Discounting Timing Strategies

Toomas Laarits*

First version: January 28, 2021
This version: February 13, 2025

Abstract

Prior work has documented a number of timing strategies that obtain superior Sharpe ratios and alphas relative to underlying buy-and-hold portfolios. I establish a novel fact: the risk-return tradeoff of such strategies deteriorates substantially as the investment horizon lengthens, providing a rationale for the seemingly good returns. The documented effect is large: multifactor alphas are more than halved going from a one-month to a 10-year horizon, emphasizing the importance of establishing portfolio performance at different horizons. I show that such return dynamics arise in an equilibrium model with seasonalities in the volatility of price of risk and expected cash-flow shocks and present a connection with the pricing of dividend strips.

*NYU Stern School of Business, 44 West 4th St., New York, NY 10012 E-mail: tlaarits@stern.nyu.edu.
I thank Alexi Savov, Yakov Amihud, Jennifer Carpenter, Hongye Guo, Ben Matthies (discussant), Robert Whitelaw, Stefanos Delikouras (discussant), Hank Bessembinder, Jonathan Lewellen, Juhani Linnainmaa, Andrei Gonçalves, Paul Karehnke and the seminar audiences at NYU Stern, the Midwest Finance Association Meeting, TalTech, the FMA Conference, Dartmouth Tuck, and the 3rd Annual Valuation Conference for valuable feedback, and Valerie Baldinger, Cody Wan, Steven Zheng, and Myeongrok Doh for outstanding research assistance.

Both the academic and practitioner literatures have documented a number of seemingly attractive timing strategies. An investor can obtain high Sharpe ratios and alphas by timing the aggregate market, factor portfolios, or individual stocks based on simple calendar- or indicator-based rules. To give an example, consider the "dividend month premium" return seasonality, constructed following Hartzmark and Solomon (2013). A portfolio taking a long position in stocks that are expected to make a dividend payment in the coming month, and a short position in stocks not expected to make a payment (based on prior dividend payment dates) would have seen a 3.4% annualized excess return and 5.7% annualized volatility in the 1927-2023 sample. These return numbers work out to an substantial Sharpe ratio of .6; furthermore the returns of the strategy are negatively correlated with the market and the CAPM alpha is 4.6% per year. It would appear, then, that an investor currently invested in the market would find it appealing to add a dividend timing component to their portfolio: the mean variance efficient (MVE) portfolio of the market return and dividend month premium return is 82% invested in the timing strategy.[1]

The results in this paper demonstrate that for a long horizon investor such a tilt toward the timing strategy is not as beneficial as it might first appear. The reason is that the timing strategy returns exhibit substantial positive autocorrelation and the longer horizon risk-return tradeoff is quite a bit poorer than the single-period data suggest. In the case of the dividend month premium, the 10-year Sharpe ratio is .4, lower than the market portfolio in the corresponding holding period. As a result, the mean-variance efficient portfolio at the 10-year horizon has less than half invested in the timing strategy.

A like phenomenon of risk-return deterioration at longer investment horizons occurs across a number of other timing strategies. I replicate and extend out of sample work that has demonstrated high Sharpe ratios and multifactor alphas from moving in and out of individual stocks, industry portfolios, or factor portfolios based on the respective historical returns in a given month (Heston and Sadka (2008), Keloharju et al. (2016)); from holding stocks in the month they are predicted to make quarterly announcements (Savor and Wilson (2016)); from holding the market in anticipation of scheduled FOMC announcements, or BLS announcements (Lucca and Moench (2015), Savor and Wilson (2013)); from weighting an investment in factor portfolios based on realized variance (Moreira and Muir (2017)); from moving in and out of anomaly portfolios based on day of the week (Birru (2018)); from holding the market in specific calendar year periods such as January (Doran et al. (2012)), November to May (Ilmanen (2011), Chapter 25).

As the main empirical result, I document that nearly all such strategies display a risk return

[1]Mean variance efficient portfolio weight calculation carried out using the Ledoit and Wolf (2017) covariance matrix.

trade-off that is considerably poorer at longer investment horizons. Their returns tend to exhibit positive autocorrelations, which means the per unit time variance increases with the length of the holding period. In other words, the variance ratio (VR) of such strategies—the ratio of per period multiperiod variance over single period variance—is above one, in many cases reaching values well in excess of three at the five-year horizon. Consequently, the long-horizon Sharpe ratios are typically well below the single-period counterparts. Factor exposures at longer holding periods are likewise affected, and long horizon alphas are substantially below the single-period counterparts. Quantitatively, the reduction in alphas as a function of investment horizon is substantial. While the average Fama-French 4-factor alpha across the set replicated strategies is 5.6%, it drops to 2.4% at the 10-year horizon, all the while with returns being more volatile. Similarly, the average Sharpe ratio at the ten-year horizon is worse than the market portfolio's. A long-term investor looking to maximize utility from terminal wealth at the ten-year horizon would therefore find such market timing strategies less appealing than might appear from conventional statistics regarding monthly holding period risk and return.[2] I obtain all the above results using long-horizon returns that are constructed by cumulating monthly rebalanced strategy returns, meaning the effects stem entirely from the dynamics of the underlying return series, and not from stale portfolio weights.

As the main theoretical result, I provide a no-arbitrage representative investor framework that establishes an economic rationale to such market timing strategies. The key idea is that various fundamental shocks induce either reversion or continuation in asset returns. Namely, stock returns are driven by three important innovations: shocks to realized dividend growth, shocks to expected dividend growth, and shocks to market-wide compensation for risk. I demonstrate that any seasonality in the relative volatility in these underlying state variables induces a profitable market timing strategy akin to those documented in the data. The timing strategy in the model is particularly motivated by the seasonalities induced by corporate events, such as the dividend month premium mentioned above. In the model, an investor taking exposure to the aggregate market only in periods where expected dividend growth news have a high volatility ("Cash Flow quarter strategy") sees high returns and positive alphas with respect to a buy-and-hold market portfolio. Such high returns, however, come part and parcel with positive return autocorrelations and hence the timing strategy offers

[2]In practice, most long-term investors are not just maximizing utility over terminal wealth, but over intermediate consumption as well. Conceptualizing the long-horizon portfolio problem as a mean-variance problem over asset returns at the target horizon (including returns of various managed portfolios), however, establishes a useful benchmark as it isolates the optimal portfolio for any given horizon. Such an approach has been used widely in the literature, for instance, see Campbell and Viceira (2005), Brandt and Santa-Clara (2006), Jurek and Viceira (2011).

a much poorer long term risk-return tradeoff. In the baseline calibration, the Cash Flow (CF) quarter strategy carries a 4.1% CAPM alpha at the one year horizon but only 2.6% per year at the 10-year holding period, similar to the drop in average alphas observed in the data. All the while, the model captures both the market risk-return relationship as well as the dynamics of the aggregate dividend payout.

Unlike in the data where the lack of independent long horizon returns makes it tough to estimate long horizon alphas, the calibrated model allows me to calculate alphas at arbitrary horizons. I find that the CAPM alpha of the CF quarter strategy at 40-year horizon is only 34bps, indicating essentially no benefit from market timing. The model allows me to establish the reason for such deterioration at longer horizons. Namely, I show that at longer horizons, the CF quarter strategy has substantially higher cumulative dividend growth rate betas compared to the complement strategy that invests in periods when discount rate news dominate. In that way the model provides an economic rationale for the apparent good performance of timing strategies: they earn high returns because they load up on long-term fundamental risk, and therefore are risky from the perspective of long-term investors.

My results have both practical and theoretical implications. The findings on long-horizon returns provide a quantitatively striking illustration that efficient portfolios differ across investment horizons. In the case of timing strategies, the drop in long-horizon performance is substantial with average alphas decreasing by more than half going from a 1-month to a 10-year investment horizon. There are scant data to estimate alphas at horizons longer than 10 years, however the model suggests that investors with a 40 year investment horizon would benefit little from such timing strategies—an endowment or a pension fund would likely find it wise to ignore these strategies altogether. The drop in long-horizon alpha (and the attendant increase in beta) is particularly noteworthy given that many of the original papers establishing the timing strategies document low exposures to risk factors. By the same logic, the results underline that evaluation of investment opportunities ought to take into account the investors' horizon. Recent asset pricing literature has included some of the timing strategies in the benchmark set of mean-variance efficient portfolios, for instance see Jensen et al. (2023). The results here imply that for a long-term investor such a benchmark might not be attainable.

The results also speak to different theories that could underpin timing strategies. One common view is that these returns represent mispricing, and persist only to the extent various limits to arbitrage prohibit prices from converging to fundamental value. From the mispricing perspective, longer investment horizon investors should be particularly attracted to the seasonality strategies as they would be less likely to have to close out the trade prior to the presumed convergence. Indeed, the market practice of lock-up periods is in part

motivated by keeping investments in the fund to facilitate such convergence to fundamental value. (For instance, Agarwal et al. (2009) document a median lock-up period of one year in a sample of hedge funds.) What I find empirically, however, is that already at the 1-year investment horizon the seasonality strategies have poorer risk-adjusted performance, cutting against the mispricing view.

Finally, the results here are focused on a set of portfolios that explicitly seek to take exposure to particular types of underlying shocks. The performance of various other strategies could in part reflect exposures to such seasonal patterns. In particular, other anomaly portfolios could be implicitly taking exposure to shocks that induce return continuation, giving rise to seemingly good performance as short investment horizons at the cost of higher long-term risk exposures. As the findings here illustrate, documenting the multi-period risk-return relationships, as well as factor exposures at longer horizons is a low-cost but potentially powerful tool to ensure that any new candidate anomaly is not reflecting this same pattern.

The literature on portfolio choice starting with Merton (1971) has recognized the distinction between the optimal myopic and intertemporal portfolios. Part of that literature has noted the mean-reversion in market returns, rendering equity investments safer from a long-term investor's perspective (see Campbell and Viceira (2002), Chapter 4 for a summary). A related, more recent literature has emphasized the importance of capturing risk exposures at different horizons to account for the cross-section of returns. For instance, Lettau and Wachter (2007) and Hansen et al. (2008) attribute the value premium to differences in cash-flow duration across the value sort: these papers argue long horizon dividend claims are safer because they benefit from mean reversion in the cash-flow process. In such a framework, growth firms are safer because more of their value stems from distant cash-flows while value firms earn a premium as they load more on the near-term risks.

The model developed in this paper demonstrates that a tightly linked phenomenon can give rise to timing strategies. These strategies do well by single month holding period metrics as they tend to take exposure to shocks that do not mean revert—they command a high risk premium precisely because such shocks are risky from the long-horizon perspective. I make this connection with dividend strip pricing explicit. I show the returns of the Cash Flow quarter strategy—the portfolio that takes exposure to the market portfolio when expected cash-flow growth news have a high volatility and earns CAPM alpha—are priced by the returns on a near-term dividend strip, while earning alpha with respect to long-term dividend strip returns. In other words, the apparent outperformance of short-term dividend strips, and the apparent outperformance of the Cash Flow quarter timing strategy have the same underlying economic rationale.

Overall, the results add to the literature on intertemporal asset pricing by documenting

how the quantitatively substantial alphas of timing strategies can be accounted for by long-horizon risk exposures. In that way the results illustrate the perils of implicit focus on single period mean variance optimization in portfolio selection as discussed in Cochrane (2022). The distinction between long- and short-horizon performance additionally suggests investment horizon as an important source of heterogeneity in determining the optimal tilt with respect to timing strategies, as well as other portfolios. Finally, the results indicate that the returns obtained from implementing such timing patterns need not be indicative of data snooping or limits to arbitrage but can instead be a reflection of different risk exposures faced by short- and long-horizon investors.

Let me provide more detail on the empirics and the theory. The empirical component of the paper documents the multiperiod risk-return tradeoffs for a large set of market timing strategies. I replicate and extend out of sample 34 strategies from prior work, organized into six thematic groups. On the whole, the strategies continue to show good performance out of sample: a strategy level regression of post-publication returns on pre-publication returns has beta of about .4 and an intercept of -1.1%, so the aggregate returns do not support the view that these strategies hold in-sample only, in keeping with the out-of-sample findings in Chen and Zimmermann (2021).

The key novel finding is that the risk-return tradeoff for these strategies deteriorates in the length of the investment horizon, both on the aggregate, as well as separately across the types of strategies. I calculate the variance ratios of the seasonality strategies and show that 79% of the seasonality strategies in the sample have variance ratios of above one at a five-year horizon, indicating that their returns have on average positive autocorrelations. As reported in Table 1 Panel A, the average VR across the 34 strategies at the five-year horizon is close to two. The variance ratio results are mirrored in the average Sharpe ratios which are below the market's at the ten-year horizon. Finally, at longer horizons the strategies tend to be more correlated with standard risk factors and for 83% of the strategies the single period Fama-French 4-factor model alphas are above the 5-year horizon counterparts. The average alpha at the 1-month horizon is 5.6%, but only 2.4% at the 10-year horizon. I plot the average alphas across the 34 strategies in Figure 1 Panel A, illustrating the persistent drop-off in abnormal returns as the investment horizon lengthens. In Panel B, I report the equivalent calculations in the model, but extend out the investment horizon to 40 years to illustrate that by then the alphas drop to effectively zero.

The aggregate pattern of high timing strategy returns corresponding to high variance ratios is also evident in the cross-section of the strategies. As I show in Figure 2, the timing strategies with the largest single-period Sharpe ratios are precisely those with the highest long-horizon variance ratios—the strategies that seem most appealing from the one-period

risk-return perspective suffer the most from the multi-horizon investment perspective. I again include data from the model in the figure to demonstrate that a quantitatively similar relationship holds in the model.

In the theory part of the paper I provide a representative agent no arbitrage model that can account for the principal empirical facts regarding timing strategies, particularly those exploiting firm event seasonalities. The model builds on the Lettau and Wachter (2011) framework and specifies two main state variables: the time-varying growth rate of the aggregate dividend process and the aggregate compensation for risk. As already described, the way these two shocks affect asset prices gives rise to contrasting return processes. Because expected cash-flow growth is a persistent process, positive expected cash-flow growth news today leads to higher-than-expected realized returns in future periods as high realized dividend growth persists. In contrast, the price of risk shocks induce negatively autocorrelated returns: high returns on account of a reduction in the price of risk predict lower expected returns going forward. The novelty in the model is the introduction of a seasonality in the underlying volatilities. In "Discount Rate quarters" (DR) price of risk shocks have a relatively high volatility. In "Cash Flow quarters" (CF) expected cash-flow shocks have a relatively high volatility. With this setup I simulate the returns of an untimed market portfolio as well as a timing strategy that invests in the market only in CF quarters. The CF quarter market timing strategy earns a CAPM alpha of over 4.3% per year—for reference equity risk premium in the model is 8.4%. At the 10-year horizon, however, the timing strategy has a variance ratio of 2.5, Sharpe ratio of .35, and only a 2.6% CAPM alpha. At the 40-year holding period, the CAPM alpha is down to 34 bps and the benefits from timing the market are negligible.

The model allows me to explore the mechanism that gives rise to these timing returns. Firstly, I document cash-flow exposures of different horizons. At short holding periods, the CF timing strategy (that has positive single-period CAPM alpha) has lower cash-flow exposure than the complement strategy that takes market exposure in Discount Rate quarters. At longer holding periods, however, the CF quarter timing strategy sees higher cash-flow betas, reflecting its riskiness for the long term investor. Secondly, I establish the magnitude of timing returns as a function of the degree of seasonality in the underlying shocks. I find that even a small degree of seasonality—a 10% adjustment in the conditional volatility of the underlying state variables from the benchmark i.i.d. calibration—gives rise to a 1% CAPM alpha on the CF quarter timing strategy. This result indicates that a mild degree of seasonality in underlying state variables can induce seemingly attractive timing returns. Finally, I provide a link to returns on different maturity dividend strips. The CF quarter strategy earns a 4.3% alpha with respect to the market portfolio, but only 1% with respect to the

1-year dividend strip return. Both the short-term dividend strip and the CF quarter strategy take exposure to shocks that do not mean revert, establishing a common economic rationale to their seemingly good risk-adjusted performance with respect to the market portfolio: they are risky from the long horizon investor's perspective.

1.1 Relationship with the Literature

The primary goal of the empirical component of the paper is to show that the single-period risk-return tradeoff characterizing such strategies overstates their value for long-term investors. More generally, the results emphasize the importance of establishing asset returns at different holding periods—the asset pricing equation has to hold at all horizons. As the market return and many popular factor portfolios have variance ratios not too far from one, their single- and multi-period return characteristics are not necessarily materially different. But portfolios other than the timing strategies explored here could show substantial risk differences across holding periods. In that respect the results highlight the importance of studying risk-return tradeoff at different horizons, as argued in Chernov et al. (2022). They show that prominent factor pricing models tend to see substantially larger pricing errors at longer holding periods, particularly those with high Sharpe ratios at the short horizon. Other related work includes Polk et al. (2022) that studies the risk-return tradeoff in value and momentum at different holding periods, finding a value-momentum correlation that increases with the holding period, and a lower optimal allocation to momentum in the portfolio of a long-horizon investor. Bessembinder et al. (2023a) find that mutual funds are less likely to outperform the market at longer horizons, and are less likely to have positive alpha at longer horizons. van Binsbergen et al. (2024) study fund value added as a function of turnover frequency. In prior related work, Kamara et al. (2016) document factor risk exposures at different horizons, while Haddad et al. (2020) study optimal timing of principal components of anomaly portfolios. Other work has sought to incorporate the long-term risk-return relationship in asset pricing tests. Cho and Polk (2023) and van Binsbergen et al. (2023) estimate measures of mispricing employing price levels, rather than short-term returns while Keloharju et al. (2019) study long-horizon discount rates across firms. Dong and Yang (2023) study anomaly returns over longer holding periods and associate them with retail trading. Driessen et al. (2019) use options data to study the pricing kernel at different horizons. Relative to these papers I provide a new equilibrium framework that can generate such return dynamics.

Also related are a number of papers that study the statistical properties of long horizon returns and risk loadings. Fama and French (2002) provide estimates of long-term equity

returns; Fama and French (2018) and Farago and Hjalmarsson (2023) document the distribution of long-horizon returns, while Lewellen (2022) studies autocorrelations in individual stock returns over time. **?** studies market-level return autocorrelations in recent data. A related literature uses spectral methods to directly capture horizon effects. On the theoretical side, Dew-Becker and Giglio (2016) derive risk prices for consumption risk at different frequencies, while on the empirical side Bandi et al. (2021) analyze factor portfolios as sums of frequency-specific components (see Bandi and Tamoni (2022) for a literature review). Karehnke and de Roon (2024) study the distribution of betas estimated over different horizons, while Gilbert et al. (2014) use the gap between low- and high-frequency betas to study mispricing. The role of infrequent rebalancing in determining return autocorrelations is studied in Bogousslavsky (2016) and Boguth et al. (2016) study the effect of slow information diffusion.

Uncertainty about the statistical properties of long-horizon returns is a key ingredient of the argument in Pástor and Stambaugh (2012) that an investor with long horizons may not find stocks to be more appealing, even in the presence of mean reversion. They show that uncertainty about expected returns increases expectations of stock market volatility at longer horizons, potentially undercutting any gains from mean reversion. While directionally in line with the argument in Pástor and Stambaugh (2012), the results documented in this paper stem from the dynamic properties of returns, and not from estimation uncertainty. Explicit modeling of uncertainty about expected returns would only strengthen the conclusion that such strategies are less appealing for long horizon investors.

Key contributions to the theoretical work that emphasizes the importance of different maturity risk exposures include Lettau and Wachter (2007) and Hansen et al. (2008). Both of those papers work within the representative investor framework; the model in this paper follows that tradition. Despite the lack of different investors in the model, the model-implied returns give rise to involved intertemporal dynamics, and for that reason the results here speak to the literature on long-term portfolio choice, such as Barberis (2000), Lynch (2001), and Jurek and Viceira (2011). Finally, the results that link timing strategies to the term structure of equity returns relate to the work on equity risk as a function of duration such as Weber (2018), Gonçalves (2021b) and Gormsen and Lazarus (2023).

2 Three Simple Examples

In this section I provide three examples in which the length of the investment horizon has a material impact on the optimal portfolio decision, the identity of the mean-variance efficient portfolio, and on the alphas and betas of portfolios with respect to factors. In the subsequent

analysis of timing strategy returns I refer back to these examples.

2.1 Example I: Mean-Variance Investors with Different Horizons

The first example illustrates that the single-period risk-return tradeoff is insufficient to describe the optimal portfolio choice for investors with long-horizon investment objectives.

Consider a set of investors with mean variance preferences over terminal payouts at different horizons. Investor k's utility is defined over the expected value and variance of the (for simplicity, log) return from current period to time k, where time is measured in months. All investors have the same risk aversion coefficient. In other words, investors are indexed by their holding period length k and their preferences are given by

$$U^k(r^A_{t\to t+k}) = \mathrm{E}[r^A_{t\to t+k}] - \mathrm{Var}(r^A_{t\to t+k}), \tag{1}$$

where $r^A_{t\to t+k} = \frac{12}{k}\sum_{i=t+1}^{t+k} r_i$ refers to annualized log returns from time t to time $t+k$.

Consider the following two securities. Security 1 has an expected return of 8% per year, annualized volatility of 25%, and the returns are i.i.d. and so the return in month $t+1$ is given by

$$r^1_{t+1} = \mu + \sigma\epsilon^1_{t+1}. \tag{2}$$

Security 2 likewise has conditional volatility of 25% but has positively autocorrelated returns and the return in month $t+1$ is given by

$$r^2_{t+1} = \mu + \rho r^2_t + \sigma\epsilon^2_{t+1}. \tag{3}$$

where $\rho = .15$. Because of this dependence on past returns, the average return of Security 2 works out to 9.4% per year. Finally, let the risk-free rate be zero.

Suppose each investor k needs to choose between Securities 1 and 2 without being able to buy a combination. At first blush Security 2 might see more appealing with a higher per period return and the same conditional volatility. However, at longer holding periods the positive autocorrelation in the returns of Security 2 makes the return distribution wider and investors with higher values of k in fact prefer Security 1.

To see this explicitly note that the variance ratio at horizon k is given by (Campbell et al. (1997), page 49)

$$VR(k) = 1 + \frac{2}{1-\rho}\left(\rho - \frac{\rho^k}{k} - \frac{\rho-\rho^k}{k(1-\rho)}\right). \tag{4}$$

With the variance ratio formula we can calculate the variance of Security 2 at different holding periods. Turns out that under the given parameters, investors with horizons longer than 6 months would prefer an investment in Security 1. Even though it has a worse single-period Sharpe ratio, the positive return autocorrelation in Security 2 makes it less appealing from the perspective of any mean-variance investor with a long investment horizon. Hence, with a material amount of autocorrelation in returns, the optimal portfolio choice of mean-variance investors is not pinned down by the single-period risk-return tradeoff.

This simple portfolio choice problem of investors with preferences specified over one particular horizon might seem overly simplified in that long-term investors in practice would additionally need to finance intermediate consumption. However, a mean-variance approach applied to available payoffs at a given horizon has widely been used in the literature as a benchmark case as it isolates the risk-return tradeoff in the particular horizon (for instance, see Campbell and Viceira (2005), Brandt and Santa-Clara (2006), Jurek and Viceira (2011)).

2.2 Example II: MVE portfolio at Different Horizons

Example II is closely related to Example I and demonstrates that a non-zero autocorrelations of security returns ensure that the Mean-Variance Efficient (MVE) portfolio differs across investors with different investment horizons.

Consider the two risky securities from Example I, and let the risk-free rate be zero as before. Further, let the correlation between innovations ϵ_1 and ϵ_2 be 0.

In this setting the MVE portfolio differs across investors k, even though the conditional variance-covariance matrix is constant across periods. Specifically, recall that the MVE weights are given by (see Back (2010), Chapter 5.3)

$$\pi = \frac{1}{\iota' \Sigma^{-1} (\mu - r_f \iota)} \Sigma^{-1} (\mu - r_f \iota), \tag{5}$$

where ι stands for a unit vector of length two and Σ is the variance-covariance matrix.

Because Security 2 has positively autocorrelated returns, its variance is larger at long holding periods. Evaluating Equation (5) at the 1- and 60-month holding period horizon using the mean returns and variances from Example I results in MVE weights for Security 2 of 54.0% and 46.6%, respectively. Hence, mean-variance investors with different horizons end up holding a different mix of Securities 1 and 2.

2.3 Example III: Factor Loadings at Different Horizons

Example III illustrates that alphas and betas with respect to return factors differ across holding period lengths. Consider the following setup with one factor portfolio—the market—and two securities. The market portfolio has i.i.d. returns with 25% volatility and mean of 8%

$$r^M_{t+1} = \mu_M + \sigma\epsilon_{t+1}. \tag{6}$$

There are two securities that load on the innovations to the market portfolio. The first security's return loads on contemporaneous market return innovations, whereas the second security's return also depends on the once lagged market return innovation

$$r^1_{t+1} = \mu_1 + \sigma_1(\epsilon_{t+1} + \epsilon^1_{t+1}), \tag{7}$$

$$r^2_{t+1} = \mu_2 + \sigma_2(\epsilon_{t+1} + \rho\epsilon_t + \epsilon^2_{t+1}). \tag{8}$$

Let $\sigma_1 = \sigma_2 = 12\%$ and let $\rho = .2$ and let the expected returns be $\mu_1 = \mu_2 = 4\%$.

In the single-period setting these parameters result in both stocks having a beta of .5 and an alpha of 2% per year. However, in the multiperiod setting the beta of the second security increases because of the lagged dependence on market returns, while the alpha sees a commensurate reduction. At the 60-month holding period length Security 2 has a market beta of .7 and an alpha of only 50 basis points.

Example III thus illustrates that factor loadings at different holding period lengths need not be equal, even if the conditional covariance matrix of asset returns is constant over time. A delayed return dependence on factor returns contributes to the risk exposure at long holding periods and hence alters the performance of a security with respect to the factor.

In all, the three examples provided here illustrate that the single-period risk-return tradeoff is not sufficient to characterize the optimal portfolio choice of long-term investors.

3 Timing Strategies

This section briefly summarizes the 34 timing strategies that form the basis of my empirical analysis. I group the seasonality strategies into six thematic groups, based on their construction and provenance. The original sources and data span for each strategy are listed in Table IA.1. The table also lists a short name for each grouping and strategy that I use in other tables and figures.

All strategies are constructed as monthly excess returns and the strategies are rebalanced

at least at a monthly frequency. When constructing long-horizon returns the underlying investments are still rebalanced, at the minimum, at a monthly frequency. In other words, the differences in short- and long-horizon performance of the strategies do not stem from stale portfolio weights.

3.1 Benchmark Strategies

To establish a benchmark for long-horizon volatility and returns, I include the factors from Fama-French 4- and 5-factor models (Fama and French (1993), Fama and French (2015)). I include these strategies in all of the tables, except for the tables on factor alphas which would be zero by construction.

3.2 Aggregate Calendar Strategies

The simplest timing strategies move in and out of the aggregate market following calendar-based rules. The turn-of-the-month strategy (labeled MONTH) of Lakonishok and Smidt (1988), invests in the equity market on the last trading day of each month, and the subsequent three trading days. It's analyzed and documented in more detail in McConnell and Xu (2008). The January (JAN) strategy invests only in January while the "Sell-in-May-Go-Away" strategy (MAY) holds the aggregate market from early November to May. The January effect is described in Rozeff and Kinney Jr (1976) and the "Sell-in-May-Go-Away" is analyzed in Bouman and Jacobsen (2002). Both strategies are described and updated in Ilmanen (2011). I construct these factors starting 1927, reflecting CRSP data availability.

3.3 Firm Event Seasonalities

A recent literature has documented high returns on strategies that holds stocks of firms that are predicted to make quarterly earnings announcements. Following Savor and Wilson (2016) I construct a strategy, labeled ERP for Earnings Risk Premium, that takes a value-weighted long position in the firms that are predicted to make their quarterly earnings announcement in the coming month, and a value-weighted short position in firms that are predicted not to make an announcement, based on previous calendar year announcement dates available from Compustat. The use of previous year announcement dates ensures that there is no look-ahead bias stemming from rescheduled announcements. Because of Compustat data availability, I am able to construct such strategies starting in 1972. Relatedly, in recent work, Chen et al. (2020) document that market days in anticipation of multiple large firm earnings announcements see even higher expected returns. However, their sample contains

only 20 years, making inference on long-horizon returns difficult (the sample is limited by availability of earnings announcement time stamps).

The second firm event seasonality takes advantage of the dividend month premium as documented in Hartzmark and Solomon (2013). This strategy is constructed in a similar manner: it takes a value-weighted long position in stocks that made a dividend payment in the upcoming month in the prior year, it takes a value-weighted short position in stocks that did not make a dividend payment in the upcoming month in the prior year. (See also the related work in Bessembinder and Zhang (2015) regarding returns around predictable corporate distributions.) I apply the same filters to the data as Hartzmark and Solomon (2013) and label this strategy DMP for Dividend Month Premium. Because the dividend data is available on the CRSP tape, I'm able to construct the strategy starting in 1927.

3.4 Same-Month Seasonalities

Same-month seasonality strategies move in and out of stocks or portfolios based on the same portfolio historical return in a given calendar month. Given a set of underlying stocks or factor portfolios, in each month the same-month seasonality strategy goes long the portfolio with the highest return in that calendar month based on the past twenty years of returns; it goes short the portfolio with the lowest twenty-year historical returns in the coming calendar month. I replicate the seasonality strategies documented in Keloharju et al. (2016). These strategies use the 10 constituent portfolios of six asset pricing factors (Book-to-market (BM), Dividend-to-price (DP), Earnings-to-price (EP), Market equity (ME), Momentum (UMD), Profitability (OP), all downloaded from Ken French's website), 17 Fama-French industry portfolios (IND), and individual stocks in the SP500. Finally, the "composite" seasonality uses 58 size, value, momentum, dividend-to-price, and industry portfolios as the set of constituent assets. The sample start dates for these strategies vary across strategies, reflecting their availability on Ken French's website. Such same-month seasonalities were previously studied by Heston and Sadka (2008). Note too the follow-up work in Keloharju et al. (2019) that finds reversals within the same-month seasonality strategies.

3.5 Volatility-Managed Portfolios

Moreira and Muir (2017) construct market timing portfolios that scale an investment in an underlying factor portfolio as a function of same factor realized variance over the past month. (Note too the recent work in DeMiguel et al. (Forthcoming) studying volatility timing of multifactor portfolios.) They show that such volatility-managed portfolios obtain high Sharpe ratios and earn alpha with respect to the underlying un-timed factors. I replicate the

volatility-managed portfolios for the following underlying factors. Firstly, I use the Fama-French 4- and 5-factor model factors, available on Ken French's website: Market Minus Risk-free (MKTRF), Small Minus Big (SMB), High Minus Low (HML), Momentum (UMD), Conservative Minus Aggressive (CMA), Robust Minus Weak (RMW). Secondly, I use the he Betting-against-beta (BAB) and Quality Minus Junk (QMJ) returns, available on Andrea Frazzini's website. Finally, I use the Expected growth (EG), Investment (IA), Market Equity (ME), and Return on Equity (ROE) factors from Lu Zhang's website. In each case, the data span reflects availability of the monthly factor returns.

3.6 Macroeconomic News Announcements

A literature starting with Savor and Wilson (2013) has studied realized returns on the market portfolio around important macroeconomic news announcements (MNAs). In order to construct a maximally long sample, I focus on Bureau of Labor Studies Employment and Producer Price Index announcements, for which the dates are available since 1958. The strategy that holds the aggregate equity market on such announcement days is labeled BLS.

I also construct strategies based on the FOMC calendar, reflecting the recent work in Lucca and Moench (2015), Cieslak et al. (2018), Laarits (2019), and Hillenbrand (2020). I construct a strategy, labeled FOMC, that is long the market in the three trading day window surrounding scheduled FOMC announcements.

3.7 Day of the Week Seasonalities

Birru (2018) studies the performance of anomaly portfolios as a function of day of the week. He demonstrates the following pattern: anomalies for which an investor needs to short the speculative leg (speculative refers to stocks that face high limits to arbitrage, or are hard to value) experience the highest returns on Mondays and lowest returns on Fridays, anomalies for which an investor needs to long the speculative leg experience the highest returns on Fridays and lowest returns on Mondays.

I replicate day-of-the-week timing strategies for the following characteristic-sorted portfolios (all part of the sample in Birru (2018)): long old, short young (AGE), long high Book-to-Market (BM), long high Earnings-to-Book (EBE), long high Sales Growth (GS), and long high Market Equity (ME). I also include a day-of-the-week strategy that uses the aggregate market return (MKTRF) as the constituent asset. The day-of-the-week strategy goes short the factor on Mondays, long the factor on Fridays, except for AGE, EBE, and ME in which case the strategy goes long the underlying factor on Mondays, short Fridays.

4 Empirics

In this section I document both the single- and multi-horizon performance of the 34 timing strategies described above. The main finding is that the risk-return tradeoff of such strategies deteriorates over time and multifactor alphas drop by more than half.

The results are summarized in Table 1. In Panel A, I report averages of excess returns, volatility, Sharpe ratios, alphas with respect to the Fama-French 4-factor model, and variance ratios across the 34 strategies. Here and in subsequent results I use four distinct investment horizons: 1, 12, 60, and 120 months. As Panel A shows, across the full set of strategies the average Sharpe drops from .55 at the one-month horizon to .37 at the 120-month horizon, and the 4-factor alpha drops from 5.6% to 2.4%. This difference in alphas is statistically significant (t-test rejects equality at the 1% level). The average variance ratio at the 120-month horizon is 2.1. Here and in Panel B I bold the Sharpe ratios and alphas that are below the 1-month benchmark, and I bold the variance ratios that are above one.

Panel B of Table 1 shows that the same pattern holds separately across the six strategy groups: Sharpe ratios and alphas are decreasing the in the investment horizon, variance ratios are increasing in the investment horizon. The sole exception to this pattern is the Macroeconomic News Announcement group where the alphas are slightly higher at longer holding periods.

In subsequent Tables 2, 3, and IA.4 I report these results strategy-by-strategy. In Table 2 I report the conventional single-period risk and return metrics: excess returns, volatility, Sharpe ratios, and alphas with respect to the market portfolio as well as the Fama-French 4-factor model. As a check on the replication data, I calculate in-sample and out-of-sample returns of the strategies and find that a strategy level regression of post-publication average returns on pre-publication average returns has a positive slope of about .4 and an intercept of -1.1%, indicating that as a group the strategies do well out of sample, even if the average returns are on average somewhat lower post-publication.

As illustrated in Example I, the long horizon risk-return tradeoff need not equal the single-period risk-return tradeoff. To capture this feature in the data, in Table 3 I report variance ratios for the strategies and find that 79% have a 5- and 10-year VRs above one, indicating higher per period volatility at longer holding periods.

As illustrated in Example III, the factor loadings at longer holding periods can differ from the single-period counterparts. This effect can stem from the dynamic behavior of both the strategies themselves, as well as the factor returns. For one, the multi-period mean-variance efficient portfolio need not coincide with the single period MVE, as shown in Example II. As reported in Table IA.4, in the data I find that 83% of the strategies have Fama-French

4-factor alphas below the single-period counterparts, suggesting that part of these apparent excess returns are in fact captured by long horizon risk exposures.

4.1 Single-Period Performance

Table 2 reports the single-period risk-return tradeoff of the seasonality strategies. For each of the strategies I report the (physical) annualized monthly return, annualized monthly volatility, and annualized monthly Sharpe ratio. In the next set of two columns I report the CAPM and Fama-French 4 factor alphas, and the final two columns I report the corresponding t-statistics.

The vast majority of the strategies have economically and statistically significant excess returns over the CAPM or Fama-French 4-factor models. Three groups of strategies—same-month seasonalities, volatility managed portfolios, and day-of-week seasonalities—are replications of single papers and almost all the strategies have statistically significant positive alphas at the 5% level. The exceptions are ME- and SMB-sorted volatility managed portfolios, GS-sorted day-of-the-week seasonality, and BM-, DP-, and OP-sorted same-month seasonality strategies. I include these strategies for completeness as they were part of the original papers. The other sets of strategies are collected from various sources and not all have statistically significant abnormal returns in the full sample, but nonetheless I include them in the analysis as they can still be informative about the long-horizon dynamics that I seek to document.

To summarize the single period performance across the set of 34 strategies, note that the Fama-French 4 factor alphas are 5.6% per year at the 1-month horizon, but only 2.4% at the ten-year horizon, respectively.

4.2 Out-of-Sample Performance

The seasonality strategies collected in this paper do well out-of-sample. In Figure IA.1 I report the returns of each strategy in two subsamples: before and after to the first working paper documenting the returns. (I report the cutoff date in Table IA.1.) As the scatterplot shows, there is a positive relationship between the two return series: the correlation between the two is .51. What is more, I estimate a regression of post-discovery returns on pre-discovery returns and find an intercept of -1.1% (t-stat of 1.2), indicating a relatively small, not statistically significant amount of under-performance post discovery.

4.3 Return Arithmetic

In order to calculate long-horizon returns, variances, and factor model alphas I cumulate the monthly returns, as well as the monthly factor returns. Let $R_{i,t}$ denote the month t return of timing strategy i. I construct all the strategy returns R_t^i as excess returns. Let $R_{f,t}$ denote the risk-free rate at time t. In order to calculate long-horizon returns I add the risk-free rate to the excess return, and sum up the log returns over the appropriate horizon. To transform back into excess returns, I sum up log risk-free returns and subtract from the cumulated portfolio return. That is, the length k holding period log excess return is given by

$$r_{i,t}^k = \sum_{j=0}^{k-1} \ln(1 + R_{i,t+j} + R_{f,t+j}) - \sum_{j=0}^{k-1} \ln(1 + R_{f,t+j}). \tag{9}$$

In order to transform the log k horizon returns $r_{i,t}^k$ into monthly returns I divide by k. In order to calculate physical long horizon returns $R_{i,t}^k$ I exponentiate the two constituent parts of Equation (9) and take the $1/k$ root:

$$R_{i,t}^k = \exp\left\{\sum_{j=0}^{k-1} \ln(1 + R_{i,t+j} + R_{f,t+j})\right\}^{1/k} - \exp\left\{\sum_{j=0}^{k-1} \ln(1 + R_{f,t+j})\right\}^{1/k} \tag{10}$$

This return calculation is representative of the investment experience of a long-term investor who reinvests any interim cash-flows back to the strategy at the end of each month. To the extent returns have non-zero volatility, these average returns are by construction lower than the arithmetic average of single-period returns. At longer holding periods these cumulated returns are well approximated by the log of the gross long holding period return, divided by the number of months. (See Bessembinder et al. (2023b) for a detailed analysis of various concepts of measuring long-horizon returns and their relationships, and Bessembinder et al. (Forthcoming) on the relationship between short and long horizon alphas under i.i.d. returns.) I follow the equivalent process to calculate the long-horizon factor returns for the Fama-French 4-factors.

4.4 Variance Ratios

In order to establish the long horizon riskiness of the seasonality strategies, I calculate variance ratios of monthly returns over horizons of up to ten years. Recall that the k-period variance ratio of log returns is the ratio of the length k holding period return volatility over

k times the single-period return volatility:

$$\mathrm{VR}(k) = \frac{\mathrm{Var}\left(r^k_{i,t+1}\right)}{k\,\mathrm{Var}\left(r^1_{t,t+1}\right)}. \tag{11}$$

Variance ratios below one indicate return reversals, meaning negative autocorrelations on average; variance ratios above one indicate return continuations, meaning positive autocorrelations on average.[3]

In order to provide a reference level for the VR data, I calculate the variance ratios of the Fama-French 4- and 5-factor models. The left panel in Figure 3 shows that the variance ratio for the market portfolio is above 1 for holding periods up to 60 months, with the maximum value of roughly 1.25 obtaining near the 20-month holding period. At holding periods longer than 60 months, however, the VRs are below one. The right panel of Figure 3 shows the Fama French four- and five-factor portfolios likewise tend to exhibit return continuations at first (as studied in detail in Ehsani and Linnainmaa (2022)) followed by reversals, meaning VRs below one at longer horizons.

I find that 79% of the 34 seasonalities described in Section 3 display variance ratios above 1 at the five year horizon. Indeed, the mean VR at the five year horizon is around two, and close to half of the strategies have VRs above two at the ten year horizon, indicating that the per period variance of the timing strategies grows substantially with holding period length. In contrast, the market portfolio variance ratio never exceeds 1.3 and is close to 1 at the five-year horizon.

This result is illustrated in Figure 4. Here I plot the variance ratios for horizons from 2 to 120 months separately for each of the six thematic groups of market timing strategies. For reference I also include the market portfolio VR in the thick solid line. As the figure shows, the VRs of most of the market timing strategies continue increasing going from 2- to 120-month holding periods. There are only a few strategies that do not follow this pattern and often they turn out to be the exceptions that prove the rule. For instance, the DP-sorted same-month seasonality has a VR of below .5 at holding periods above 60 months—but that timing strategy also has the smallest CAPM alpha within its group, not statistically significant at the 5% level. Note that for many of the strategies the VRs keep increasing as the investment horizon lengthens. For instance, the Earnings Risk Premium strategy sees a 60-month VR of 2.5 and a 120-month VR of 3.4. This feature indicates that the positive autocorrelations that characterize timing strategy returns occur at many different

[3]To see this explicitly note that the VR can be equivalently expressed as an average of 1st to kth order autocorrelations with linearly decreasing weights: $\mathrm{VR}(k) = 1 + 2\sum_{i=1}^{k-1} \frac{k-i}{k}\rho_i$, see Campbell et al. (1997). Zero autocorrelations hence indicate a VR of 1.

horizons—as shown in footnote 3, the VR is just a weighted average of different horizon autocorrelation coefficients.[4]

I report the 12-, 60-, and 120-month variance ratios in Table 3. In this table I also report t-statistics of the VRs against the null of VR=1. There is a long literature on variance ratios and issues pertaining to statistical inference, for instance see Richardson and Stock (1989) and Deo and Richardson (2003)[5]. To construct standard errors I employ the results in Kan (2011). Specifically, under the assumption that returns follow an elliptical distribution with a diagonal covariance matrix the finite sample variance of the k-period variance ratio estimator is given by:

$$\text{Var}\left(\text{VR}(k)\right) = \frac{2(T-1)}{T+1}\left[1 - \frac{T(n+1)}{2m} + \frac{((T-k)_3 - (T-2k)_3)\left(n-k+\frac{4k^2}{T}\right)}{6m^2}\right] - \frac{2}{T+1} \tag{12}$$

where $(a)_3 = a(a+1)(a+2)$, $n = T-k+1$, and $m = kn(n-1)T$.

Note that the Kan (2011) formula is exact in the case of elliptic return distributions. However, the returns of timing strategies are heteroskedastic, in part by construction, raising potential concerns about the applicability of that result. To alleviate such concerns, Kan (2011) carries out two simulation exercises with time-varying volatility, and finds that the test over-rejects the null of VR=1 for short horizons, but already at 50 month horizon the actual size of the test is very close to the nominal size. The intuition is straightforward: to the extent the return heteroskedasticity occurs at high frequencies relative to the investment horizon, it tends to "wash out" in the longer return windows.

While 79% of the variance ratios are above one at the 5-year horizon (I bold these coefficients in Table 3), 47% of the associated t-statistics indicate significance at the 5% level against the null of VR=1 using the one-sided t-test. In part this reflects the difficulty in calculating long horizon variance ratios with limited samples. Still, on the whole the variance ratio results indicate that the market timing strategies as a group tend to see return continuations at longer holding periods, a result particularly evident in Figure 4. The average variance ratio at the 5-year horizon is 1.95 and a t-test rejects the hypothesis that the

[4]This feature further indicates that it is not trivial to add another layer of timing to these strategies. Because of the positive autocorrelations in timing strategy returns, it would seem that an investor could just reduce a position after a period of negative returns, for instance, similar to the factor portfolio transformations carried out in Ehsani and Linnainmaa (2022). However, as the positive autocorrelations accrue at multiple horizons it is not straightforward to construct such "timed" timing strategies. It is possible, however, that such an additional layer of timing would improve the returns of the strategies, at least in-sample. The results in this paper focus on the timing strategies as presented in the prior literature.

[5]Charles and Darné (2009) provide an overview.

average VR is equal to one (t value of 5.2).

4.5 Sharpe Ratios

The previous section documents that over long holding periods the per period volatility of the market timing strategies tends to increase. These increases in long holding period volatility also translate into lower long horizon Sharpe ratios. In Appendix Table IA.2 I report the Sharpe ratios at 1-, 12-, 60-, and 120-month horizons. A majority of the market timing strategies see long-term Sharpe ratios below the single-period counterparts: at the five-year horizon, 74% of the strategies have a lower Sharpe ratio than the single-period counterpart. For comparison, the market portfolio Sharpe ratio at the five-year horizon is practically identical to the single-period one. For ease of reading Appendix Table IA.2, I bold the Sharpe ratios that are lower than the single-period counterparts. To calculate standard errors of Sharpe ratios in a setting where returns are not i.i.d., I use the formula derived in Lo (2002), specifically Equation (14), that uses the delta method with a Newey-West type of variance estimator (I use 120 lags).

4.6 CAPM and Multifactor Alphas over Long Horizons

The results regarding variance ratios and Sharpe ratios both indicate a worse risk-return tradeoff at longer periods for the timing strategies. Thus, when considered in isolation these strategies are less appealing to an investor with a long horizon investment objective. At the same time, these results leave open the chance that these strategies could still be valuable in a diversified portfolio. As illustrated in Example III, the long horizon risk exposures need not coincide with short horizon risk exposures: depending on the dynamics of the risk factors and the strategies to be priced, alphas could be either higher or lower at longer holding periods (see Chernov et al. (2022) for a detailed analysis of factor model performance at longer holding periods).

As the principal empirical result, I find that the timing strategy alphas tend to deteriorate in the holding period length. In Table IA.4 I report the 1-, 12-, 60-, and 120-month Fama-French 4-factor alphas. To calculate these alphas I first cumulate up factor returns according to Equation (9) to construct long horizon counterparts. I then regress the long horizon (physical) annualized excess returns on the equivalent holding period (physical) annualized factor returns. Standard errors are Newey-West with the number of lags corresponding to the number of months in the holding period.

The majority of the strategies have positive and statistically significant alpha with respect to the Fama-French four factor model at the one-month horizon. At longer horizons, however,

the market timing strategies tend to show weaker outperformance. At the 60-month holding period, 83% of the 4 factor alphas are lower than the single-period counterparts. For ease of reading I bold such alphas in Table IA.4. As I report in Appendix Table IA.3, the CAPM alphas follow a similar pattern. The majority of these alphas are statistically significant at the 5% level: 70%. However, 81% of the strategies see 60-month holding period CAPM alphas that are below the single-period counterparts. I again bold the coefficients that are below the single period counterparts.

On the whole the results on Fama-French 4-factor alphas affirm the message that the market timing strategies present a less appealing prospect to a long horizon investor. The average Fama-French 4-factor alpha at the single month horizon is 5.6% annualized, while the 60- and 120-month holding period alphas are 3.0% and 2.4%, respectively. A t-test rejects the equality between the single month and 60-, or 120-month alphas with respective t values of 4.4 and 4.5. Returns from portfolios that take an equal-weighted position in the constituent strategies of each strategy group send the same message. As shown in Panel B of Table 1, alphas are dropping in the investment horizon for five of the six strategy groups (with MNAs being the exception).

This reduction in alphas stems from exposure to multiple factors: UMD, HML, and to a smaller degree, MKTRF. In Internet Appendix Figure IA.2 I report the multi-factor betas across 1-120 month holding periods. While at the 1-month horizon the factor betas are close to zero, at the 120-month horizon both the value and momentum betas are close to .3 on average. For comparison I also report the risk loadings within the model, finding values close to .3 at the 120-month investment horizon.

The drop in multifactor alphas is depicted in Panel A of Figure 1. While the figure shows a steady decline going from the single-month to 10-year investment horizon, the average alphas of the strategies are still positive. Even when taking into account that the average out-of-sample timing strategy return are one percentage point lower than in sample, some alpha remains at the 10-year horizon. Looking ahead, the model presented in the next section suggests, that the decay in alpha continues with even longer investment horizons. In the baseline model calibration I generate timing strategies with about 4% alpha in the single period analysis, 2.5% at the 10-year horizon, and just over 34bps at the 40-year horizon.

4.7 Discussion

In sum, the market timing strategies as a whole show increasing variance ratios, lower Sharpe ratios, and lower alphas with respect to factor models as the investment horizon increases. I have documented these facts for a set of timing strategies using holding periods of up to

ten years. There is nothing special about the ten-year horizon, but increasing the holding period length reduces the number of independent observations available. The strategies with the longest available sample start in 1927, reflecting data availability in CRSP. I therefore have just under ten independent ten-year windows of data.

Figure 2 summarizes the main results in a different way. Here I plot the single period Sharpe ratio against the 10-year variance ratio. I indicate the different groupings of timing strategies with different color markers. There is a strong positive relationship between the two measures—the strategies that have the best risk-return tradeoff at the single-period horizon are precisely the ones that see the worst relative risk-return tradeoff at long horizons. This relationship holds on the aggregate, as well as within strategy groupings.

A strategy-level regression of single-period Sharpe ratio on the 10-year variance ratio results in a slope coefficient of .16 (t-stat 7.5) and an intercept of .21, statistically significant at the 1% level. In other words, a strategy with a ten-year VR of two is expected to see a ten-year Sharpe ratio that is .3 below the single-period Sharpe ratio. In the subsequent section I present a theoretical model that generates a market timing strategy in line with the facts described in this section, including this relationship between single period Sharpe and long horizon variance ratios.

5 Model

The goal of the model is to provide an representative investor equilibrium framework that features a timing strategy akin to those documented in the previous section. In particular, I seek to capture a strategy that invests in the aggregate market portfolio only part of the time, has positive alpha with respect to the buy-and-hold market portfolio, but also shows poorer risk-return at longer holding periods as well as an alpha that decreases with the holding period length.

To this end I use a slightly simplified version of the affine framework in Lettau and Wachter (2011). The model features two main state variables: a time varying expected growth rate of the aggregate dividend process, and a time-varying aggregate compensation for risk. Reflecting the results in Lettau and Wachter (2011), the model is able to generate a realistic equity risk premium, a value premium, as well as yield curve predictability.

The innovation here with respect to the existing model is to introduce a predictable seasonality in the conditional volatilities of these two main state variables. I split model periods (quarters in the calibration) into "Cash Flow" (CF) and "Discount Rate" (DR) types. Price of risk shocks have a higher volatility in DR periods than in CF periods; expected cash flow shocks have a higher volatility in CF periods than in DR periods. On average, though, the

volatilities of these two state variables are very close to the original Lettau and Wachter (2011) calibration. The shocks to realized dividend growth—the only priced risk in the model—have a constant volatility. Outside of these adjustments the model is standard and can be solved recursively in closed form with the alteration that the pricing equations have to keep track of the alternating CF and DR periods.

Because of the focus on cash-flow and price of risk shock volatilities, the timing strategy in the model is reminiscent of the Earnings Risk Premium (ERP) seasonality. The CF period timing strategy takes exposure to the aggregate equity market in times when expected cash-flow news have a high volatility, just like the ERP strategy takes exposure to stocks predicted to make earnings announcements. As I will show, the model calibration fits closely the data on the ERP: alphas across investment horizons, Sharpe ratio, and variance ratio.

5.1 Model Setup

The model has four fundamental shocks and three state variables. The aggregate log dividend growth is given by

$$\Delta d_{t+1} = z_t + \sigma_d \epsilon_{t+1}, \tag{13}$$

where z_t represents a time-varying component of the dividend growth rate and ϵ_{t+1} is a 4×1 vector of normally distributed unit variance shocks.

The three state variables are the time-varying dividend growth rate

$$z_{t+1} = (1 - \phi_z)g + \phi_z z_t + \sigma_z^{t+1} \epsilon_{t+1}, \tag{14}$$

the risk-free rate

$$r_{t+1}^f = (1 - \phi_r)\bar{r}^f + \phi_r r_t^f + \sigma_r \epsilon_t \tag{15}$$

and the price of risk process x_t

$$x_{t+1} = (1 - \phi_x)\bar{x} + \phi_x x_t + \sigma_x^{t+1} \epsilon_{t+1}. \tag{16}$$

For ease of algebra in calculating asset prices, I follow Lettau and Wachter (2011) and combine the three state variables and four shocks in matrix notation. Specifically, I let H_t represent the three state variables of the economy, evolving according to

$$H_{t+1} = \Theta_0 + \Theta H_t + \sigma_H^{t+1} \epsilon_{t+1}, \tag{17}$$

where ϵ is a 4×1 vector of unit standard deviation normally distributed shocks representing the realized dividend growth shock (the first entry), and the three state variable innovations

$$\sigma_H^{t+1} = \begin{bmatrix} 0 & \sigma_z^{t+1} & 0 & 0 \\ 0 & 0 & \sigma_r & 0 \\ 0 & 0 & 0 & \sigma_x^{t+1} \end{bmatrix}. \tag{18}$$

Further, for notational convenience let me again follow Lettau and Wachter (2011) and re-express the state variables as

$$\begin{aligned} z_t =& \delta_0 + \delta' H_t \\ r_{t+1}^f =& \alpha_0 + \alpha' H_t \\ x_t =& \xi_0 + \xi' H_t. \end{aligned}$$

The key departure from the Lettau and Wachter (2011) model is that the conditional volatility of innovations to the state variable vector H_t depend on the time period. Specifically, the value of the vector σ_H^{t+1} is a function of the period $t+1$

$$\sigma_H^{t+1} = \begin{cases} \sigma_{CF} & \text{if mod(t+1,2)=1} \\ \sigma_{DR} & \text{otherwise.} \end{cases}. \tag{19}$$

Finally, the SDF is given by

$$M_{t+1} = \exp\{-r_{t+1}^f - .5|\lambda|^2 x_t^2 - x_t \lambda' \epsilon_{t+1}\}. \tag{20}$$

Recall the variable x_t is defined in Equation (16) and captures time variation in the aggregate compensation for risk. Note that it appears together with the 4-by-1 vector λ and multiplies the 4-by-1 vector of innovations ϵ_{t+1}. The vector λ has no time subscript, meaning that compensation for a given type of risk only changes as a function of the variable x_t. In the calibration I follow Lettau and Wachter (2011) and specify that only the realized dividend growth shocks $\sigma_d \epsilon_{t+1}$ are priced, limiting the degrees of freedom in the model.

5.2 Solving the Model

The model solution method follows Lettau and Wachter (2011). I find the prices of equity strips—assets that are claims on the aggregate dividend amount in a given period—by recursively applying the single period asset pricing formula, recognizing that the equity strip of maturity n today will have maturity $(n-1)$ the next period. Because the underlying

shock volatilities differ across DR and CF quarters, the resulting pricing functions have to keep track of the two types of periods, denoted by DR and CF. In particular, the price $P_{n,t}^{DR}$ of maturity n dividend strip in an Discount Rate quarter has to satisfy

$$P_{n,t}^{DR} = \mathrm{E}_t \left[m_{t,t+1} P_{n-1,t+1}^{CF} \right]. \tag{21}$$

Likewise, in Cash Flow quarters the price of maturity n dividend strip has to satisfy

$$P_{n,t}^{CF} = \mathrm{E}_t \left[m_{t,t+1} P_{n-1,t+1}^{DR} \right]. \tag{22}$$

I guess and verify that price dividend ratios in both periods follow an exponential affine form and find the recursive parameters implied by Equations (21) and (22). Because these derivations are otherwise standard I relegate them to Internet Appendix IA.1.

5.3 Model Calibration

The parametrization is based on Lettau and Wachter (2011) with the following exceptions. Firstly, because under their calibration expected inflation does not impact equity valuation, I drop the expected inflation state variable. Secondly, I use a slightly lower value for the price of risk variable x_t, and a slightly higher value for the dividend volatility, working out to a very similar market risk premium, but better matching market Sharpe ratio in this sample. Thirdly, as already described, I introduce a seasonality in the volatility of two of the state variables.

The model calibration is reported in Table 5. The first row shows that the annualized volatility of the dividend growth shocks is 12%, close to the value in the post-war data. (Here, as in subsequent two rows, the numbers are reported on an annualized basis.)

The second to fourth rows report the values for the three state variables, expected dividend growth rate, the risk-free rate, and the price of risk process. The log expected dividend growth rate has the same level and persistence as in Lettau and Wachter (2011): 1.3% growth per year with persistence of .9. The average volatility of the expected growth rate is also equal to their calibration—.32% annualized—however in this calibration it represents volatility of .48% in CF quarters, and .16% in DR quarters. The price of risk process is unitless and has the mean of 6.5 and persistence of .85. The level of the price of risk process is slightly lower than in Lettau and Wachter (2011) and the persistence is exactly the same. The volatility of the price of risk process is 2 in CF quarters when expected cash-flow volatility is relatively high, and 6 in DR quarters when expected cash-flow volatility is relatively low. The level, persistence and volatility of the risk-free rate are exactly equal to

those in Lettau and Wachter (2011).

The last column of Table 5 Panel A reports the values of the vector λ. Recall that the shocks ϵ_{t+1} enter the SDF multiplied with the term $x_t\lambda'$ (Equation (20)) and so the product $x_t\lambda'$ can be thought of as the price of risk. Following Lettau and Wachter (2011) only the realized dividend growth shocks are priced and $\lambda = \sigma_d$. Because the average value of x_t is $\bar{x} = 6.5$ and the annualized volatility of realized dividend growth rate shocks is $\sigma_d = 12\%$ the maximum annualized Sharpe ratio in the model works out to $6.5 * .12 = .78$. (Note that in the quarterly simulation the value of λ equals the quarterly value of dividend growth volatility, meaning $12\%/\sqrt{4} = 6\%$.)

Panel B of Table 5 reports the correlation matrix of the four underlying shocks which is identical to that in Lettau and Wachter (2011). The key non-zero correlation is that between realized and expected dividend growth shocks: -.83. This parameter ensures that poor realized dividend growth news coincide with good expected dividend growth news, rendering the cash-flow process mean reverting. Note too that the correlation matrix is the same across the DR and CF quarters.

5.4 Principal Model Moments

The resulting principal asset pricing moments of the market portfolio are reported in Panel A of Table 6. As the first row shows, the mean excess (physical) return of the market portfolio is 8.4% with 20.7% standard deviation, working out to a Sharpe ratio of .40. The second and third row of Panel A report the same objects but at the 10- and 40-year holding period lengths. The standard deviations at these longer holding periods are 18.0% and 15.9%, respectively, reflecting mean reversion in aggregate returns. Indeed, the market variance ratio of .74 at the 10-year horizon (calculated using log returns following Equation (11)) is in keeping with the empirical counterpart reported in Figure 3.

Panels B and C report the same set of quantities, but for two market timing strategies: a strategy investing in the market portfolio in CF quarters only, and a strategy investing in the market in DR quarters only. Panel B shows that the CF quarter strategy—the portfolio that invests in the aggregate market when expected cash-flow innovations are relatively large—has a high annualized return of 5.7% and a Sharpe ratio of .58 at the one year holding period. At longer holding periods, however, the annualized standard deviation of this strategy increases substantially and the 10- and 40-year Sharpe ratios are only .35 and .28. Correspondingly, the variance ratio of this strategy is substantially above 1, reaching values of 2.5 at the 10-year horizon.

Panel C shows that the DR quarter strategy—the portfolio that invests in the aggregate

market when price of risk innovations are relatively more important—has an annualized excess return of only 1.26% at the 10-year investment horizon along with 16.2% annualized volatility.

Finally, Panel D reports the means and standard deviations of the realized dividend growth process. The average log dividend growth rate is 1.3% and the annualized volatility at the one year horizon is 12%, as reflected in Table 5. Because of the negative correlation between realized and expected dividend growth, the longer holding period annualized standard deviations are below the single-period counterparts, even with the high persistence of the expected dividend growth process z_t. This feature of the calibration is in keeping with the data: long horizon dividend growth tends to be less volatile than short horizon growth, as documented in detail by Belo et al. (2015).

5.5 Economics of Timing Strategies

The return moments reported in Table 6 are indicative of the main result of the model: they reflect a market timing strategy that does well by conventional measures at short investment horizons. Panel A of Table 7 establishes the CAPM alphas of these two timing strategies over three different holding periods: 1, 10, and 40 years. The two strategies are defined like in the prior table: they invest in the aggregate equity market in the indicated quarters, CF or DR, and in the risk-free rate otherwise.

In the first column I confirm a substantial positive alpha of the CF quarter strategy. The strategy has a CAPM beta of .17 and earns a 4.3% annualized alpha. (This alpha is quantitatively similar to that earned by the Earnings Risk Premium timing strategy that takes exposure to firms making earnings announcements: 5.33%). As shown in the third column, at the 10-year horizon the CF quarter strategy carries a beta of over .4 and the annualized alpha is reduced to 2.6%. At the 40-year horizon, the CF quarter timing strategy has a CAPM beta of .77 and almost all of the original alpha has disappeared—the strategy earns only 34 basis points over the CAPM-implied return per year. The returns on the DR quarter strategy display the opposite pattern: they earn negative alpha with respect to the market that disappears at longer investment horizons.

The results in Panel A in Table 7, together with results in Panels B and C of Table 6, capture the main message of the model: market timing strategies may appear appealing on a short-horizon basis with positive alpha but over longer holding periods two robust features render the strategies less attractive. One, the variance ratios are substantially above one meaning the return volatilities are higher so on a stand-alone basis the strategies offer a poorer risk-return tradeoff. Two, the factor loadings tend to change and the returns

are increasingly captured by the market portfolio, meaning the timing strategy offers a substantially diminished alpha.

Panel B of Table 7 further illustrates the economic mechanism. In this table I estimate regressions of the two timing strategy returns at different horizons on corresponding holding period cumulative dividend growth rates. As the table shows, the realized dividend growth explains only a small part of the CF quarter strategy returns at the 1-year horizon with an R^2 below 5%. The realized dividend growth explains a bit more of the yearly DR quarter returns. At the long holding period of forty years the relationship is flipped—realized cash-flow growth now explains over 11% of the CF quarter returns but only 7% for the DR strategy returns. Betas reflect the same pattern: at the 40-year horizon the cash-flow strategy returns has a considerably higher dividend growth beta. The results in Panel B of Table 7 thus underline that at longer periods the CF quarter strategy is riskier because it has a stronger loading on the aggregate cash-flows, in line with the argument in Cochrane (2014) that long-term betas are cash-flow betas.

To give a sense of how the model return dynamics compare with the data, in Figure 5 I plot variance ratios of the three strategies in the model. The solid navy line shows the variance ratio of the market portfolio while the neon green line shows the variance ratio of the DR period timing strategy. At a ten-year horizon the market variance ratio is .74, basically identical to the empirical value of about .72. The red short dashed line shows the variance ratio of the strategy that only holds the market in CF quarters, meaning when expected cash-flow shocks are realized. This variance ratio grows with the horizon, reaching values above 2.5 at the ten year horizon, compared to just above three in the empirical counterpart. Recall from footnote 3 that the variance ratio statistic is just a weighted average of return autocorrelations at different horizons and so the large values for the CF strategy are indicative of return continuation. Overall, the CF period strategy variance ratio shows a similar shape to many of the strategies shown in Figure 4.

Finally, the model is able to recreate the strategy-level relationship between single-period Sharpe ratio and long-horizon variance ratio. I include the single period Sharpe and ten-year variance ratios of the two timing strategies, as well as the market portfolio in Figure 2. The model-implied data is denoted with diamond shapes and the line of best fit is in the black solid line. As the figure shows, the model captures well the quantitative relationship estimated in the cross-section of 34 such strategies, the two respective lines of best fit essentially overlap.

5.6 Importance of Underlying State Variable Volatility

The results in the previous section establish a seasonality strategy in line with the empirical findings. In particular, the CF quarter timing strategy in the model closely resembles the earnings risk premium seasonality premium in the data. In the principal parameters the calibration follows Lettau and Wachter (2011) but the degree of seasonality is a parameter that is novel to this calibration and in this section I document the strength of the market timing strategies as a function of the underlying fundamental seasonality.

Each row in Table 8 represents one simulation of 50,000 years using the main model parameters, except for the amount of seasonality in the price of risk and expected cash-flow growth innovations. The calibrations are parametrized by κ that represents the deviation from a no seasonality benchmark. The expected cash-flow innovations have volatility of $\sigma_z = .32\%$ in the no seasonality baseline, and in calibration κ the expected cash-flow growth rate volatility is $\sigma_z(1+\kappa)$ in CF periods and $\sigma_z(1-\kappa)$ in DR periods. Similarly, the volatility of price of risk shocks is $\sigma_x = 4$ in the no seasonality baseline. In CF quarters the volatility is instead $\sigma_x(1-\kappa)$ and in DR quarters it's $\sigma_x(1+\kappa)$. The parameter κ ranges from 0 to .5, representing no seasonality and the main model calibration documented above, respectively.

In each of the rows I report the mean and standard deviation of the market portfolio, as well as the CF and DR period timing portfolios. In the last column I report the CAPM alpha of the CF period market timing strategy. The first set of six rows report statistics at the single year horizon. As the degree of seasonality κ increases, the CF quarter returns increase while the standard deviation decreases. The reverse is true for DR period returns: the average returns decrease while their volatility increases. As the last column shows, the alpha on the CF period timing strategy increases from zero in the no seasonality baseline to 4.34% under $\kappa = .5$. Note that already under a minor amount of seasonality—with $\kappa = .1$—a substantial market timing alpha of 1% emerges.

At the longer holding periods, however, the differences in timing strategy standard deviations are more muted, in line with the main argument in the paper. In the bottom set of six rows I repeat the analysis over 40-year horizons. With higher degrees of seasonality (meaning higher values of κ) the two strategies still show different amounts of volatility. All the while, the alphas of the timing strategies are essentially negligible in all calibrations, emphasizing again that over long holding periods the seasonality strategies do not offer a way to substantially outperform the market.

In the model exploration so far I have always implemented seasonalities in both the expected cash-flow growth shocks, as well as the price of risk shocks. The model mechanism, however, is not dependent on such "synchronized" underlying seasonalities. A seasonality in the relative importance of the two shocks is all that is required. In Internet Appendix Table

IA.5 I report a two additional calibrations to illustrate that timing strategy alphas arise with a seasonality in just one of the underlying shock. The table format reflects Table 8. The first set of three rows just report the no-seasonality benchmark calibration for investment horizons of 1, 10, and 40 years. In the second set of three rows I introduce price of risk news seasonality only with the parameter $\kappa = .5$, meaning the conditional volatilities of the shocks to x_t are $\sigma_x(1-\kappa)$ and $\sigma_x(1+\kappa)$, depending on the quarter. In this calibration, at the one-year investment horizon a timing alpha of 1.34% appears, though already at the ten year horizon the alpha becomes negligible. In the third set of three rows I introduce expected cash-flow growth news seasonality only, again using $\kappa = .5$ like in the baseline calibration. Under this calibration, a substantial CR quarter strategy alpha of 3.48% emerges, and it persists even at the 40-year horizon. In all, the results in Table IA.5 underline that the relative importance of the two underlying shocks is what drives the seasonality strategies, with the expected cash-flow news seasonality contributing more in the baseline calibration.

5.7 Connection with Short and Long-term Dividend Strip Returns

A recent literature starting with van Binsbergen et al. (2012) has documented that short-term dividend claims tend to earn higher returns than longer-term dividend strips (though note too more recent estimates in Golez and Jackwerth (2022) finding a flatter slope). A rationale for such return differential across the cash-flow horizon emerges naturally in the Lettau and Wachter (2011) framework I use in this paper. An investor holding exposure to the short-term dividend claim only is likely to see returns that are positively autocorrelated because of the persistence in the time-varying expected dividend growth rate. By contrast, an investor holding a claim on a long horizon dividend strip is much less exposed to dividend shocks as the realized dividend shocks are negatively correlated with the persistent, time-varying expected growth rate (recall Panel D of Table 6 showing variance ratios of below one for the aggregate dividend process.) Correspondingly, the short term dividend claims have the highest average returns.

A closely related phenomenon underlies the differential pricing of CF and DR quarter strategies. The CF quarter strategy takes exposure to shocks that don't mean revert; the DR quarter strategy takes exposure to shocks that do mean revert. Hence, the CF quarter strategy is akin to a short term dividend claim and the DR quarter strategy is akin to a long term dividend claim.

I show this connection explicitly in Table 9. I use as the right hand side variables the yearly returns on 1- and 10-year dividend strips, representing the short to long run dividend claims. On the left hand side I have the corresponding annual returns of the CF and DR quarter

market timing strategies. In the first and fourth column I report the average returns of these two strategies. The second column shows that the CF quarter strategy—the strategy that takes exposure to cash-flow shocks and earns a CAPM alpha—comoves strongly with the short term dividend claim. In fact, the return of the CF strategy is essentially priced by the 1-year dividend strip return (in the model, just like in the data, the 1-year strip earns alpha with respect to the market). At the same time, the DR quarter strategy—the strategy that takes exposure to price of risk shocks primarily—moves much more strongly with the long-term dividend claim. Indeed, the 10-year dividend strip return accounts for 83% of the variation in the DR quarter strategy, but only 5.7% of the CF quarter strategy.

Unfortunately, the existing sample for dividend strip prices is quite short, making it difficult to estimate long-horizon variance ratios of dividend strips empirically. In the data that does exist, I find that the 1-year dividend claim has a 5-year variance ratio of 1.24, while the 2-year dividend claim has a 5-year variance ratio of .82, in line with the idea that shorter maturity strips are riskier as they exhibit more return continuation. Note too the recent work in Gonçalves (2021b) that associates the riskiness of short-duration cash-flows with reinvestment risk (Gonçalves (2021a)), likewise highlighting the role of long horizon investors in capturing these return differentials.

6 Discussion

6.1 Sources of State Variable Shock Seasonalities

The model takes as given a degree of seasonality in the state variables' conditional volatility. The modeling choice of seasonality in expected cash-flow news is inspired by the seasonality in earnings announcements. In the U.S., most publicly traded firms are on a January, April, July, October earnings announcement calendar. For instance, in 2020, 70% of the total market cap was made up of firms that made their first quarterly announcement in a three-week window starting in the middle of January. Seasonal peaks, then, in the conditional volatilities of expected cash-flow news are to be expected. However, a bevy of other underlying factors could drive seasonalities in stock returns.

Reporting requirements can induce seasonalities in other ways. For instance, many intermediated investment vehicles face monthly or quarterly disclosure requirements, potentially inducing a period window-dressing demand for trading. Absent disclosure-induced trading, delegated investment could lead to seasonalities when funds with investment allocation rules need to periodically rebalance.

A different type of underlying seasonality could stem from the timing of investor funds.

Paychecks typically clear on a weekly, biweekly, or monthly calendar. Retail investor flows might inherit such seasonality, particularly among stocks preferred by retail traders (Laarits and Sammon (2024)). Dividend payouts can similarly generate seasonalities in investment flows, see Hartzmark and Solomon (2022). Tax reporting periods can induce loss harvesting at the end of the year, and purchases of the same stock later on, a phenomenon that has been linked to the January seasonality. Similarly, the monthly payment cycle of corporations has been shown to have a material impact on financing costs, see Etula et al. (2019).

Other types of seasonalities could arise from "physical" causes. Production-related seasonalities are pervasive in agricultural and commodities markets, and materialize in seasonalities in the associated futures markets. For instance, Boudoukh et al. (2007) demonstrate that half of the variation in orange juice futures prices can be traced to temperature variations in Florida in a small subset of days when temperatures are near freezing.

Seasonal patterns can emerge over shorter periods still. The opening times of major stock exchanges around the world tend to determine liquidity as well as investor composition in global equity and currency markets. Prior research has documented substantial return seasonalities during a trading day, for instance see Bondarenko and Muravyev (2023). Throughout a single calendar day different investor clienteles could be active in financial markets: Lou et al. (2019) study return reversals and continuations in intraday and overnight returns and argue they are caused by clientele effects. Bogousslavsky (2016) attributes autocorrelations in returns at the daily horizon to infrequent rebalancing of investors. In recent work, Barardehi et al. (2023) document that overnight and intraday returns tend to be driven by news and trading, respectively.

While I have motivated the model timing strategy with the earnings seasonality, I have not provided a rationale for each of the timing strategies separately. Whatever such underling forces, though, the evidence on poor long-horizon performance constitutes a unifying feature.

6.2 Who Are the Short-term Investors?

The results in this paper establish that the length of investment horizon determines how appealing an investor might find various timing strategies. The apparent good returns of timing strategies are therefore consistent with the observation that not all investors can time the market in the same way—short horizon investors ought to tilt their portfolios towards timing strategies while long-term investors ought to tilt their portfolios away from timing strategies, in keeping with the argument in Cochrane (2022) that portfolio tilts need to satisfy a zero-sum constraint.

Practically speaking, measuring the effective investment horizon of various investors is

not straightforward. Using detailed household-level portfolio holdings data, Calvet et al. (2021) estimate risk aversion, elasticity of intertemporal substitution, and time preference parameters for a set of Swedish investors, finding a substantial degree of heterogeneity in each of the parameters. Other prior literature has proxied for the investment horizon by portfolio turnover (for instance, Gaspar et al. (2005)). Regardless of measurement, it is clear that a substantial proportion of funds belong to investors with explicit long-term objectives: retirement funds, endowments, and insurance companies. Many other investors purport to take the long term view.

Who, however, are investors with short horizons? One answer is that a considerable set of investors don't necessarily have a short investment horizon, but invest with managers who are compensated based on their short-term performance. (Such misalignment between manager and end-investor horizons is studied theoretically in Hodor and Zapatero (2023).) Consistent with this view, Bessembinder et al. (2023a) find that the number of mutual funds that outperform the SPY exchange-traded fund is smaller at longer holding periods. One interpretation of their findings, then, is that mutual funds may face the temptation to tilt towards some of the timing strategies that do well at short holding periods, potentially reflecting a cost of delegated investing. Along the same lines, Lo (2002) finds that Sharpe ratios for a set of hedge funds are much lower at longer holding periods.

7 Conclusion

This paper documents the long term risk-return tradeoff of a set of market timing strategies. I show that a number of previously documented market timing strategies tend to exhibit variance ratios substantially above one at longer horizons. I also find these strategies have lower multifactor alphas at long horizons. Taken as a group, the 34 timing strategies included in the sample have an average VR ratio close to 2 at the five-year horizon, and the average five-year Fama-French 4-factor alpha is about half of the single-period average alpha. Hence such timing strategies are less appealing from the perspective of a long-term investor than might at first appear.

I seek to capture these empirical results in a model that features seasonalities in the volatility of underlying shocks. I show that such a model—calibrated to match principal asset pricing facts—can generate market timing strategies that have substantial variance ratios as well as positive alphas with respect to the buy-and-hold portfolio. The model shows, however, that the good performance of timing strategies need not indicate such strategies reflect mispricing or data snooping. Instead, the returns of the timing strategy in the model can be rationalized by their poorer risk-adjusted performance over longer horizons, suggesting a rationale for the staying power of such timing strategies in the data. Practically speaking,

any given investor might still find it optimal to tilt towards such strategies, but the degree of such tilt would crucially depend on the length of their investment horizon.

References

Agarwal, Vikas, Naveen D Daniel, and Narayan Y Naik, "Role of managerial incentives and discretion in hedge fund performance," *The Journal of Finance*, 2009, *64* (5), 2221–2256.

Back, Kerry, *Asset pricing and portfolio choice theory*, Oxford University Press, 2010.

Bandi, Federico M and Andrea Tamoni, "Spectral financial econometrics," *Econometric Theory*, 2022, *38* (6), 1175–1220.

_ , Shomesh E Chaudhuri, Andrew W Lo, and Andrea Tamoni, "Spectral factor models," *Journal of Financial Economics*, 2021, *142* (1), 214–238.

Barardehi, Yashar H, Vincent Bogousslavsky, and Dmitriy Muravyev, "What drives momentum and reversal? Evidence from day and night signals," 2023. Working Paper.

Barberis, Nicholas, "Investing for the long run when returns are predictable," *The Journal of Finance*, 2000, *55* (1), 225–264.

Belo, Frederico, Pierre Collin-Dufresne, and Robert S Goldstein, "Dividend dynamics and the term structure of dividend strips," *The Journal of Finance*, 2015, *70* (3), 1115–1160.

Bessembinder, Hendrik and Feng Zhang, "Predictable corporate distributions and stock returns," *The Review of Financial Studies*, 2015, *28* (4), 1199–1241.

_ , Michael J Cooper, and Feng Zhang, "Mutual fund performance at long horizons," *Journal of Financial Economics*, 2023, *147* (1), 132–158.

_ , _ , and _ , "What You See May Not Be What You Get: Return Horizon and Investment Alpha," *Critical Finance Review*, Forthcoming.

_ , Te-Feng Chen, Goeun Choi, and KC Wei, "How Should Returns to Long Term Investors be Measured?," 2023. Working Paper.

Birru, Justin, "Day of the week and the cross-section of returns," *Journal of Financial Economics*, 2018, *130* (1), 182–214.

Bogousslavsky, Vincent, "Infrequent rebalancing, return autocorrelation, and seasonality," *The Journal of Finance*, 2016, *71* (6), 2967–3006.

Boguth, Oliver, Murray Carlson, Adlai Fisher, and Mikhail Simutin, "Horizon effects in average returns: The role of slow information diffusion," *The Review of Financial*

Studies, 2016, *29* (8), 2241–2281.

Bondarenko, Oleg and Dmitriy Muravyev, "Market return around the clock: A puzzle," *Journal of Financial and Quantitative Analysis*, 2023, *58* (3), 939–967.

Boudoukh, Jacob, Matthew Richardson, YuQing Jeff Shen, and Robert F Whitelaw, "Do asset prices reflect fundamentals? Freshly squeezed evidence from the OJ market," *Journal of Financial Economics*, 2007, *83* (2), 397–412.

Bouman, Sven and Ben Jacobsen, "The Halloween indicator, "Sell in May and go away": Another puzzle," *American Economic Review*, 2002, *92* (5), 1618–1635.

Brandt, Michael W and Pedro Santa-Clara, "Dynamic portfolio selection by augmenting the asset space," *The journal of Finance*, 2006, *61* (5), 2187–2217.

Calvet, Laurent E, John Y Campbell, Francisco Gomes, and Paolo Sodini, "The cross-section of household preferences," 2021. Working Paper.

Campbell, John Y and Luis M Viceira, *Strategic asset allocation: portfolio choice for long-term investors*, Clarendon Lectures in Economics, 2002.

_ **and** _ , "The term structure of the risk–return trade-off," *Financial Analysts Journal*, 2005, *61* (1), 34–44.

_ **, Andrew W Lo, A Craig Mackinlay, and Andrew Y Lo Lo**, *The Econometrics of Financial Markets*, Princeton University Press, 1997.

Charles, Amélie and Olivier Darné, "Variance-ratio tests of random walk: an overview," *Journal of Economic Surveys*, 2009, *23* (3), 503–527.

Chen, Andrew Y and Tom Zimmermann, "Open source cross-sectional asset pricing," *Critical Finance Review*, 2021.

Chen, Yixin, Randolph B Cohen, and Zixuan Kevin Wang, "Famous Firms, Earnings Clusters, and the Stock Market," 2020. Working Paper.

Chernov, Mikhail, Lars A Lochstoer, and Stig RH Lundeby, "Conditional dynamics and the multihorizon risk-return trade-off," *The Review of Financial Studies*, 2022, *35* (3), 1310–1347.

Cho, Thummim and Christopher Polk, "Putting the price in asset pricing," *Journal of Finance*, 2023.

Cieslak, Anna, Adair Morse, and Annette Vissing-Jorgensen, "Stock returns over the FOMC cycle," *The Journal of Finance*, 2018.

Cochrane, John H, "A mean-variance benchmark for intertemporal portfolio theory," *The Journal of Finance*, 2014, *69* (1), 1–49.

_ , "Portfolios for long-term investors," *Review of Finance*, 2022, *26* (1), 1–42.

DeMiguel, Victor, Alberto Martin-Utrera, and Raman Uppal, "A multifactor per-

spective on volatility-managed portfolios," *Journal of Finance*, Forthcoming.

Deo, Rohit S and Matthew Richardson, "On the asymptotic power of the variance ratio test," *Econometric Theory*, 2003, pp. 231–239.

Dew-Becker, Ian and Stefano Giglio, "Asset pricing in the frequency domain: theory and empirics," *The Review of Financial Studies*, 2016, *29* (8), 2029–2068.

Dong, Xi and Cathy Yang, "Anomalies Never Disappeared: The Case of Stubborn Retail Investors," 2023. Working Paper.

Doran, James S, Danling Jiang, and David R Peterson, "Gambling preference and the new year effect of assets with lottery features," *Review of Finance*, 2012, *16* (3), 685–731.

Driessen, Joost, Joren Koëter, and Ole Wilms, "Horizon effects in the pricing kernel: How investors price short-term versus long-term risks," 2019. Working paper.

Ehsani, Sina and Juhani T Linnainmaa, "Time-series efficient factors," 2022. Working Paper.

Etula, Erkko, Kalle Rinne, Matti Suominen, and Lauri Vaittinen, "Dash for Cash: Monthly Market Impact of Institutional Liquidity Needs," *The Review of Financial Studies*, 05 2019, *33* (1), 75–111.

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

Fama, Eugene F and Kenneth R French, "The Equity Premium," *The Journal of Finance*, 2002, *57* (2), 637–659.

_ and _, "A five-factor asset pricing model," *Journal of Financial Economics*, 2015, *116* (1), 1–22.

_ and _, "Long-horizon returns," *The Review of Asset Pricing Studies*, 2018, *8* (2), 232–252.

Farago, Adam and Erik Hjalmarsson, "Long-horizon stock returns are positively skewed," *Review of Finance*, 2023, *27* (2), 495–538.

Gaspar, José-Miguel, Massimo Massa, and Pedro Matos, "Shareholder investment horizons and the market for corporate control," *Journal of Financial Economics*, 2005, *76* (1), 135–165.

Gilbert, Thomas, Christopher Hrdlicka, Jonathan Kalodimos, and Stephan Siegel, "Daily data is bad for beta: Opacity and frequency-dependent betas," *The Review of Asset Pricing Studies*, 2014, *4* (1), 78–117.

Golez, Benjamin and Jens Carsten Jackwerth, "Holding period effects in dividend strip returns," 2022. Working Paper.

Gonçalves, Andrei S, "Reinvestment risk and the equity term structure," *The Journal of Finance*, 2021, *76* (5), 2153–2197.

_ , "The short duration premium," *Journal of Financial economics*, 2021, *141* (3), 919–945.

Gormsen, Niels Joachim and Eben Lazarus, "Duration-Driven Returns," *The Journal of Finance*, 2023, *78* (3), 1393–1447.

Haddad, Valentin, Serhiy Kozak, and Shrihari Santosh, "Factor timing," *The Review of Financial Studies*, 2020, *33* (5), 1980–2018.

Hansen, Lars Peter, John C Heaton, and Nan Li, "Consumption strikes back? Measuring long-run risk," *Journal of Political Economy*, 2008, *116* (2), 260–302.

Hartzmark, Samuel M. and David H. Solomon, "The dividend month premium," *Journal of Financial Economics*, 2013, *109* (3), 640–660.

Hartzmark, Samuel M and David H Solomon, "Predictable price pressure," 2022. Working Paper.

Heston, Steven L and Ronnie Sadka, "Seasonality in the cross-section of stock returns," *Journal of Financial Economics*, 2008, *87* (2), 418–445.

Hillenbrand, Sebastian, "The Secular Decline in Long-Term Yields around FOMC Meetings," 2020. Working Paper.

Hodor, Idan and Fernando Zapatero, "Asset Pricing Implications of Heterogeneous Investment Horizons," 2023. Working Paper.

Ilmanen, Antti, *Expected returns: An investor's guide to harvesting market rewards*, John Wiley & Sons, 2011.

Jensen, Theis Ingerslev, Bryan Kelly, and Lasse Heje Pedersen, "Is there a replication crisis in finance?," *The Journal of Finance*, 2023, *78* (5), 2465–2518.

Jurek, Jakub W and Luis M Viceira, "Optimal value and growth tilts in long-horizon portfolios," *Review of Finance*, 2011, *15* (1), 29–74.

Kamara, Avraham, Robert A Korajczyk, Xiaoxia Lou, and Ronnie Sadka, "Horizon pricing," *Journal of Financial and Quantitative Analysis*, 2016, pp. 1769–1793.

Kan, Raymond, "Exact variance ratio test with overlapping data," 2011. Working Paper.

Karehnke, Paul and Frans de Roon, "Beta Horizons," 2024. Working Paper.

Keloharju, Matti, Juhani T Linnainmaa, and Peter Nyberg, "Return seasonalities," *The Journal of Finance*, 2016, *71* (4), 1557–1590.

_ , _ , and _ , "Are return seasonalities due to risk or mispricing?," *Journal of Financial Economics*, 2019, *139* (1), 138–161.

Laarits, Toomas, "Pre-Announcement Risk," 2019. Working Paper.

_ and Marco Sammon, "The Retail Habitat," 2024. Working Paper.

Lakonishok, Josef and Seymour Smidt, "Are seasonal anomalies real? A ninety-year perspective," *The Review of Financial Studies*, 1988, *1* (4), 403–425.

Ledoit, Olivier and Michael Wolf, "Nonlinear shrinkage of the covariance matrix for portfolio selection: Markowitz meets Goldilocks," *The Review of Financial Studies*, 2017, *30* (12), 4349–4388.

Lettau, Martin and Jessica A. Wachter, "Why is long-horizon equity less risky? A duration-based explanation of the value premium," *The Journal of Finance*, 2007, *62* (1), 55–92.

_ and _, "The term structures of equity and interest rates," *Journal of Financial Economics*, 2011, *101* (1), 90–113.

Lewellen, Jonathan, "Autocorrelation of stock and bond returns, 1960–2019," 2022. Working Paper.

Lo, Andrew W, "The statistics of Sharpe ratios," *Financial Analysts Journal*, 2002, *58* (4), 36–52.

Lou, Dong, Christopher Polk, and Spyros Skouras, "A tug of war: Overnight versus intraday expected returns," *Journal of Financial Economics*, 2019, *134* (1), 192–213.

Lucca, David O. and Emanuel Moench, "The pre-FOMC announcement drift," *The Journal of Finance*, 2015, *70* (1), 329–371.

Lynch, Anthony W, "Portfolio choice and equity characteristics: Characterizing the hedging demands induced by return predictability," *Journal of Financial Economics*, 2001, *62* (1), 67–130.

McConnell, John J and Wei Xu, "Equity Returns at the Turn of the Month," *Financial Analysts Journal*, 2008, *64* (2), 49–64.

Merton, Robert, "Optimum consumption and portfolio rules in a continuous-time model," *Journal of Economic Theory*, 1971, *3* (4), 373–413.

Moreira, Alan and Tyler Muir, "Volatility-managed portfolios," *The Journal of Finance*, 2017, *72* (4), 1611–1644.

Pástor, L'uboš and Robert F Stambaugh, "Are stocks really less volatile in the long run?," *The Journal of Finance*, 2012, *67* (2), 431–478.

Polk, Christopher, Dimitri Vayanos, and Paul Woolley, "Long-Horizon Investing in a Non-CAPM World," 2022. Working Paper.

Richardson, Matthew and James H Stock, "Drawing inferences from statistics based on multiyear asset returns," *Journal of Financial Economics*, 1989, *25* (2), 323–348.

Rozeff, Michael S and William R Kinney Jr, "Capital market seasonality: The case of stock returns," *Journal of Financial Economics*, 1976, *3* (4), 379–402.

Savor, Pavel and Mungo Wilson, "How much do investors care about macroeconomic risk? Evidence from scheduled economic announcements," *Journal of Financial and Quantitative Analysis*, 2013, *48* (2), 343–375.

_ and _ , "Earnings announcements and systematic risk," *The Journal of Finance*, 2016, *71* (1), 83–138.

van Binsbergen, Jules H, Martijn Boons, Christian C Opp, and Andrea Tamoni, "Dynamic asset (mis) pricing: Build-up versus resolution anomalies," *Journal of Financial Economics*, 2023, *147* (2), 406–431.

van Binsbergen, Jules, Jungsuk Han, Hongxun Ruan, and Ran Xing, "A Horizon-Based Decomposition of Mutual Fund Value Added Using Transactions," *The Journal of Finance*, 2024, *79* (3), 1831–1882.

_ , Michael Brandt, and Ralph Koijen, "On the timing and pricing of dividends," *American Economic Review*, 2012, *102* (4), 1596–1618.

Weber, Michael, "Cash flow duration and the term structure of equity returns," *Journal of Financial Economics*, 2018, *128* (3), 486–503.

8 Figures

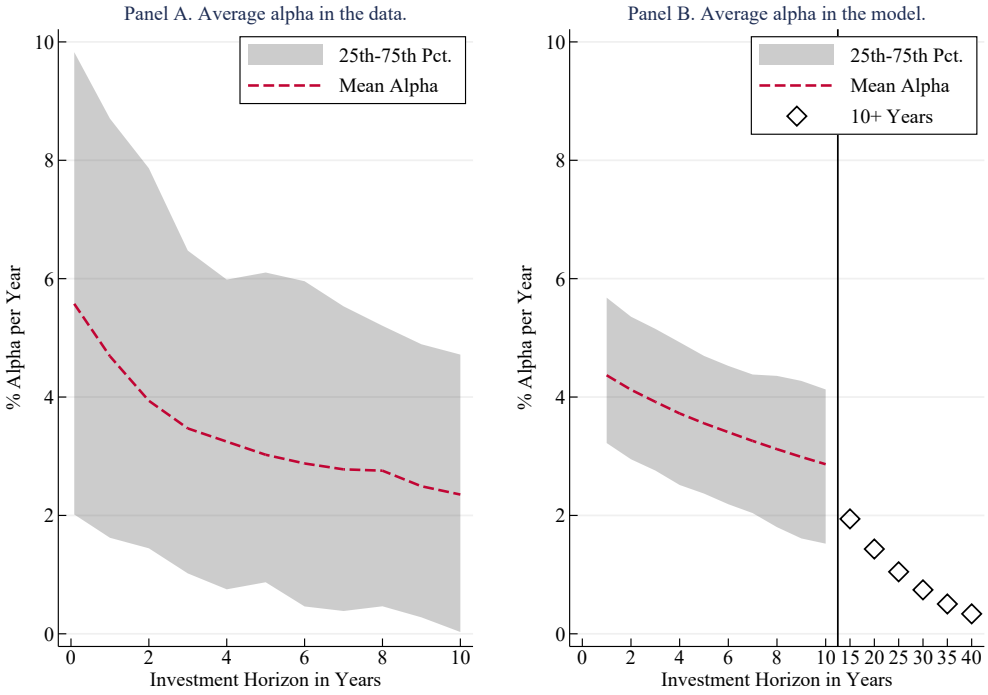


Figure 1: Alpha Decay as a Function of Investment Horizon Length. Panel A depicts the average Fama-French 4-factor alpha of the 34 trading strategies as a function of holding period length. The shaded area denotes the 25th to 75th percentile of the alpha distribution. Panel B depicts the corresponding model-implied calculation, where alphas are calculated with respect to the market portfolio and the 25th and 75th percentiles are calculated over separate 100-year samples. The diamonds on Panel B depict model-implied alphas at investment horizons beyond 10 years (note the change in axis spacing).

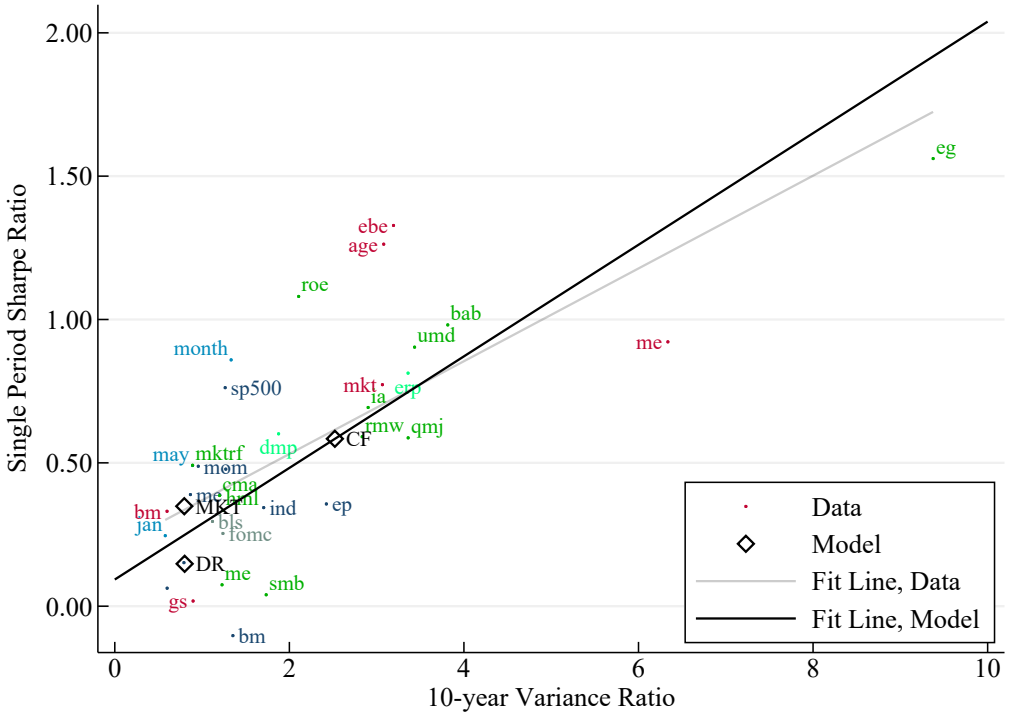


Figure 2: Meta-Analysis of Timing Strategies. Annualized one-month Sharpe ratio and the ten-year variance ratio. Strategies with the best single-period risk-return tradeoff see the highest ten-year variance ratios. Variance ratio defined in Equation (11); strategies described in Table IA.1. Data through end of 2023, strategy start dates vary and are reported in Table IA.1. Values corresponding to model-implied strategies are denoted with diamonds. Light and dark solid lines depict the line of best fit in the data and model, respectively.

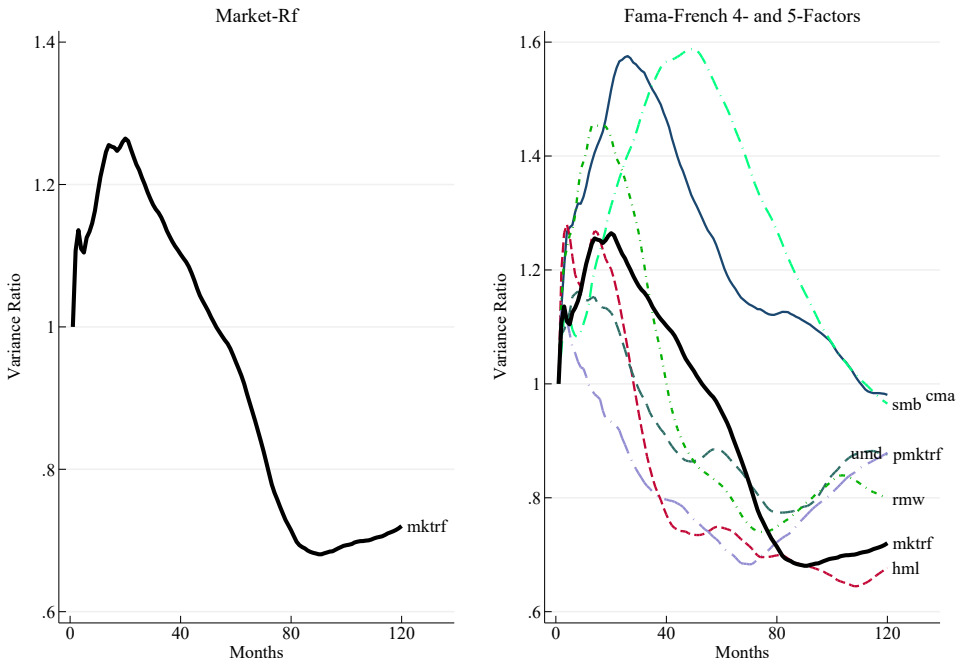


Figure 3: Variance Ratios of the Market Portfolio and Fama-French 4- and 5-Factor Models. Horizons of 2 to 120 months. Variance ratio defined in Equation (11). Note the vertical axes have different scaling across panels. Monthly return data from 1926 to 2023, except for RMW and CMA which start in 1963. Included for reference, pmktrf is the market excess return series post 1962.

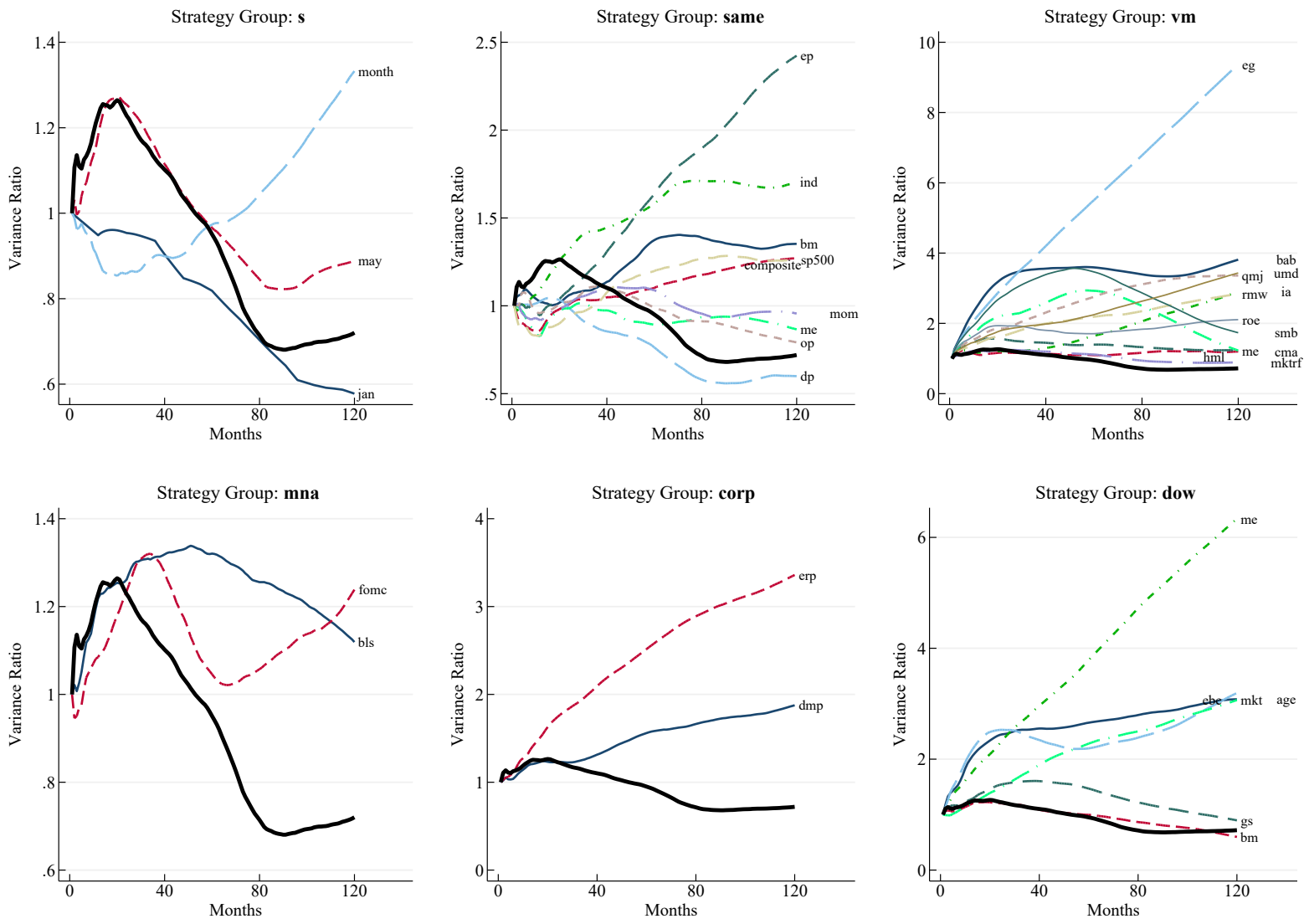


Figure 4: Variance Ratios of Timing Strategies. Horizons from 2 to 120 months. Thick solid line is the variance ratio of the market portfolio. Note the vertical axes have different scaling across panels. Strategy groups are: **s**: Aggregate market seasonalities; **same**: same-month seasonalities; **vm**: volatility-managed portfolios; **mna**: macroeconomic announcements; **corp**: corporate events; **dow**: day-of-week seasonalities. Variance ratio defined in Equation (11). Strategies described in Table IA.1. Strategy start dates listed in Table IA.1.

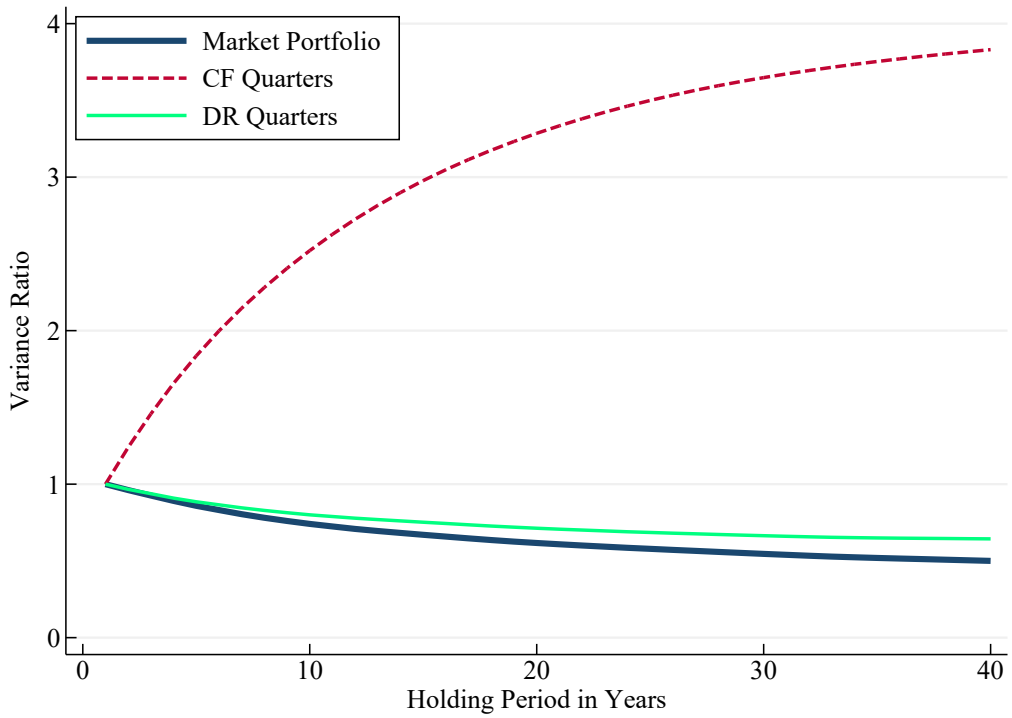


Figure 5: Variance Ratios of Model-Implied Timing Strategies. Quarterly returns with investment horizons up to forty years. The dashed red line is the variance ratio of the DR quarter strategy: strategy that invests in the aggregate market when expected cash-flow news have a relatively high volatility. The neon green line is the variance ratio of the Even quarter strategy: strategy that invests in the aggregate market when price of risk news have a relatively high volatility. Model parameters in Table 5.

9 Tables

Strategy	#	Months	E[R]	SD(R)	Sharpe	FF4 α	VR
Panel A.							
Across All	34	1	6.31	11.16	0.55	5.58	
		12	5.63	12.79	**0.47**	**4.69**	**1.35**
		60	5.59	14.63	**0.40**	**3.03**	**1.85**
		120	5.60	15.12	**0.37**	**2.35**	**2.14**
Panel B.							
Aggregate Market	3	1	4.60	8.11	0.51	2.66	
		12	4.25	8.22	0.52	**2.56**	**1.01**
		60	4.05	7.81	**0.50**	**2.26**	0.92
		120	4.11	7.83	**0.48**	**1.95**	0.93
Same-Month Seasonalities	9	1	5.94	16.45	0.27	5.77	
		12	4.52	16.83	0.28	**3.47**	0.94
		60	4.59	18.88	**0.26**	**0.87**	**1.18**
		120	4.85	19.09	**0.27**	**0.66**	**1.25**
Volatility-managed Port.	12	1	7.19	10.88	0.64	5.62	
		12	6.62	13.89	**0.50**	**5.04**	**1.67**
		60	6.47	16.25	**0.42**	**3.17**	**2.47**
		120	6.42	16.55	**0.37**	**2.42**	**2.84**
Corporate Events	2	1	4.83	6.03	0.77	5.06	
		12	4.72	6.75	**0.69**	**5.03**	**1.26**
		60	4.55	8.55	**0.53**	**4.52**	**2.04**
		120	4.28	9.65	**0.44**	**4.13**	**2.62**
Macroeconomic News Ann.	2	1	1.68	5.16	0.30	0.96	
		12	1.58	5.53	**0.29**	1.57	**1.15**
		60	1.70	5.59	**0.30**	1.39	**1.18**
		120	1.66	5.62	**0.29**	1.63	**1.18**
Day-of-Week	6	1	8.03	9.05	0.82	8.37	
		12	7.67	11.27	**0.63**	**7.83**	**1.58**
		60	7.75	13.46	**0.54**	**6.40**	**2.23**
		120	7.56	14.94	**0.48**	**4.60**	**2.86**

Table 1: Summary Results. Averages across 34 strategies. Panel A summarizes data across all strategies; Panel B summarizes data across strategy groupings. Investment horizon of 1, 12, 60, or 120 months. Physical returns, average returns and return volatilities in annualized terms. Annualized Sharpe ratios. Annualized Fama-French 4-factor alpha. Bolded numbers indicate Sharpe ratios and Fama-French 4-factor alphas below the corresponding 1-month values, and variance ratios above one. In Panel A, t tests across the 34 strategies reject that the 12-, 60-, and 120-month statistic is equal to the 1-month counterpart at the 1% level for Sharpe ratios, Fama-French 4-factor alphas, and variance ratios.

Table 2: Single Period Statistics of Market Timing Strategies. Physical returns. Average returns and return volatilities in annualized terms. Annualized Sharpe ratios. Annualized CAPM alpha and Fama-French 4-factor alpha. Strategies described in Table IA.1.

				Alpha		t-stat	
Strategy	$E[R]$	$\sigma(R)$	Sharpe	CAPM	FF4	CAPM	FF4
Panel A. Benchmark: Untimed Factors							
cma	3.27	7.19	0.45	5.00	2.14	5.20	2.96
hml	4.18	12.36	0.34	3.54		2.54	
mktrf	8.14	18.51	0.44				
rmw	3.40	7.71	0.44	3.80	3.87	3.32	3.40
smb	2.24	10.99	0.20	1.19		1.05	
umd	7.48	16.29	0.46	10.54		6.15	
Panel B. Aggregate Market							
jan	1.20	4.88	0.25	0.74	0.52	1.47	1.00
may	5.96	12.15	0.49	2.64	2.22	2.67	2.18
month	6.26	7.29	0.86	5.43	5.24	7.95	7.37
Panel C. Same-month Seasonalities							
bm	-2.72	26.43	-0.10	0.05	-0.05	0.02	-0.02
composite	5.99	12.52	0.48	6.56	5.75	4.92	4.19
dp	1.02	16.33	0.06	2.88	2.67	1.64	1.49
ep	5.21	14.62	0.36	6.24	4.79	3.27	2.47
ind	5.28	15.34	0.34	6.13	7.02	3.91	4.34
me	6.12	15.71	0.39	6.21	6.35	3.54	3.50
mom	10.08	20.65	0.49	11.94	7.82	5.54	3.82
op	1.81	11.91	0.15	2.47	2.96	1.48	1.70
sp500	12.06	15.83	0.76	13.29	14.65	7.43	8.07

Continues...

				Alpha		t-stat	
Strategy	$E[R]$	$\sigma(R)$	Sharpe	CAPM	FF4	CAPM	FF4
...Continued							
Panel D. Volatility-managed Portfolios							
bab	11.06	11.27	0.98	11.36	10.71	7.86	7.29
cma	2.78	7.20	0.39	4.10	2.02	3.75	2.06
eg	11.59	7.42	1.56	13.65	12.89	11.50	10.90
hml	3.96	11.83	0.33	4.77	1.79	3.33	1.49
ia	5.00	7.22	0.69	7.00	4.99	6.12	4.64
me	0.79	10.65	0.07	0.59	-1.74	0.34	-1.39
mktrf	9.12	18.55	0.49	4.64	2.27	2.73	1.35
qmj	4.59	7.82	0.59	5.74	7.43	5.09	7.02
rmw	4.55	7.70	0.59	5.21	6.68	4.20	5.56
roe	9.69	8.97	1.08	10.85	11.39	7.04	7.82
smb	0.43	10.69	0.04	-0.10	-0.85	-0.08	-0.79
umd	13.78	15.25	0.90	15.18	9.83	8.25	5.83
Panel E. Corporate Events							
dmp	3.43	5.71	0.60	4.64	4.78	8.00	8.52
erp	4.97	6.11	0.81	5.72	5.33	5.69	5.19
Panel F. Macroeconomic News Announcements							
bls	1.43	4.85	0.30	1.06	1.00	1.78	1.64
fomc	1.43	5.64	0.25	0.96	0.92	1.19	1.11
Panel G. Day-of-Week Seasonalities							
age	9.70	7.68	1.26	11.02	11.25	9.63	9.67
bm	2.85	8.62	0.33	2.59	2.80	2.27	2.39
ebe	13.38	10.08	1.33	14.88	14.65	9.85	9.50
gs	0.14	7.71	0.02	0.56	0.61	0.57	0.60
me	9.46	10.26	0.92	10.77	10.33	8.98	8.34
mkt	8.31	10.76	0.77	9.66	10.55	8.44	8.96

Table 3: Variance Ratios of Market Timing Strategies. Logarithmic returns. Average returns and return volatilities in annualized terms. Variance ratio of holding period k is defined in Equation (11). Holding periods of 12, 60, and 120 months. t-statistics calculated against the null of VR = 1. Bolded coefficients indicate VR values above 1. Strategies described in Table IA.1.

			VR			t-stat		
Strategy	$E[r]$	$\sigma(r)$	12	60	120	12	60	120
Panel A. Benchmark: Untimed Factors								
cma	3.69	6.90	**1.37**	**1.22**	0.98	**2.41**	**0.57**	-0.03
hml	4.07	11.84	**1.23**	0.75	0.68	**1.98**	-0.90	-0.78
mktrf	5.98	18.78	**1.23**	0.95	0.72	**1.96**	-0.17	-0.68
rmw	2.81	7.80	**1.44**	0.82	0.80	**2.83**	-0.47	-0.36
smb	2.05	10.83	**1.14**	**1.50**	0.97	**1.21**	**1.78**	-0.08
umd	6.62	18.39	1.00	0.72	0.88	-0.02	-1.00	-0.29
Panel B. Aggregate Market								
jan	1.13	4.77	0.95	0.82	0.58	-0.44	-0.64	-1.02
may	5.10	12.02	**1.18**	0.97	0.89	**1.57**	-0.12	-0.27
month	6.40	7.27	0.89	0.97	**1.33**	-0.93	-0.09	**0.80**
Panel C. Same-month Seasonalities								
bm	-2.09	28.29	**1.02**	**1.37**	**1.35**	**0.17**	**1.24**	**0.79**
composite	5.37	13.99	0.86	**1.10**	**1.27**	-1.19	**0.36**	**0.65**
dp	0.49	17.22	**1.03**	0.76	0.60	**0.23**	-0.83	-0.96
ep	5.02	14.59	0.94	**1.63**	**2.42**	-0.40	**1.86**	**2.82**
ind	4.86	14.73	**1.10**	**1.58**	**1.71**	**0.83**	**2.05**	**1.70**
me	4.56	16.60	0.83	0.89	0.87	-1.48	-0.38	-0.32
mom	8.49	21.26	0.92	**1.09**	0.96	-0.69	**0.31**	-0.11
op	0.96	11.94	0.96	0.99	0.79	-0.27	-0.03	-0.36
sp500	11.68	17.77	0.83	**1.20**	**1.26**	-1.36	**0.66**	**0.60**

Continues...

			VR			t-stat		
Strategy	$E[r]$	$\sigma(r)$	12	60	120	12	60	120
...Continued								
Panel D. Volatility-managed Portfolios								
bab	10.74	11.38	**2.54**	**3.59**	**3.81**	**12.88**	**8.95**	**6.61**
cma	3.26	7.40	**1.11**	**1.10**	**1.20**	**0.68**	**0.26**	**0.36**
eg	12.35	7.63	**2.24**	**5.51**	**9.38**	**7.75**	**11.41**	**14.25**
hml	3.87	12.23	**1.52**	**1.40**	**1.24**	**4.43**	**1.40**	**0.58**
ia	6.18	7.39	**1.17**	**1.65**	**2.90**	**1.05**	**1.64**	**3.24**
me	0.79	11.55	**1.84**	**2.93**	**1.23**	**5.24**	**4.88**	**0.39**
mktrf	7.54	19.09	**1.22**	**1.11**	0.89	**1.91**	**0.40**	-0.26
qmj	4.48	8.17	**1.61**	**2.75**	**3.36**	**4.17**	**4.92**	**4.46**
rmw	4.71	8.17	**1.44**	**2.19**	**2.83**	**2.85**	**3.13**	**3.25**
roe	10.21	9.42	**1.72**	**1.71**	**2.11**	**4.50**	**1.79**	**1.88**
smb	0.04	11.23	**2.08**	**3.46**	**1.73**	**9.30**	**8.74**	**1.77**
umd	13.77	15.28	**1.51**	**2.25**	**3.43**	**4.37**	**4.41**	**5.87**
Panel E. Corporate Events								
dmp	3.67	5.72	**1.19**	**1.56**	**1.88**	**1.63**	**1.98**	**2.11**
erp	5.58	6.19	**1.32**	**2.52**	**3.36**	**1.90**	**3.58**	**3.75**
Panel F. Macroeconomic News Announcements								
bls	1.65	4.68	**1.22**	**1.32**	**1.12**	**1.50**	**0.89**	**0.22**
fomc	1.43	5.61	**1.08**	**1.05**	**1.24**	**0.51**	**0.11**	**0.38**
Panel G. Day-of-Week Seasonalities								
age	10.24	7.22	**2.00**	**2.66**	**3.08**	**6.47**	**4.37**	**3.69**
bm	2.47	7.78	**1.18**	1.00	0.60	**1.16**	-0.01	-0.71
ebe	13.98	9.79	**2.11**	**2.20**	**3.19**	**7.20**	**3.15**	**3.89**
gs	0.11	7.38	**1.27**	**1.47**	0.90	**1.95**	**1.39**	-0.21
me	10.02	10.54	**1.72**	**3.79**	**6.34**	**6.14**	**9.88**	**12.88**
mkt	8.47	10.70	**1.19**	**2.28**	**3.07**	**1.61**	**4.55**	**5.00**

Table 4: Multiperiod Fama-French 4 factor alphas of market timing strategies. Physical returns reported in annualized terms. Fama- French 4-factor alphas. 1-, 12-, 60-, 120-month holding period returns. Newey-West standard errors with lags corresponding to the holding period length. Strategies are described in Table IA.1. Bolded coefficients indicate alphas smaller than at the 1-month holding period. I remove mktrf, hml, smb, and umd from Panel A as all entires are zeroes.

	FF4 Alpha				S.E.			
Strategy	1	12	60	120	1	12	60	120
Panel A. Benchmark: Untimed Factors								
cma	2.14	2.82	2.79	2.36	0.72	0.82	0.75	0.42
mkt	3.43	**3.18**	**2.33**	**2.76**	0.13	**0.36**	**0.74**	**1.02**
rmw	3.87	**3.82**	4.17	**2.49**	1.14	**1.29**	1.21	**1.24**
Panel B. Aggregate Market								
jan	0.52	0.55	**0.14**	**0.34**	0.52	0.46	**0.48**	**0.52**
may	2.22	**1.62**	**1.33**	2.64	1.02	**0.78**	**0.86**	0.74
month	5.24	5.50	5.30	**2.88**	0.71	0.58	0.89	**1.12**
Panel C. Same-month Seasonalities								
bm	-0.05	**-4.38**	**-8.50**	**-8.44**	2.84	**2.99**	**4.15**	**4.61**
composite	5.75	**4.77**	**1.78**	**2.14**	1.37	**1.36**	**1.35**	**1.31**
dp	2.67	**0.85**	**-0.62**	**-1.62**	1.79	**1.71**	**1.69**	**1.69**
ep	4.79	**3.93**	**0.87**	**-0.68**	1.94	**1.95**	**3.64**	**4.54**
ind	7.02	**3.96**	**-0.17**	**-2.74**	1.62	**1.65**	**1.81**	**1.61**
me	6.35	**3.56**	**1.27**	**4.76**	1.81	**1.53**	**1.71**	**1.85**
mom	7.82	**5.57**	**5.41**	**5.59**	2.05	**1.81**	**2.24**	**2.16**
op	2.96	**2.64**	**1.69**	**-0.07**	1.74	**1.52**	**1.78**	**1.94**
sp500	14.65	**10.33**	**6.10**	**7.01**	1.82	**1.77**	**2.03**	**2.44**

Continues...

	FF4 Alpha				S.E.			
Strategy	1	12	60	120	1	12	60	120
...Continued								
Panel D. Volatility-managed Portfolios								
bab	10.71	**8.70**	**9.08**	14.16	1.47	**2.08**	**3.19**	3.40
cma	2.02	2.76	**1.77**	**0.36**	0.98	0.99	**1.23**	**1.21**
eg	12.89	**12.20**	**6.49**	**4.00**	1.18	**1.74**	**2.74**	**3.26**
hml	1.79	**0.33**	**-0.93**	**0.16**	1.20	**1.21**	**1.17**	**1.02**
ia	4.99	5.63	**3.54**	**1.57**	1.07	1.17	**1.58**	**1.86**
me	-1.74	**-2.69**	**-3.52**	**-2.80**	1.25	**1.35**	**1.47**	**0.85**
mktrf	2.27	**2.03**	**0.97**	**1.00**	1.68	**1.61**	**1.61**	**1.43**
qmj	7.43	**6.63**	**4.29**	**1.02**	1.06	**1.33**	**2.23**	**2.12**
rmw	6.68	**6.13**	**3.75**	**-0.04**	1.20	**1.40**	**2.12**	**2.26**
roe	11.39	**10.11**	**6.80**	**4.54**	1.46	**1.81**	**2.10**	**2.15**
smb	-0.85	**-2.26**	**-4.21**	**-4.97**	1.07	**1.22**	**1.43**	**1.31**
umd	9.83	10.89	9.97	10.07	1.69	1.82	2.15	2.47
Panel E. Corporate Events								
dmp	4.78	4.80	**4.19**	**3.54**	0.56	0.53	**0.69**	**0.91**
erp	5.33	**5.26**	**4.85**	**4.72**	1.03	**1.20**	**1.50**	**1.68**
Panel F. Macroeconomic News Announcements								
bls	1.00	1.10	**0.12**	**0.03**	0.61	0.67	**0.94**	**0.92**
fomc	0.92	2.03	2.66	3.23	0.83	0.89	1.12	1.33
Panel G. Day-of-Week Seasonalities								
age	11.25	**9.15**	**7.11**	**4.02**	1.16	**1.54**	**2.05**	**1.93**
bm	2.80	2.91	2.98	4.84	1.17	1.21	1.34	0.96
ebe	14.65	**13.27**	**9.55**	**5.12**	1.54	**2.22**	**2.07**	**1.95**
gs	0.61	1.40	2.62	**0.59**	1.02	1.13	1.48	**1.20**
me	10.33	**9.39**	**7.51**	**8.63**	1.24	**1.54**	**3.02**	**4.82**
mkt	10.55	10.83	**8.65**	**4.43**	1.18	1.19	**2.26**	**3.28**

Panel A.

Variable	Notation	Mean	Persistence	Cond. volatility σ^{CF}	Cond. volatility σ^{DR}	λ
Realized Dividend Growth	Δd			12	12	12
Expected Dividend Growth	z_t	1.29	.9	.48	.16	0
Risk-free Rate	r_t^f	.96	.92	.19	.19	0
Price of Risk	x_t	6.5	.85	2	6	0

Panel B. Conditional correlations.

Variable name, notation	Δd_t	z_t	r_t^f	x_t
Realized Dividend Growth	1	-.83	-.3	0
Expected Dividend Growth		1	0	.35
Risk-free Rate			1	0
Price of Risk				1

Table 5: Model Calibration. Panel A shows the state variables' means and persistences, as well as the dividend growth volatility and the price of risk vector λ. The model is simulated quarterly and means of expected dividend growth and risk-free rate processes reported as an annualized percentages, meaning multiplied by four. Persistence parameters reported in annualized terms, meaning taken to the 4th power. Conditional standard deviations are reported in annualized percentage terms, meaning multiplied by two. Price of risk vector also reported in annualized terms, meaning multiplied by two. Panel B shows the correlation matrix which is constant across Cash Flow and Discount Rate periods.

Years	Strategy	Mean	SD	Sharpe	VR
Panel A.					
1	Market Ex. Return	8.37	20.69	0.40	1.00
10	Market Ex. Return	6.62	18.00	0.37	0.74
40	Market Ex. Return	6.51	15.86	0.41	0.50
Panel B.					
1	Market Ex. Ret. CF Quarters	5.72	9.80	0.58	1.00
10	Market Ex. Ret. CF Quarters	5.39	15.43	0.35	2.52
40	Market Ex. Ret. CF Quarters	5.33	18.91	0.28	3.83
Panel C.					
1	Market Ex. Ret. DR Quarters	2.75	18.62	0.15	1.00
10	Market Ex. Ret. DR Quarters	1.26	16.20	0.08	0.80
40	Market Ex. Ret. DR Quarters	1.17	14.36	0.08	0.64
Panel D.					
1	Dividend Growth	2.02	12.36	0.16	1.00
10	Dividend Growth	1.35	11.47	0.12	0.88
40	Dividend Growth	1.30	10.48	0.12	0.74

Table 6: Main Model Moments. 200,000 quarters of return and dividend data simulated according to parameter values in Table 5, collapsed to a yearly frequency. Panels A to C report means, standard deviations, Sharpe ratios and variance ratios of excess returns of three investment strategies: the market portfolio; the market portfolio in CF quarters, risk-free otherwise; the market portfolio in DR quarters, risk-free otherwise. Years indicates the length of holding period in years. Panel D reports the same moments for aggregate dividend growth. In CF quarters primarily expected cash-flow growth rate shocks have a relatively high volatility; in DR quarters price of risk shocks have a relatively high volatility.

Panel A.

	1 Year		10 Years		40 Years	
	CF Q.	DR Q.	CF Q.	DR Q.	CF Q.	DR Q.
R^M-R^f, N Year	0.17***	0.78***	0.42***	0.54***	0.77***	0.21***
	(83.14)	(398.77)	(127.51)	(168.40)	(187.46)	(54.38)
Constant	4.34***	-3.81***	2.58***	-2.32***	0.34***	-0.23***
	(97.98)	(-86.84)	(88.58)	(-82.78)	(11.83)	(-8.30)
Observations	50000	50000	50000	50000	50000	50000
R^2	0.121	0.761	0.245	0.362	0.413	0.056

Panel B.

	1 Year		10 Years		40 Years	
	CF Q.	DR Q.	CF Q.	DR Q.	CF Q.	DR Q.
Δd, N Year	0.16***	0.42***	0.33***	0.42***	0.59***	0.36***
	(47.25)	(65.37)	(57.19)	(69.51)	(76.96)	(61.49)
Observations	50000	50000	50000	50000	50000	50000
R^2	0.043	0.079	0.061	0.088	0.106	0.070

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: CAPM in the Model. Dividend Betas in the Model. 200,000 quarters of data simulated according to parameter values in Table 5, collapsed to 50,000 yearly observations. Panel A reports the CAPM betas and alphas of CF and DR quarter strategies over the indicated holding period length. Panel B reports the cumulative dividend growth betas of CF and DR quarter strategies over the indicated holding period length.

	HP	Market			CF Quarters			DR Quarters			CF Strat.
κ	Years	E $[R]$	SD (R)	SR (R)	E $[R]$	SD (R)	SR (R)	E $[R]$	SD (R)	SR (R)	CAPM α
0	1	8.54	18.27	0.47	4.23	12.43	0.34	4.15	12.44	0.33	0.16
.1	1	8.43	18.28	0.46	4.40	11.58	0.38	3.91	13.52	0.29	1.02
.2	1	8.50	18.56	0.46	4.80	10.72	0.45	3.60	14.69	0.25	2.06
.3	1	8.52	19.06	0.45	5.26	10.17	0.52	3.21	15.88	0.20	3.06
.4	1	8.45	19.86	0.43	5.42	9.84	0.55	3.04	17.20	0.18	3.67
.5	1	8.37	20.69	0.40	5.72	9.80	0.58	2.75	18.62	0.15	4.34
0	10	7.19	16.55	0.43	3.57	11.90	0.30	3.50	11.62	0.30	0.02
.1	10	7.06	16.32	0.43	3.84	11.80	0.32	3.13	12.04	0.26	0.51
.2	10	7.10	16.45	0.43	4.34	12.25	0.35	2.68	12.72	0.21	1.11
.3	10	7.04	17.05	0.41	4.86	13.07	0.37	2.12	13.70	0.15	1.74
.4	10	6.85	17.45	0.39	5.06	13.93	0.36	1.76	14.87	0.12	2.16
.5	10	6.62	18.00	0.37	5.39	15.43	0.35	1.26	16.20	0.08	2.58
0	40	7.10	15.02	0.47	3.53	11.44	0.31	3.46	11.13	0.31	-0.01
.1	40	6.98	15.13	0.46	3.79	12.21	0.31	3.08	10.81	0.28	-0.07
.2	40	7.01	14.66	0.48	4.29	13.34	0.32	2.62	10.97	0.24	-0.02
.3	40	6.95	15.63	0.44	4.81	14.88	0.32	2.06	11.69	0.18	0.28
.4	40	6.75	15.57	0.43	5.01	16.68	0.30	1.68	13.05	0.13	0.32
.5	40	6.51	15.86	0.41	5.33	18.91	0.28	1.17	14.36	0.08	0.34

Table 8: Returns to Market Timing as a Function of the Seasonality in Underlying Shocks. Each row represents a simulation of 200,000 quarters of data. The simulations use parameter values in Table 5, except for the volatilities of expected cash-flow and price of risk shocks. The parameter κ captures the amount of seasonality: the price if risk shocks have the volatility of $\sigma_x(1+\kappa)$ and $\sigma_x(1-\kappa)$ in DR and CF quarters respectively, where σ_x is the average volatility. The baseline calibration is represented by $\kappa = .5$ while $\kappa = 0$ indicates no seasonality. Expected growth rate volatility is calculated analogously. HP length refers to holding period length in years. Expected returns and standard deviations in annualized terms. The final column shows the annualized alpha of the timing strategy that holds the market in CF quarters only.

	CF Quarters Strat.			DR Quarters Strat.		
1-year Strip Return		0.26***			0.36***	
		(125.78)			(86.74)	
10-year Strip Return			0.09***			0.69***
			(54.98)			(484.48)
Constant	5.72***	0.99***	5.20***	2.75***	-3.88***	-1.05***
	(130.57)	(18.40)	(119.14)	(33.05)	(-35.64)	(-29.27)
Observations	50000	50000	50000	50000	50000	50000
R^2	0.000	0.240	0.057	0.000	0.131	0.824

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Timing Strategies and Dividend Strip Returns in the Model. 200,000 quarters of data simulated according to parameter values in Table 5, collapsed to 50,000 yearly observations. Left hand side variables are the annual returns on DR and CF quarter strategies. Right hand side variables are annual returns of dividend strips of 1-, 5-, and 10-year maturities.

IA Internet Appendix

IA.1 Model Derivations

I first derive asset prices in DR quarters. Let me guess and verify that the pricing function is in the form

$$P_{n,t}^{DR} = D_t \exp\left\{A_n^{DR} + B_n^{DR} H_t\right\} \tag{23}$$

To find the coefficients A_n^{DR} B_n^{DR} let's first substitute the assumed equations for dividend prices (23) into the pricing relation (21) and re-express H_{t+1}

$$D_t \exp\left\{A_n^{DR} + B_n^{DR} H_t\right\} = \mathrm{E}_t\left[M_{t+1} D_{t+1} \exp\left\{A_{n-1}^{CF} + B_{n-1}^{CF} H_{t+1}\right\}\right] \tag{24}$$

$$\implies \exp\left\{A_n^{DR} + B_n^{DR} H_t\right\} = \mathrm{E}_t\left[M_{t+1} \frac{D_{t+1}}{D_t} \exp\left\{A_{n-1}^{CF} + B_{n-1}^{CF}\left(\Theta_0 + \Theta H_t + \sigma_H^{t+1} \epsilon_{t+1}\right)\right\}\right] \tag{25}$$

Now, let's plug in the assumed SDF from Equation (20) and the aggregate cash-flow process $\exp\{\Delta d_{t+1}\}$

$$\exp\left\{A_n^{DR} + B_n^{DR} H_t\right\} = \mathrm{E}_t\Big[\exp\{-r_{t+1}^f - .5|\lambda|^2 x_t^2 - x_t \lambda' \epsilon_{t+1}\} \exp\{z_t + \sigma_d \epsilon_{t+1}\} \tag{26}$$

$$\exp\left\{A_{n-1}^{CF} + B_{n-1}^{CF}\left(\Theta_0 + \Theta H_t + \sigma_{CF} \epsilon_{t+1}\right)\right\}\Big] \tag{27}$$

Taking the expectation and recognizing that ϵ_{t+1} is multivariate normal results in the following relationships for coefficients for prices in DR quarters

$$\begin{aligned}\exp\left\{A_n^{DR} + B_n^{DR} H_t\right\} = \exp\Big\{&-\alpha_0 - \alpha' H_t - .5(\xi_0 + \xi' H_t)^2 |\lambda|^2 + \delta_0 + \delta' H_t \\ &+ A_{n-1}^{DR} + B_{n-1}^{DR}\left(\Theta_0 + \Theta H_t\right) + .5\left(\sigma_d - (\xi_0 + \xi' H_t)\lambda' + B_{n-1}^{CF} \sigma_{CF}\right) \\ &+ \left(\sigma_d - (\xi_0 + \xi' H_t)\lambda' + B_{n-1}^{CF} \sigma_{CF}\right)'\Big\}.\end{aligned} \tag{28}$$

Matching coefficients we can solve for A_n^{DR} and B_n^{DR}

$$\begin{aligned}A_n^{DR} = &-\alpha_0 + \delta_0 + A_{n-1}^{CF} + B_{n-1}^{CF}\Theta_0 - (\sigma_d + B_{n-1}^{CF}\sigma_{CF})\lambda\xi_0 + .5\sigma_d\sigma_d' + B_{n-1}^{CF}\sigma_{CF}\sigma_d + \\ &.5 B_{n-1}^{CF}\sigma_{CF}\sigma_{CF'} B_{n-1}^{CF'},\end{aligned} \tag{29}$$

$$B_n^{DR} = -\alpha' + \delta' + B_{n-1}^{CF}\Theta - \left(\sigma_d + B_{n-1}^{CF}\sigma_{CF}\right)\lambda\xi'. \tag{30}$$

To derive the pricing recursion for CF period prices, let's again guess and verify that the counterpart to the Even period pricing function in Equation 23 is

$$P_{n,t}^{CF} = D_t \exp\left\{A_n^{CF} + B_n^{CF} H_t\right\}. \tag{31}$$

Following the exact same process results in the pricing recursion

$$\begin{aligned} A_n^{CF} =& -\alpha_0 + \delta_0 + A_{n-1}^{DR} + B_{n-1}^{DR}\Theta_0 - (\sigma_d + B_{n-1}^{DR}\sigma^{DR})\lambda\xi_0 + .5\sigma_d\sigma_d' + B_{n-1}^{DR}\sigma_{DR}\sigma_d + \\ & .5B_{n-1}^{DR}\sigma_{DR}\sigma_{DR'}B_{n-1}^{DR'} \end{aligned} \tag{32}$$

$$B_n^{CF} = -\alpha' + \delta' + B_{n-1}^{DR}\Theta - \left(\sigma_d + B_{n-1}^{DR}\sigma_{DR}\right)\lambda\xi'. \tag{33}$$

IA.2 Internet Appendix Figures

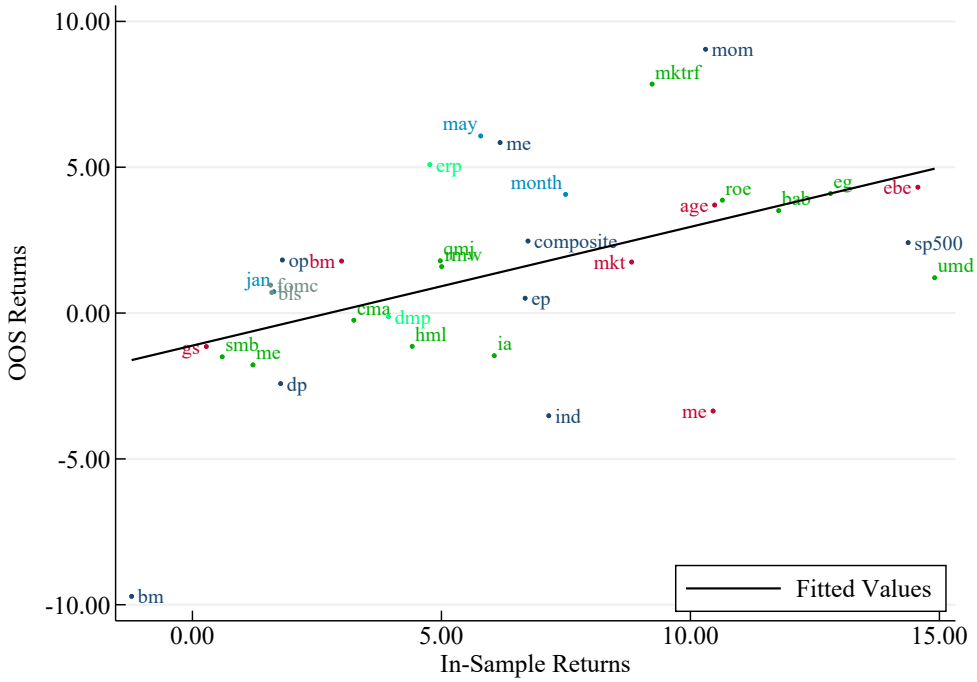


Figure IA.1: In-sample and Out-of-Sample Returns of Timing Strategies. Strategies described in Table IA.1. Strategy start dates listed in Table IA.1.

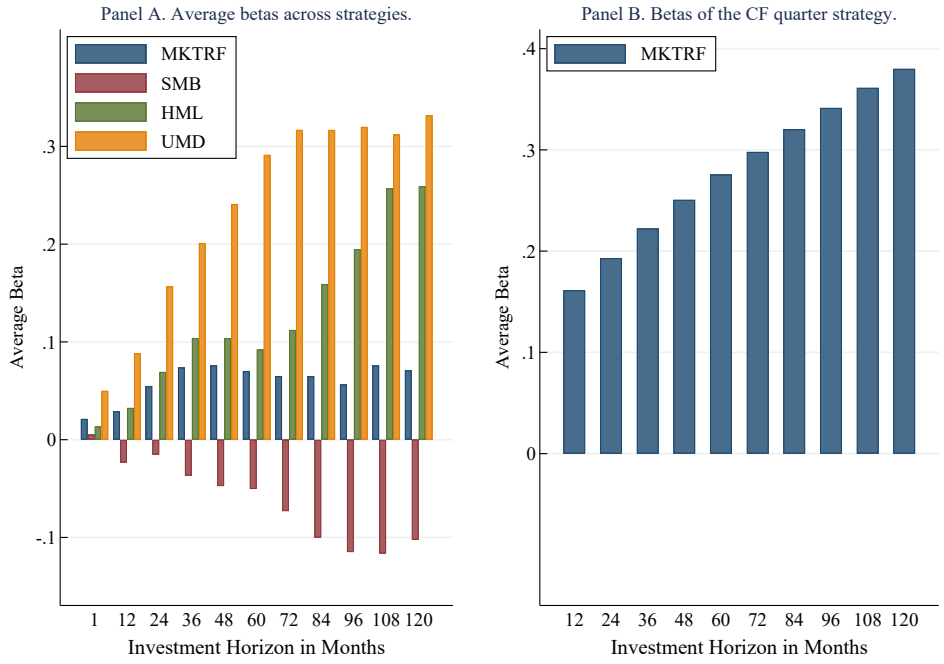


Figure IA.2: Factor Betas as a Function of Holding Period. Panel A shows the average betas across the 34 strategies at the indicated investment horizon. Panel B shows the average market beta at the indicated investment horizon in the data.

CA

IA.3 Internet Appendix Tables

Table IA.1: Descriptions of Timing Strategies. Sample start and end date used in this paper. Citation of the original source describing the strategy. Cutoff year used to compare in- and out-of-sample returns.

Name	Start	End	Description	Original Source	Cutoff
Panel A. Aggregate Market					
jan	1926/7	2023/12	Holds the aggregate equity market only in January.	Ilmanen (2011)	1976
may	1926/7	2023/12	–from November to May	Ilmanen (2011)	1964
month	1926/7	2023/12	–on first three and the last trading day of every month	Lakonishok and Smidt (1988)	1988
Panel B. Same-month Seasonalities					
bm	1927/7	2023/12	Seasonality portfolio based on historic same-month returns of book-to-market portfolios over 20-year lookback window.	Keloharju et al. (2016)	2006
composite	1927/7	2023/12	–of 58 underlying size, value, momentum, dividend-to-price, and industry portfolios.		2006
dp	1928/7	2023/12			2006
ep	1952/7	2023/12	–of 10 earnings-to-price portfolios		2006
ind	1927/7	2023/12	–of 17 industry portfolios		2006
me	1927/7	2023/12	–of market equity portfolios		2006
mom	1928/1	2023/12	–of momentum portfolios		2006
op	1964/7	2023/12	–of profitability portfolios		2006
sp500	1936/1	2023/12	–of stocks in the SP500		2006

Continues...

...Continued

Panel C. Volatility-managed Portfolios

bab	1931/1	2023/12	Long position in the BAB factor, scaled by the inverse of realized variance in the prior month.	Moreira and Muir (2017)	2015
cma	1963/8	2023/12	–in the CMA factor		2015
eg	1967/2	2023/12	–in the EG factor		2015
hml	1926/8	2023/12	–in the HML factor		2015
ia	1967/2	2023/12	–in the IA factor		2015
me	1967/2	2023/12	–in the ME factor		2015
mktrf	1926/8	2023/12	–in the MKTRF factor		2015
qmj	1957/8	2023/12	–in the QMJ factor		2015
rmw	1963/8	2023/12	–in the RMW factor		2015
roe	1967/2	2023/12	–in the ROE factor		2015
smb	1926/8	2023/12	–in the SMB factor		2015
umd	1926/12	2023/12	–in the UMD factor		2015

Panel D. Corporate Events

dmp	1927/1	2023/12	Long CRSP stocks in the month they are predicted to pay dividends, short CRSP stocks predicted not to pay dividends.	Hartzmark and Solomon (2013)	2011
erp	1972/7	2023/12	Long Compustat stocks in the month they are predicted to make an earnings announcement, short Compustat stocks not predicted to make an earnings announcement.	Savor and Wilson (2016)	1991

Continues...

...Continued

Panel D. Macroeconomic News Announcements

bls	1958/1	2023/12	Hold the equity market around BLS announcements.	Savor and Wilson (2013)	2011
fomc	1971/8	2023/12	Hold the equity market on three days straddling scheduled FOMC announcements.	Lucca and Moench (2015)	2011

Panel E. Day-of-Week Seasonalities

age	1963/7	2023/12	Long AGE factor on Mondays, short on Fridays.	Birru (2018)	2016
bm	1963/7	2023/12	Short BM factor on Mondays, long on Fridays.		2016
ebe	1963/7	2023/12	Long EBE factor on Mondays, short on Fridays.		2016
gs	1952/1	2023/12	Short GS-sorted factor on Mondays, long on Fridays.		2016
me	1926/10	2023/12	Long AGE on Mondays, short on Fridays.		2016
mkt	1926/7	2023/12	Short MKT on Mondays, long on Fridays.		2016

Table IA.2: Multiperiod Sharpe Ratios of Timing Strategies. Sharpe ratios of 1-, 12-, 60-, and 120-month holding periods, reported on an annualized basis. Standard errors calculated after Lo (2002). Strategies described in Table IA.1. Bolded coefficients indicate Sharpe ratios smaller than at the 1-month holding period.

	Sharpe Ratio				S.E.			
Strategy	1	12	60	120	1	12	60	120
Panel A. Benchmark: Long Only Factors								
cma	0.54	**0.46**	**0.47**	**0.50**	0.08	**0.20**	**0.48**	**0.65**
mkt	0.50	**0.46**	0.51	0.65	0.05	**0.18**	0.40	0.42
rmw	0.36	**0.31**	0.42	0.44	0.07	**0.21**	0.36	0.48
Panel B. Aggregate Market								
jan	0.24	0.24	0.24	0.28	0.05	0.16	0.25	0.26
may	0.42	**0.39**	**0.42**	0.46	0.06	**0.19**	**0.46**	0.59
month	0.88	0.92	**0.85**	**0.72**	0.06	0.21	**0.50**	**0.70**
Panel C. Same-month Seasonalities								
bm	-0.07	**-0.09**	**-0.08**	-0.06	0.05	**0.16**	**0.27**	0.28
composite	0.38	0.42	0.39	**0.37**	0.07	0.23	0.34	**0.39**
dp	0.03	0.03	0.05	0.05	0.04	0.12	0.24	0.30
ep	0.34	0.35	**0.26**	**0.21**	0.07	0.22	**0.33**	**0.37**
ind	0.33	**0.32**	**0.29**	**0.30**	0.06	**0.19**	**0.36**	**0.47**
me	0.27	0.31	0.31	0.34	0.06	0.22	0.34	0.38
mom	0.40	0.42	**0.39**	0.45	0.06	0.21	**0.42**	0.47
op	0.08	0.08	0.10	0.13	0.06	0.19	0.33	0.38
sp500	0.66	0.72	**0.62**	**0.61**	0.09	0.29	**0.40**	**0.52**

Continues...

	Sharpe Ratio				S.E.			
Strategy	1	12	60	120	1	12	60	120
...Continued								
Panel D. Volatility-managed Portfolios								
bab	0.94	**0.61**	**0.53**	**0.51**	0.07	**0.12**	**0.28**	**0.42**
cma	0.44	**0.42**	**0.41**	**0.39**	0.07	**0.21**	**0.39**	**0.45**
eg	1.62	**1.10**	**0.70**	**0.50**	0.12	**0.33**	**0.48**	**0.50**
hml	0.32	**0.25**	**0.26**	**0.28**	0.04	**0.12**	**0.22**	**0.29**
ia	0.84	**0.79**	**0.62**	**0.43**	0.10	**0.29**	**0.48**	**0.48**
me	0.07	**0.02**	**0.01**	0.07	0.07	**0.18**	**0.23**	0.21
mktrf	0.39	**0.35**	**0.35**	0.40	0.03	**0.09**	**0.23**	0.34
qmj	0.55	**0.43**	**0.34**	**0.31**	0.06	**0.13**	**0.20**	**0.26**
rmw	0.58	**0.49**	**0.40**	**0.35**	0.08	**0.18**	**0.32**	**0.38**
roe	1.08	**0.82**	**0.81**	**0.73**	0.06	**0.16**	**0.38**	**0.49**
smb	0.00	**0.00**	0.01	0.01	0.05	**0.11**	0.16	0.23
umd	0.90	**0.72**	**0.58**	**0.46**	0.05	**0.14**	**0.30**	**0.36**
Panel E. Corporate Events								
dmp	0.64	**0.58**	**0.49**	**0.41**	0.07	**0.19**	**0.32**	**0.36**
erp	0.90	**0.80**	**0.57**	**0.47**	0.10	**0.33**	**0.56**	**0.70**
Panel F. Macroeconomic News Announcements								
bls	0.35	**0.32**	**0.28**	**0.27**	0.10	**0.25**	**0.36**	**0.52**
fomc	0.26	0.26	0.33	0.31	0.10	0.30	0.57	0.80
Panel G. Day-of-Week Seasonalities								
age	1.42	**1.00**	**0.89**	**0.83**	0.10	**0.22**	**0.34**	**0.54**
bm	0.32	**0.31**	0.35	0.43	0.05	**0.13**	0.29	0.54
ebe	1.43	**0.98**	**0.99**	**0.81**	0.12	**0.24**	**0.40**	**0.53**
gs	0.01	0.01	0.02	0.03	0.05	0.14	0.26	0.45
me	0.95	**0.72**	**0.50**	**0.38**	0.10	**0.19**	**0.21**	**0.22**
mkt	0.79	**0.73**	**0.50**	**0.40**	0.08	**0.21**	**0.29**	**0.34**

Table IA.3: Multiperiod CAPM Alphas of Timing Strategies. 1-, 12-, 60-, and 120-month holding period returns. Returns reported on an annualized basis. Newey-West standard errors with number of lags corresponding to the holding period length. Strategies described in Table IA.1. Bolded coefficients indicate alphas smaller than at the 1-month holding period. I remove mktrf from the first panel as all entires are zeroes.

	CAPM Alpha				S.E.			
Strategy	1	12	60	120	1	12	60	120
Panel A. Benchmark: Long Only Factors								
cma	5.00	**4.76**	**4.84**	5.11	0.96	**0.91**	**0.75**	0.67
hml	3.54	3.61	3.89	4.71	1.39	1.21	0.89	1.14
mkt	3.47	3.55	3.77	4.53	0.13	0.33	0.72	1.12
rmw	3.80	**3.73**	**3.12**	**2.44**	1.15	**1.11**	**0.87**	**0.90**
smb	1.19	**1.02**	2.20	3.84	1.13	**1.09**	1.27	1.09
umd	10.54	**7.30**	**5.44**	**5.13**	1.71	**1.62**	**1.54**	**2.23**
Panel B. Aggregate Market								
jan	0.74	0.75	0.85	0.91	0.51	0.41	0.40	0.42
may	2.64	**2.20**	**2.12**	**1.98**	0.99	**0.76**	**0.80**	**1.08**
month	5.43	**5.31**	**5.17**	**4.68**	0.68	**0.52**	**0.67**	**1.02**
Panel C. Same-month Seasonalities								
bm	0.05	**-4.35**	**-5.44**	**-3.19**	2.76	**2.70**	**3.71**	**4.00**
composite	6.56	**5.69**	**4.69**	**4.25**	1.33	**1.24**	**1.51**	**1.97**
dp	2.88	**0.97**	**-0.32**	**0.13**	1.76	**1.63**	**1.37**	**1.42**
ep	6.24	**4.62**	**5.17**	6.38	1.91	**1.63**	**2.64**	3.57
ind	6.13	**5.01**	**3.87**	**3.73**	1.57	**1.51**	**1.89**	**2.38**
me	6.21	**5.03**	**4.48**	**5.36**	1.76	**1.45**	**1.62**	**1.92**
mom	11.94	**9.70**	**8.01**	**9.47**	2.15	**1.90**	**2.26**	**2.56**
op	2.47	**1.17**	**0.30**	**0.08**	1.67	**1.42**	**1.47**	**1.47**
sp500	13.29	**11.42**	**11.15**	**11.73**	1.79	**1.64**	**2.41**	**2.86**

Continues...

	CAPM Alpha				S.E.			
Strategy	1	12	60	120	1	12	60	120
...Continued								
Panel D. Volatility-managed Portfolios								
bab	11.36	**10.08**	**10.61**	13.50	1.45	**1.91**	**2.58**	3.22
cma	4.10	**3.79**	**3.58**	**4.09**	1.09	**0.94**	**1.00**	**1.18**
eg	13.65	13.66	**13.21**	14.00	1.19	1.57	**2.84**	4.15
hml	4.77	**3.86**	**4.01**	6.03	1.43	**1.43**	**1.39**	1.44
ia	7.00	**6.64**	**6.35**	7.17	1.14	**1.01**	**1.35**	2.05
me	0.59	**-0.31**	**-0.40**	2.58	1.74	**2.10**	**2.67**	1.53
mktrf	4.64	**3.48**	**2.48**	**1.27**	1.70	**1.47**	**1.24**	**1.10**
qmj	5.74	**5.25**	**3.63**	**2.84**	1.13	**1.27**	**1.84**	**2.11**
rmw	5.21	**4.90**	**4.24**	**3.91**	1.24	**1.27**	**1.67**	**2.13**
roe	10.85	**10.62**	**8.86**	**9.63**	1.54	**1.67**	**1.63**	**2.31**
smb	-0.10	**-0.68**	**-0.72**	0.30	1.30	**1.64**	**1.99**	1.61
umd	15.18	**13.57**	**12.35**	**11.77**	1.84	**1.88**	**2.50**	**3.85**
Panel E. Corporate Events								
dmp	4.64	4.70	4.93	5.01	0.58	0.47	0.61	0.86
erp	5.72	5.87	6.32	6.92	1.01	1.04	1.59	2.19
Panel F. Macroeconomic News Announcements								
bls	1.06	1.10	1.23	1.59	0.59	0.58	0.69	0.61
fomc	0.96	1.11	1.90	2.43	0.81	0.79	0.87	1.12
Panel G. Day-of-Week Seasonalities								
age	11.02	**10.82**	**10.39**	**10.21**	1.14	**1.35**	**1.62**	**1.81**
bm	2.59	2.97	3.23	3.40	1.14	1.04	0.92	0.65
ebe	14.88	**14.52**	**13.65**	**12.94**	1.51	**1.91**	**1.93**	**2.68**
gs	0.56	0.57	1.01	1.00	0.99	0.96	1.05	0.84
me	10.77	**10.53**	**9.51**	**9.93**	1.20	**1.40**	**2.34**	**3.71**
mkt	9.66	**9.65**	**9.33**	**8.13**	1.14	**1.09**	**1.75**	**2.59**

Table IA.4: Multiperiod Fama-French 4 factor alphas of market timing strategies. Log returns reported in annualized terms. Fama- French 4-factor alphas. 1-, 12-, 60-, 120-month holding period returns. Newey-West standard errors with lags corresponding to the holding period length. Strategies are described in Table IA.1. Bolded coefficients indicate alphas smaller than at the 1-month holding period. I remove mktrf, hml, smb, and umd from Panel A as all entires are zeroes.

	FF4 Alpha				S.E.			
Strategy	1	12	60	120	1	12	60	120
Panel A. Benchmark: Untimed Factors								
cma	2.04	2.79	2.78	2.35	0.71	0.81	0.75	0.41
mkt	3.40	**3.16**	**2.33**	**2.77**	0.13	**0.35**	**0.72**	**1.00**
rmw	3.40	3.74	4.15	**2.49**	1.13	1.27	1.20	**1.24**
Panel B. Aggregate Market								
jan	0.55	**0.55**	**0.14**	**0.34**	0.51	**0.45**	**0.47**	**0.52**
may	2.21	**1.64**	**1.33**	2.63	0.99	**0.77**	**0.86**	0.73
month	5.30	5.47	**5.27**	**2.86**	0.70	0.57	**0.89**	**1.11**
Panel C. Same-month Seasonalities								
beta	1.41	**-0.18**	**-2.09**	**-1.97**	2.40	**2.15**	**2.14**	**1.81**
bm	-4.03	**-4.74**	**-8.52**	**-8.40**	3.17	**3.03**	**4.17**	**4.62**
composite	4.89	**4.68**	**1.76**	**2.14**	1.48	**1.35**	**1.34**	**1.29**
dp	0.58	0.63	**-0.64**	**-1.64**	1.82	1.69	**1.68**	**1.68**
ep	3.86	**3.76**	**0.88**	**-0.63**	1.89	**1.91**	**3.60**	**4.51**
ind	5.80	**3.84**	**-0.20**	**-2.75**	1.59	**1.63**	**1.79**	**1.60**
me	4.89	**3.42**	**1.25**	**4.73**	1.83	**1.52**	**1.70**	**1.84**
mom	6.00	**5.34**	**5.29**	**5.52**	2.06	**1.79**	**2.23**	**2.14**
op	1.96	2.52	**1.67**	**-0.05**	1.71	1.50	**1.76**	**1.93**
sp500	12.96	**10.16**	**6.04**	**6.96**	1.95	**1.76**	**2.00**	**2.41**

Continues...

	FF4 Alpha				S.E.			
Strategy	1	12	60	120	1	12	60	120
...Continued								
Panel D. Volatility-managed Portfolios								
bab	10.07	**8.59**	**9.03**	14.12	1.41	**2.02**	**3.13**	3.32
cma	1.88	2.72	**1.78**	**0.37**	0.95	0.97	**1.22**	**1.20**
eg	12.40	**12.04**	**6.47**	**4.03**	1.13	**1.70**	**2.69**	**3.21**
hml	1.12	**0.26**	**-0.93**	**0.15**	1.17	**1.19**	**1.15**	**1.01**
ia	4.85	5.56	**3.54**	**1.58**	1.04	1.14	**1.56**	**1.85**
me	-1.92	**-2.71**	**-3.52**	**-2.80**	1.26	**1.34**	**1.46**	**0.85**
mktrf	1.89	2.07	**0.98**	**0.99**	1.64	1.58	**1.59**	**1.42**
qmj	6.62	**6.50**	**4.28**	**1.06**	1.02	**1.30**	**2.20**	**2.09**
rmw	6.07	**6.01**	**3.74**	**-0.01**	1.17	**1.38**	**2.10**	**2.24**
roe	10.79	**9.97**	**6.78**	**4.57**	1.41	**1.76**	**2.07**	**2.12**
smb	-1.33	**-2.31**	**-4.20**	**-4.96**	1.05	**1.21**	**1.43**	**1.31**
umd	10.25	10.88	**9.91**	**10.02**	1.62	1.77	**2.11**	**2.43**
Panel E. Corporate Events								
dmp	4.33	4.73	**4.17**	**3.52**	0.55	0.52	**0.69**	**0.90**
erp	5.29	**5.25**	**4.83**	**4.68**	0.99	**1.17**	**1.48**	**1.67**
Panel F. Macroeconomic News Announcements								
bls	1.02	1.13	**0.13**	**0.02**	0.60	0.66	**0.94**	**0.91**
fomc	0.95	2.03	2.65	3.21	0.81	0.88	1.11	1.33
fomcb	1.14	1.80	2.41	2.39	0.66	0.57	0.50	0.35
Panel G. Day-of-Week Seasonalities								
age	10.80	**9.11**	**7.09**	**4.02**	1.10	**1.49**	**2.02**	**1.91**
bm	2.54	2.84	2.95	4.82	1.15	1.19	1.33	0.96
ebe	14.01	**13.13**	**9.49**	**5.15**	1.48	**2.16**	**2.03**	**1.92**
gs	0.27	1.37	2.61	0.57	1.01	1.11	1.47	1.19
me	9.86	**9.26**	**7.47**	**8.56**	1.22	**1.50**	**2.96**	**4.74**
mkt	9.39	10.68	**8.57**	**4.39**	1.14	1.17	**2.23**	**3.25**

	FF4 Alpha				S.E.			
Strategy	1	12	60	120	1	12	60	120
retvol	24.96	25.56	**20.11**	**13.97**	2.15	2.13	**2.53**	**3.25**

	HP	Market			CF Quarters			DR Quarters			CF Strat.
	Years	E [R]	SD (R)	SR (R)	E [R]	SD (R)	SR (R)	E [R]	SD (R)	SR (R)	CAPM α
	1	8.57	18.33	0.47	4.19	12.43	0.34	4.22	12.43	0.34	0.10
	10	7.21	16.37	0.44	3.53	11.73	0.30	3.57	11.81	0.30	0.08
	40	7.12	14.85	0.48	3.48	11.23	0.31	3.52	11.26	0.31	0.05
DR	1	8.40	19.82	0.42	3.06	9.33	0.33	5.28	17.34	0.30	1.34
DR	10	6.80	17.36	0.39	2.71	11.84	0.23	4.00	14.01	0.29	0.05
DR	40	6.70	15.66	0.43	2.68	13.71	0.20	3.93	11.04	0.36	-1.52
CF	1	8.59	18.56	0.46	6.93	12.02	0.58	1.63	13.60	0.12	3.48
CF	10	7.19	16.73	0.43	6.35	13.20	0.48	0.83	12.49	0.07	2.77
CF	40	7.10	15.19	0.47	6.30	14.04	0.45	0.77	11.85	0.07	2.14

Table IA.5: Returns to Market Timing. Alternative Parameters. Each row represents a simulation of 200,000 quarters of data. The simulations use parameter values in Table 5, except for the volatilities of expected cash-flow shocks and price of risk shocks. In the first set of three rows the volatilities of cash-flow and price of risk shocks have no seasonality. In the rows indicated DR, the price of risk shocks have volatility $\sigma_x(1+\kappa)$ and $\sigma_x(1-\kappa)$ with $\kappa = .5$ in DR and CF quarters respectively. In the rows indicated CF, the expected cash-flow shocks have volatility $\sigma_z(1+\kappa)$ and $\sigma_z(1-\kappa)$ with $\kappa = .5$ in CR and DR quarters respectively. HP length refers to holding period length in years. Expected returns and standard deviations in annualized terms. The final column shows the annualized alpha of the timing strategy that holds the market in CF quarters only.