1991-08-01	-0.3076	48	3	45

(b) Unmanaged portfolio

Table 2: Comparison of the five biggest drawdowns per strategy from 1929 to 2019.

	ftm	Mkt.RF.mgd	SMB.mgd	HML.mgd
(Intercept)	3.02**	2.99**	−0.27	1.57*
	(1.01)	(1.01)	(0.57)	(0.66)
ft	0.84***			
	(0.05)			
Mkt.RF		0.85***		
		(0.05)		
SMB			0.85***	
			(0.08)	
HML				0.81***
				(0.07)
R^2	0.71	0.72	0.72	0.66
Adj. R^2	0.71	0.72	0.72	0.66
Num. obs.	1092	1092	1092	1092
RMSE	34.43	34.26	20.31	24.51

Note: robust standard errors.

Table 3: Alpha versus unmanaged portfolio 1929 to 2019, standard errors are in parantheses and adjust for heteroscedasticity. All factors are in percent per year by multiplying monthly returns by 12.

	ftm	Mkt.RF.mgd	SMB.mgd	HML.mgd	RMW.mgd	CMA.mgd
(Intercept)	1.53	1.44	0.02	1.06	1.53^{*}	0.17
	(0.95)	(0.94)	(0.58)	(0.63)	(0.60)	(0.41)
ft	0.89^{***}					
	(0.03)					
Mkt.RF		0.90^{***}				
		(0.03)				
SMB			0.91^{***}			
			(0.04)			
HML				0.87^{***}		
				(0.04)		
RMW					0.82^{***}	
					(0.08)	
CMA						0.88^{***}
						(0.04)
R^2	0.80	0.80	0.82	0.76	0.68	0.78
Adj. R^2	0.80	0.80	0.82	0.76	0.68	0.78
Num. obs.	677	677	677	677	677	677
RMSE	23.57	23.36	15.25	16.48	14.74	11.26

Note: robust standard errors.

Table 4: Alpha versus unmanaged portfolio 1963-08 to 2019, standard errors are in parantheses and adjust for heteroscedasticity. All factors are in percent per year by multiplying monthly returns by 12.

	ftm	Mkt.RF.mgd	SMB.mgd	HML.mgd
(Intercept)	3.43^{***}	3.55^{***}	-0.09	2.17^{**}
	(1.00)	(1.00)	(0.56)	(0.67)
Mkt.RF	0.87^{***}	0.87^{***}	-0.01	-0.10^{***}
	(0.04)	(0.04)	(0.01)	(0.02)
SMB	-0.00	-0.01	0.86^{***}	-0.01
	(0.05)	(0.05)	(0.08)	(0.05)
HML	-0.17^{**}	-0.17^{**}	-0.03	0.85^{***}
	(0.06)	(0.06)	(0.04)	(0.06)
R^2	0.73	0.73	0.72	0.68
Adj. R^2	0.73	0.73	0.72	0.68
Num. obs.	1092	1092	1092	1092
RMSE	33.56	33.59	20.28	23.73

Note: robust standard errors.

Table 5: Alpha versus Fama-French 3 factors 1929 to 2019, standard errors are in parantheses and adjust for heteroscedasticity. All factors are in percent per year by multiplying monthly returns by 12.

	ftm	Mkt.RF.mgd	SMB.mgd	HML.mgd	RMW.mgd	CMA.mgd
(Intercept)	0.38	0.47	−0.64	2.41***	2.26***	0.67
	(0.97)	(0.97)	(0.69)	(0.63)	(0.61)	(0.43)
Mkt.RF	0.91***	0.92***	0.02	−0.04**	0.00	0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
SMB	0.05	0.05	0.93***	−0.04	−0.02	−0.03*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
HML	−0.03	−0.02	0.02	0.91***	−0.14***	0.03
	(0.06)	(0.06)	(0.04)	(0.05)	(0.04)	(0.02)
RMW	0.15***	0.17***	0.12*	−0.26***	0.83***	−0.16***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)	(0.03)
CMA	0.09	0.08	0.00	−0.09	−0.07	0.85***
	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(0.04)
R^2	0.81	0.81	0.83	0.80	0.73	0.81
Adj. R^2	0.81	0.81	0.83	0.79	0.73	0.81
Num. obs.	677	677	677	677	677	677
RMSE	23.00	23.08	14.97	15.30	13.57	10.55

Note: robust standard errors.

Table 6: Alpha versus Fama-French 5 factors 1963-08 to 2019, standard errors are in parantheses and adjust for heteroscedasticity. All factors are in percent per year by multiplying monthly returns by 12.

	Treynor-Mazuy	Henriksson-Merton	Specification (8)	Specification (9)
(Intercept)	0.01^{***}	0.01^{**}	0.00	-0.00^{**}
	(0.00)	(0.00)	(0.00)	(0.00)
f_t	0.87^{***}	0.97^{***}		
	(0.04)	(0.07)		
f_t^2	-0.94^{**}			
	(0.31)			
$\max(0, f_t)$		-0.24	1.23^{***}	1.33^{***}
		(0.15)	(0.05)	(0.06)
$\min(0, f_t)$			1.18^{***}	0.84^{***}
			(0.09)	(0.06)
$-\min(0, f_t)^2$			-2.30^{**}	
			(0.74)	
$\max(0, f_t)^2$			-2.73^{***}	-3.02^{***}
			(0.23)	(0.25)
R^2	0.74	0.72	0.80	0.79
Adj. R^2	0.74	0.72	0.80	0.79
Num. obs.	1092	1092	1092	1092
RMSE	0.03	0.03	0.02	0.02

Note: robust standard errors.

Table 7: Timing regressions models for CRSP value-weighted returns from 1929 to 2019, standard errors are in parantheses and adjust for heteroscedasticity.

	ft	ftm	fo
(Intercept)	0.03^{***}	0.03^{***}	0.00
	(0.00)	(0.00)	(0.00)
crsp.vol	-2.39^{***}	-2.69^{***}	-0.30
	(0.57)	(0.37)	(0.38)
R^2	0.07	0.09	0.00
Adj. R^2	0.07	0.09	0.00
Num. obs.	1092	1092	1092
RMSE	0.05	0.05	0.03

Note: robust standard errors.

Table 8: Regression of CRSP value-weighted excess returns, vol-managed returns and the outperformance of the vol-managed strategy on monthly volatility of the underlying factor from 1929 to 2019, standard errors are in parantheses and adjust for heteroscedasticity.

	Var(ft)	Cov(ft, mdr)	Cov(ft, cf)	share mdr	share cf
Var(ft)	0.002869	0.001924	0.000885	0.670750	0.308415

(a) Variance decomposition

	Cov(ftm, ft)	Cov(ftm, mdr)	Cov(ftm, cf)	share mdr	share cf
Cov(ftm, ft)	0.002423	0.001666	0.000745	0.687414	0.307485

(b) Covariance decomposition

Table 9: These tables show the decomposition of the variance of the unmanaged index (panel (a)) and the covariance of the managed index with the unmanaged index (panel (b)) into covariances with minus discount-rate and cash-flow news. Both time series are mostly driven by discount-rate news.

	ft	ftm	fo
cf	1.00^{***}	0.82^{***}	-0.18
	(0.04)	(0.08)	(0.10)
mdr	0.99^{***}	0.87^{***}	-0.12^{*}
	(0.02)	(0.04)	(0.05)
R^2	0.96	0.70	0.06
Adj. R^2	0.96	0.70	0.06
Num. obs.	1092	1092	1092
RMSE	0.01	0.03	0.03

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Note: robust standard errors.

Table 10: Regression of CRSP value-weighted excess returns, vol-managed CRSP value-weighted excess returns and the outperformance over the unmanaged factor from 1929 to 2019 on cash-flow and minus discount-rate news. Standard errors are in parantheses and adjust for heteroscedasticity.

	ft	ftm	fo
(Intercept)	0.00^{*}	0.01^{***}	0.01^{*}
	(0.00)	(0.00)	(0.00)
pmax(cf, 0)	1.10^{***}	0.76^{***}	-0.34
	(0.07)	(0.21)	(0.26)
pmin(cf, 0)	0.92^{***}	0.86^{***}	-0.06
	(0.03)	(0.13)	(0.12)
pmax(mdr, 0)	1.09^{***}	0.79^{***}	-0.30^{*}
	(0.05)	(0.08)	(0.12)
pmin(mdr, 0)	0.92^{***}	0.92^{***}	0.00
	(0.02)	(0.08)	(0.09)
R^2	0.98	0.72	0.10
Adj. R^2	0.98	0.72	0.09
Num. obs.	1092	1092	1092
RMSE	0.01	0.03	0.03

Note: robust standard errors.

Table 11: Regressions of unmanaged and managed factor as well as the factor outperformance based on CRSP value weighted excess returns from 1929 to 2019, standard errors are in parantheses and adjust for heteroscedasticity.

	nObs	ft	ftm	fo	fo_t_stat
rCFup	597	0.3873	0.4537	0.0409	2.9831
rCFdo	495	-0.2374	-0.2493	-0.0191	-1.0333
rmDRup	590	0.5434	0.6232	0.0450	3.2178
rmDRdo	502	-0.3215	-0.3345	-0.0228	-1.2907
rUnconditional	1092	0.0578	0.0774	0.0133	1.7326

(a) 1 month

	nObs	ft	ftm	fo	fo_t_stat
rBothUp	376	0.7704	0.8964	0.0612	2.9145
rBothDo	281	-0.4644	-0.4861	-0.0458	-1.6901
rCFupmDRdo	221	-0.0837	-0.0753	0.0074	0.6974
rCFdomDRup	214	0.2128	0.2349	0.0171	1.5320
rUnconditional	1092	0.0578	0.0774	0.0133	1.7326

(b) 1 month

	nObs	ft	ftm	fo	fo_t_stat
rCFup	607	0.2959	0.3513	0.0388	2.9852
rCFdo	483	-0.1812	-0.1898	-0.0175	-0.7913
rmDRup	609	0.3392	0.4093	0.0490	3.7620
rmDRdo	481	-0.2161	-0.2335	-0.0297	-1.4725
rUnconditional	1090	0.0573	0.0772	0.0135	1.7514

(c) 3 months

	nObs	ft	ftm	fo	fo_t_stat
rBothUp	455	0.4076	0.5081	0.0675	4.1126
rBothDo	329	-0.3032	-0.3134	-0.0238	-0.8635
rCFupmDRdo	152	0.0117	-0.0271	-0.0424	-1.4355
rCFdomDRup	154	0.1560	0.1538	-0.0037	-0.0325
rUnconditional	1090	0.0573	0.0772	0.0135	1.7514

(d) 3 months

	nObs	ft	ftm	fo	fo_t_stat
rCFup	610	0.2181	0.2537	0.0256	2.1070
rCFdo	477	-0.1160	-0.1110	-0.0018	0.1986
rmDRup	588	0.2703	0.3354	0.0493	3.8465
rmDRdo	499	-0.1466	-0.1621	-0.0270	-1.2328
rUnconditional	1087	0.0583	0.0782	0.0135	1.7511

(e) 6 months

	nObs	ft	ftm	fo	fo_t_stat
rBothUp	456	0.2891	0.3665	0.0577	3.7803
rBothDo	345	-0.2154	-0.2156	-0.0103	-0.2458
rCFupmDRdo	154	0.0301	-0.0284	-0.0636	-1.7143
rCFdomDRup	132	0.2074	0.2332	0.0208	0.9648
rUnconditional	1087	0.0583	0.0782	0.0135	1.7511

(f) 6 months

	nObs	ft	ftm	fo	fo_t_stat
rCFup	616	0.1695	0.1967	0.0219	1.9075
rCFdo	468	-0.0769	-0.0652	0.0021	0.4590
rmDRup	609	0.2145	0.2656	0.0409	3.5556
rmDRdo	475	-0.1175	-0.1268	-0.0209	-0.7198
rUnconditional	1084	0.0559	0.0756	0.0133	1.7312

(g) 9 months

	nObs	ft	ftm	fo	fo_t_stat
rBothUp	471	0.2270	0.2864	0.0475	3.4281
rBothDo	330	-0.1649	-0.1570	-0.0047	0.0986
rCFupmDRdo	145	0.0007	-0.0538	-0.0567	-1.3684
rCFdomDRup	138	0.1730	0.1969	0.0186	1.0106
rUnconditional	1084	0.0559	0.0756	0.0133	1.7312

(h) 9 months

	nObs	ft	ftm	fo	fo_t_stat
rCFup	607	0.1638	0.1919	0.0250	2.1914
rCFdo	474	-0.0575	-0.0505	-0.0051	0.0769
rmDRup	608	0.1877	0.2198	0.0264	2.3668
rmDRdo	473	-0.0822	-0.0788	-0.0068	0.0064
rUnconditional	1081	0.0610	0.0788	0.0117	1.5852

(i) 12 months

	nObs	ft	ftm	fo	fo_t_stat
rBothUp	461	0.2092	0.2440	0.0283	2.0935
rBothDo	327	-0.1288	-0.1278	-0.0162	-0.3350
rCFupmDRdo	146	0.0313	0.0412	0.0146	0.7185
rCFdomDRup	147	0.1227	0.1468	0.0202	1.1388
rUnconditional	1081	0.0610	0.0788	0.0117	1.5852

(j) 12 months

	nObs	ft	ftm	fo	fo_t_stat
rCFup	570	0.1127	0.1449	0.0330	3.0347
rCFdo	499	0.0128	0.0144	-0.0132	-0.2638
rmDRup	591	0.1097	0.1293	0.0214	2.1413
rmDRdo	478	0.0121	0.0262	-0.0013	0.3623
rUnconditional	1069	0.0649	0.0820	0.0112	1.5252

(k) 24 months

	nObs	ft	ftm	fo	fo_t_stat
rBothUp	412	0.1229	0.1522	0.0288	2.3482
rBothDo	320	-0.0228	-0.0198	-0.0229	-0.4465
rCFupmDRdo	158	0.0867	0.1262	0.0439	1.9364
rCFdomDRup	179	0.0797	0.0785	0.0044	0.3665
rUnconditional	1069	0.0649	0.0820	0.0112	1.5252

(l) 24 months

Table 12: Average annualized geometric returns depending on news-states. The tables on the left distinguish between positive and negative cash-flow and discount-rate news, i.e. cash-flow and discount-rates are only pairwise disjoint (up or down). The tables on the right are disjoint, i.e. the sum of the observations equals the overall amount of months since start. The news are cumulated from 3 to 24 months up to and including the month that is observed for tables 12c to 12l. The rightmost column shows t-values for H_0: there is no difference between the managed and unmanaged strategy.

start	end	ft6m	ftm6m	fo6m	CF6m	mDR6m
Sep 2008	Feb 2009	-0.4305	-0.1718	0.2587	-0.2121	-0.3504
Oct 1937	Mar 1938	-0.3550	-0.1572	0.1979	-0.1866	-0.2612
Apr 1931	Sep 1931	-0.4129	-0.2774	0.1355	-0.1831	-0.3710
Dec 1931	May 1932	-0.4807	-0.2143	0.2664	-0.1740	-0.5062
Mar 1974	Aug 1974	-0.2911	-0.2426	0.0485	-0.1683	-0.1736
Oct 1932	Mar 1933	-0.2462	-0.1071	0.1391	-0.1510	-0.2012
Apr 1930	Sep 1930	-0.2673	-0.2102	0.0571	-0.1496	-0.1562
Jan 1970	Jun 1970	-0.2528	-0.2433	0.0095	-0.1491	-0.1338
May 1929	Oct 1929	-0.1260	-0.0529	0.0731	-0.1345	0.0243
Jun 1987	Nov 1987	-0.2279	-0.1208	0.1071	-0.1247	-0.1529

(a) 10 worst periods according to cash-flow news

start	end	ft6m	ftm6m	fo6m	CF6m	mDR6m
Mar 1933	Aug 1933	1.0026	0.2196	-0.7829	0.1499	0.4178
Apr 1938	Sep 1938	0.4342	0.2375	-0.1967	0.1341	0.1695
Jul 1950	Dec 1950	0.2106	0.2165	0.0060	0.1304	0.0077
Oct 1999	Mar 2000	0.2161	0.1450	-0.0711	0.1209	0.1023
Dec 1942	May 1943	0.3508	0.5751	0.2244	0.1128	0.1185
Jun 1949	Nov 1949	0.1730	0.2518	0.0788	0.1008	-0.0016
Mar 2009	Aug 2009	0.4311	0.1712	-0.2599	0.0954	0.1862
Sep 1998	Feb 1999	0.2624	0.1446	-0.1178	0.0879	0.1702
Apr 1997	Sep 1997	0.2495	0.2363	-0.0132	0.0849	0.1356
Nov 1954	Apr 1955	0.2321	0.3574	0.1253	0.0810	0.0703

(b) 10 best periods according to cash-flow news

start	end	ft6m	ftm6m	fo6m	CF6m	mDR6m
Dec 1931	May 1932	-0.4807	-0.2143	0.2664	-0.1740	-0.5062
Jun 2008	Nov 2008	-0.3861	-0.2056	0.1804	-0.1170	-0.3591
Sep 1932	Feb 1933	-0.2912	-0.1253	0.1659	-0.1186	-0.3430
Apr 1974	Sep 1974	-0.3559	-0.2797	0.0763	-0.1490	-0.2760
Aug 1937	Jan 1938	-0.3429	-0.2564	0.0864	-0.1425	-0.2744
May 1930	Oct 1930	-0.3159	-0.2420	0.0739	-0.1067	-0.2501
Apr 2002	Sep 2002	-0.2776	-0.1850	0.0926	-0.0837	-0.2327
Oct 1941	Mar 1942	-0.1858	-0.2556	-0.0698	-0.0333	-0.2072
Jan 1962	Jun 1962	-0.2412	-0.3305	-0.0893	-0.0782	-0.1979
Sep 1987	Feb 1988	-0.1943	-0.1834	0.0109	-0.0530	-0.1890

(c) 10 worst periods according to minus discount-rate news

start	end	ft6m	ftm6m	fo6m	CF6m	mDR6m
Mar 1933	Aug 1933	1.0026	0.2196	-0.7829	0.1499	0.4178
Apr 1935	Sep 1935	0.3497	0.3172	-0.0325	0.0077	0.2102
Nov 1998	Apr 1999	0.2022	0.1467	-0.0555	0.0069	0.1941
Apr 2009	Sep 2009	0.3765	0.1727	-0.2038	0.0382	0.1930
Jan 1975	Jun 1975	0.4089	0.3110	-0.0979	0.0724	0.1863
Mar 1929	Aug 1929	0.1592	0.1832	0.0240	-0.0162	0.1852
Jun 1938	Nov 1938	0.3804	0.1939	-0.1865	0.0658	0.1795
May 1936	Oct 1936	0.2564	0.2946	0.0382	0.0354	0.1550
Oct 1986	Mar 1987	0.2235	0.2584	0.0349	0.0014	0.1509
Aug 1945	Jan 1946	0.3117	0.3629	0.0512	0.0777	0.1484

(d) 10 best periods according to minus discount-rate news

start	end	ft6m	ftm6m	fo6m	CF6m	mDR6m
Mar 1933	Aug 1933	1.0026	0.2196	-0.7829	0.1499	0.4178
Mar 2009	Aug 2009	0.4311	0.1712	-0.2599	0.0954	0.1862
Apr 1938	Sep 1938	0.4342	0.2375	-0.1967	0.1341	0.1695
May 1940	Oct 1940	-0.0740	-0.2456	-0.1716	-0.0340	-0.0702
Dec 1961	May 1962	-0.1720	-0.3098	-0.1378	-0.0716	-0.1291
Sep 2018	Feb 2019	-0.0454	-0.1750	-0.1296	0.0043	-0.0263
Oct 1974	Mar 1975	0.3132	0.1874	-0.1258	0.0657	0.1408
Nov 1933	Apr 1934	0.2120	0.0877	-0.1243	0.0153	0.1047
Jul 1948	Dec 1948	-0.0837	-0.2075	-0.1238	-0.0095	-0.1017
Sep 1998	Feb 1999	0.2624	0.1446	-0.1178	0.0879	0.1702

(e) 10 worst periods according to outperformance versus an unmanaged portfolio

start	end	ft6m	ftm6m	fo6m	CF6m	mDR6m
Oct 1942	Mar 1943	0.3577	0.7298	0.3722	0.1076	0.1236
Dec 1931	May 1932	-0.4807	-0.2143	0.2664	-0.1740	-0.5062
Jan 1954	Jun 1954	0.2044	0.4701	0.2657	0.0694	0.0490
Sep 2008	Feb 2009	-0.4305	-0.1718	0.2587	-0.2121	-0.3504
Feb 1995	Jul 1995	0.1825	0.4116	0.2291	0.0387	0.1092
Aug 1965	Jan 1966	0.1047	0.3301	0.2255	0.0256	0.0669
Jan 1964	Jun 1964	0.0832	0.2832	0.2001	0.0173	0.0500
Oct 1937	Mar 1938	-0.3550	-0.1572	0.1979	-0.1866	-0.2612
Nov 1960	Apr 1961	0.2454	0.4415	0.1961	0.0423	0.1235
Jan 1944	Jun 1944	0.1416	0.3367	0.1951	0.0560	0.0310

(f) 10 best periods according to outperformance versus an unmanaged portfolio

Table 13: These tables show the cumulative performance of an unmanaged (ft6m) and a volatility-managed (ftm6m) portfolio and the outperformance generated by volatility-management (fo6m) over disjoint 6-month periods, their start and end date as well as the cumulated cash-flow and minus discount-rate news over that period.

	ft	ftm	fo
(Intercept)	0.02^{***}	0.02^{***}	0.00
	(0.00)	(0.00)	(0.00)
mNr	1.05^{***}	0.78^{***}	-0.27^{*}
	(0.07)	(0.06)	(0.11)
Ncf	0.99^{***}	0.87^{***}	-0.13
	(0.07)	(0.08)	(0.11)
Nv	-0.15	0.61^{***}	0.76^{***}
	(0.11)	(0.13)	(0.16)
R^2	0.91	0.70	0.22
Adj. R^2	0.91	0.69	0.21
Num. obs.	332	332	332
RMSE	0.03	0.06	0.06

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Note: robust standard errors.

Table 14: Regression of quarterly CRSP value-weighted excess returns, vol-managed CRSP value-weighted excess returns and the outperformance over the unmanaged factor from 1929 Q1 to 2011 Q4 on cash-flow, minus discount-rate and volatility news as in "An Intertemporal CAPM with Stochastic Volatility". Data was provided by Christopher Polk. Standard errors are in parantheses and adjust for heteroscedasticity.

	ft	ftm	fo	Ncf	mNr	Nv
2008 Q4	-0.2381	-0.0580	0.1801	0.0320	-0.2812	0.1855
1931 Q4	-0.1507	-0.0517	0.0990	0.0434	-0.2009	0.1182
1933 Q3	-0.0946	-0.0461	0.0486	-0.1407	-0.0597	0.0741
1932 Q4	-0.1466	-0.0310	0.1156	0.0301	-0.2447	0.0630
1974 Q4	0.0690	0.0270	-0.0419	0.0136	0.0159	0.0563
1932 Q2	-0.3529	-0.1541	0.1988	0.0647	-0.5260	0.0554
1931 Q2	-0.1136	-0.0751	0.0385	0.1258	-0.2284	0.0501
1998 Q4	0.2015	0.1188	-0.0827	0.0233	0.1868	0.0479
2010 Q2	-0.1086	-0.0593	0.0493	-0.1044	-0.0427	0.0466
2003 Q2	0.1670	0.1099	-0.0571	-0.0190	0.1584	0.0460

Table 15: Average annualized performance of quarterly returns. The table shows the top 10 quarters with the highest value for Nv, i.e. volatility news and the corresponding performance for the unmanaged and managed strategy as well as the outperformance generated by volatility management.

	nObs	ft	ftm	fo	fo_t_stat
rCFup	182	0.1862	0.2256	0.0038	1.0327
rCFdo	150	-0.0917	-0.0894	0.0003	0.2500
rmDRup	184	0.3288	0.3726	0.0089	1.2442
rmDRdo	148	-0.2141	-0.2122	-0.0061	-0.1109
rNVup	151	0.1040	0.1836	0.0623	3.9222
rNVdo	181	0.0095	-0.0136	-0.0454	-1.0987
rUnconditional	332	0.0515	0.0716	0.0022	1.0536

(a) 1 quarter

	nObs	ft	ftm	fo	fo_t_stat
rCFup	177	0.1721	0.2037	-0.0002	0.8687
rCFdo	154	-0.0725	-0.0624	0.0054	0.6496
rmDRup	169	0.2550	0.3268	0.0418	2.6369
rmDRdo	162	-0.1263	-0.1424	-0.0372	-1.3095
rNVup	144	0.1058	0.1716	0.0303	1.9121
rNVdo	187	0.0110	0.0005	-0.0186	-0.5232
rUnconditional	331	0.0512	0.0716	0.0024	1.0654

(b) 2 quarters

	nObs	ft	ftm	fo	fo_t_stat
rCFup	186	0.1684	0.2047	0.0054	1.1010
rCFdo	144	-0.0836	-0.0786	-0.0007	0.2402
rmDRup	179	0.1892	0.2234	0.0147	1.4697
rmDRdo	151	-0.0924	-0.0840	-0.0112	0.0472
rNVup	149	0.0828	0.1352	0.0173	1.4113
rNVdo	181	0.0252	0.0222	-0.0090	-0.0148
rUnconditional	330	0.0508	0.0717	0.0028	1.0893

(c) 3 quarters

	nObs	ft	ftm	fo	fo_t_stat
rCFup	176	0.1428	0.1493	-0.0184	0.1215
rCFdo	153	-0.0471	-0.0138	0.0261	1.8958
rmDRup	170	0.1794	0.2142	0.0147	1.4411
rmDRdo	159	-0.0724	-0.0646	-0.0114	0.0259
rNVup	141	0.1215	0.1511	-0.0170	0.3208
rNVdo	188	-0.0003	0.0135	0.0165	1.5612
rUnconditional	329	0.0502	0.0704	0.0020	1.0408

(d) 4 quarters

	nObs	ft	ftm	fo	fo_t_stat
rCFup	173	0.1170	0.1304	-0.0116	0.3911
rCFdo	152	-0.0065	0.0157	0.0139	1.1228
rmDRup	170	0.0837	0.1002	0.0184	1.6784
rmDRdo	155	0.0294	0.0486	-0.0193	0.2005
rNVup	122	0.0530	0.0708	-0.0366	-0.2165
rNVdo	203	0.0601	0.0780	0.0230	2.0519
rUnconditional	325	0.0574	0.0753	0.0002	0.9205

(e) 8 quarters

Table 16: Average annualized geometric returns depending on news-states. The tables distinguish between positive and negative cash-flow, discount-rate and volatility news, i.e. the news are only pairwise disjoint (up or down). The news are cumulated from 1 to 8 quarters up to and including the observation month. The rightmost column shows t-values for H0: there is no difference between the managed and unmanaged strategy.

Appendix

In order to preserve space in the main text we delineate additional Tables and results in this appendix.
The following Table 17 contains summary statistics on the VAR state variables that we used to impute discount-rate and cash-flow news.

[Table 17 about here.]

We show a clear indication of both time-varying cash-flow and discount-rate betas of the volatility-managed market factor (see Figure 7) by plotting coefficients from the following regression over the past 60-month rolling window, with at least 24-month observations available:

$$f_t^{\sigma} = \alpha_t + \beta_{1,t} N_{cf,t} + \beta_{2,t} N_{mdr,t} \tag{20}$$

Figure 7 plots the intercept and rolling betas to news of the volatility-managed portfolio:

[Figure 7 about here.]

As we found in the main body of our paper that volatility management levers up good times without significantly increasing risk exposures or underperformance in bad states, this return convexity reminds us of option-like strategies. Thus, we compare the performance of the volatility-managed market factor to portfolios combining the unmanaged market factor (90%) and one-month ATM call options (10%). As shown in Figure 8 a combined strategy involving the unmanaged market and call options substantially underperforms over time. If one times the use of call options (if one adds options to the unmanaged market only if implied volatility is historically cheap) the resulting performance looks more like the volatility-managed market factor. However, regressions of the volatility-managed market factor on the unmanaged market factor and a rolling call option strategy show that the success of volatility-managed portfolios is unrelated to the call option performance (see Table 18).

[Figure 8 about here.]

[Table 18 about here.]

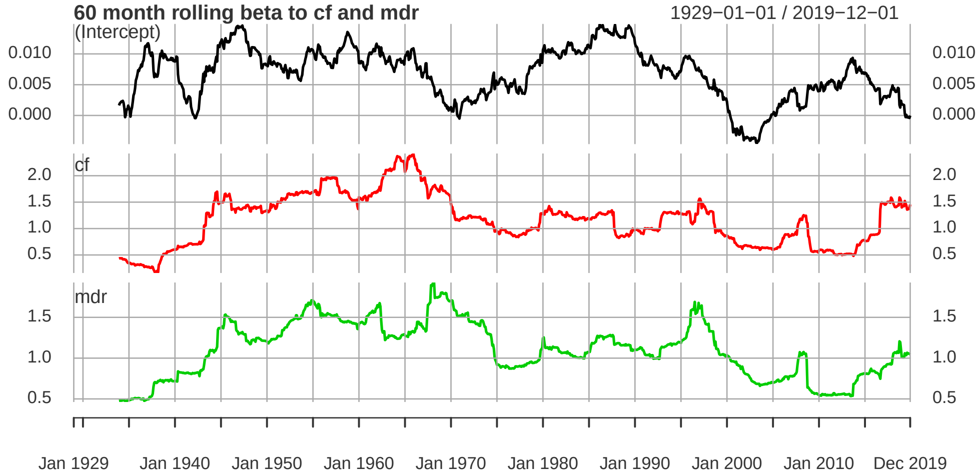

Figure 7: This figure shows the volatility-managed strategy's 60-month rolling beta to cash-flow and discount-rate news from December 1933 to December 2019.

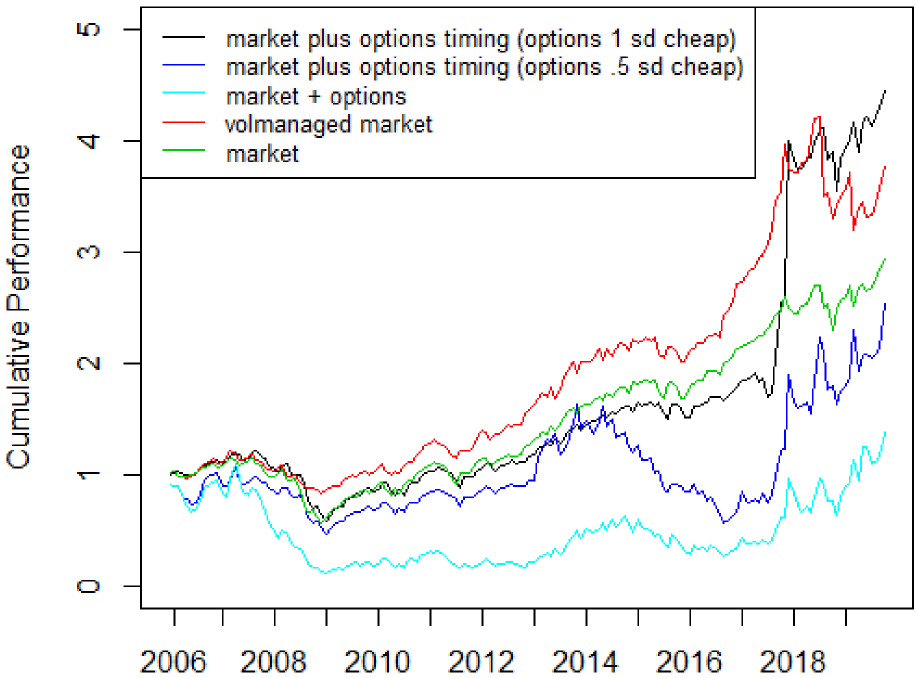

Figure 8: This figure shows the performance of the volatility-managed market factor and combinations of the unmanaged market factor and rolling call option strategies.

	n	mean	median	sd	min	max	autocorr
R_e_log	1093	0.00464	0.00976	0.05363	-0.34656	0.33198	0.10278
TY	1093	1.52317	1.52000	1.09895	-1.91000	4.39000	0.95012
PE	1093	2.96085	2.97304	0.38241	1.49469	3.89780	0.99226
VS	1093	1.68918	1.58952	0.35787	1.14704	3.09035	0.97274
DEF	1093	1.12614	0.90000	0.69324	0.32000	5.64000	0.97421

Table 17: Summary statistics of VAR state variables from December 1928 to 2019.

Vol-Managed Portfolio	Coef	t-stat
Intercept	0.0032	1.883
Market	0.7698	19.436
Call Options	-0.0076	-0.652
R-Squared	0.6949	

Table 18: Regression of volatility-managed returns on the unmanaged market factor and a rolling one-month ATM call option strategy