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Active asset allocation for retirement funds using the fed model

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Abstract

Active asset allocation, also known as market timing, is controversial but potentially effective for individual investors and financial advisors. Many studies support market timing based on the relationship between the aggregate earnings yield on equities and the intermediate Treasury bond yield, known as the Fed model. Nevertheless, skeptics point to common flaws in these studies and challenge the validity of the Fed model. In general, returns from timing models are difficult to adjust for transaction costs and tax effects from short term gains and losses. In almost all cases, there is data mining from reporting results over the same period used to build the timing model. Our study addresses these concerns directly. We control the transaction costs and tax effects by focusing on funds available for retirement accounts within a Vanguard fund family allowing costless monthly transfers. We use a "risk on" or "risk off" approach rather than experiment with arbitrary cutoff rules for switching funds. We first test for the time series properties of the Fed model to build a prediction model and then apply it over a recent five-year holdout of period. Our findings show that the switching portfolio offers attractive performance compared to either of the Vanguard funds, especially with respect to enhancing upside to downside risk ratios. © 2017 Academy of Financial Services. All rights reserved.

Keywords: Market Timing; Kalman Filter; Active Asset Allocation

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1. Introduction

Individual investors and investment advisors make asset allocation decisions as part of an overall investment strategy. Efficient market theory supports using a passive buy and hold approach linked to long run objectives and investment horizons with periodic rebalancing as objectives and horizons change. On the other hand, active asset allocation has the potential to increase portfolio returns dramatically if executed successfully. Xiong, Ibbotson, Idzorek, and Chen (2010) show that portfolio returns split evenly between asset allocation and active management when overall market moves are accounted for. Shilling (1992) concludes that avoiding the 50 weakest months of the stock market would have doubled investor returns. There is a vast literature on active asset allocation, often called market timing, with few definitive conclusions. The volume of timing research is a testament to the importance of the topic to investors.

In this article, we examine the investment performance of an active asset allocation model based on monthly signals from the time varying relationship between the aggregate equity earnings yield and the 10-year Treasury yield, often called the Fed model. We address key criticisms of prior work to build and then test timing performance of the Fed model. First, we test for the appropriate time series of the Fed model to define the switch points for asset allocation, rather than experiment to find points that worked in past data or simply assume the spread is a random variable. Next, important deficiencies of prior studies come from a failure to adequately control for transaction costs and tax effects from gains and losses because of switches. We control for these effects by using Vanguard's S&P500 Index Fund (VFINX) and Treasury Index Fund (VFITX). Because transfers between these funds in the Vanguard family do not have buying and selling costs for the investor, we avoid the criticism of not accounting for transaction costs from asset switches.[1] Changes in asset allocation result in short term realized gains and losses that lead to tax effects that many studies ignore. Since the Vanguard family of funds is widely used in tax deferred retirement accounts, the tax effects from realized gains and losses because of switches are irrelevant for tax-exempt retirement fund investors. The analysis is limited to retirement fund investors using a family of funds but that segment of the investing population is significant and growing.

Many studies report attractive performance after searching through past data with multiple models and arbitrary switch points. Critics point out that a regularity in past data discovered in this way does not mean the model that works best in past periods is predictable going forward. To avoid this data mining criticism, we test for the time series properties of the Fed model over long periods of time and then use out of sample data from January 2012 through December 2016 to test the investment performance of the model. We find the performance characteristics of the active asset allocation portfolio to be attractive to many investors seeking higher returns than a buy and hold equity fund with only moderately more risk than a buy and hold 10-year treasury fund. Potentially more important, the investment performance results in a more favorable upside to downside volatility ratio favored by investors who fear losses more than they covet gains.

We use the following organization for the article. Section 2 provides a review of the literature on active asset allocation and the criticisms leveled at these studies. We follow in Section 3 by reviewing the traditional use of the Fed model to time the markets. We also present the conceptual arguments for using the Fed model and address the common problems with the way it has been tested and applied in other studies. We present the time series version of the Fed model in Section 4 along with the estimated parameters that define the switch points for the active asset allocation moves. Portfolio performance from applying the Fed model in an out-of-sample investment period of recent markets using the Vanguard index funds appears in Section 5. The final section contains the conclusions and suggestions for added research.

2. Literature review

While many studies find return enhancement from active asset allocation, other studies point out critical measurement and research design flaws affecting the findings. Sharpe (1975) was one of the first to point out the difficulty of timing the market and reported that an investor would need to tell a good year from a bad year seven out of 10 times to be successful. More recently, Bauer and Dahlquist (2001) calculate that an investor would need to be able to switch correctly 66% of the time on a monthly basis to outperform a buy and hold strategy. Early studies of timing ability outlined by Pinches (1970) generated mixed results where superior performance from timing rules tended to be offset by trading costs.

The literature on timing continues to grow with new and more complex trading rules based on fundamentals (Feldman, Jung, & Klein, 2015), macroeconomic variables (Breen, Glosten, & Jagamathan, 1989 and Guido, Peral, & Walsh, 2011), nonfinancial indicators (Krueger & Kennedy, 1990), mean reversion (Campbell, Andrew, & McKinley, 1999), and technical indicators (Lo, Mamaysky, & Wang, 2000). Critics of these studies point to problems of transaction costs, tax effects, and data mining (Aronson, 2006; Asness, 2003; and Sullivan, Timmerman, & White, 1999). A good example of the dialogue on timing appears in the *Journal of Portfolio Management* where Pruitt and White (1988) provide a defense for technical analysis to beat the market while Ball, Kothari, and Wasley (1995) present the problems of actually implementing technical trading rules in the real world.

Proponents of the efficient market hypothesis refute the view that the equity market could over- and under-react in a predictable way to allow successful timing strategies (Fama, 1998 and Malkiel, 2003). The blending of psychology and finance by Kahneman and Tversky provides a paradigm to counterbalance the efficient market hypothesis and offers a conceptual foundation for potential market timing anomalies.[2] Behavioral biases and heuristics make predictably irrational outcomes in the market possible. Campbell (2000), Campbell, Andrew, and Mckinley (1999), Daniel, Hirshleifer, and Subrahmanyam (1998), DeBont and Thaler (1985), and Shleifer (2000) are a few of the studies suggesting that overreaction to information makes the stock market deviate from fundamentals, allowing potential gains from market timing. The overreaction hypothesis, based on “follow the herd” and “regret aversion” concepts originally developed in psychology, is now part of the mainstream literature. Recent overreaction in the stock market during the late 1990s and in the housing market in the 2005–2008 period reinforces the view that predictable irrationality in the market may be viable, encouraging more study of timing rules.

3. The fed model

In a speech on irrational exuberance in 1991, Alan Greenspan used the relationship between the aggregate equity earnings yield and the 10-year Treasury yield to evaluate "abnormal" market conditions.[3] When the stock market is abnormally high the earnings yield (aggregate earnings divided by the market index price) is low relative to the long term bond yield. This interpretation of the relationship between the equity yield and the Treasury yield suggests a predictive model for stock market valuation commonly called the "Fed" model, even though the Fed never officially recognized that usage. The Fed model specification appears as Eq. (1) below.

$$(E/P)_t = \lambda(Y10)_t \tag{1}$$

For each point in time (t), the measure of the equity market yield is the ratio of trailing aggregate equity market earnings to the aggregate equity market price index (E/P). The right side of Eq. (1) is the 10-year Treasury bond yield (Y10) times a multiplier (λ).[4] In the strict version of the Fed model, the equilibrium multiplier (λ) is one, but this need not be the case. Most uses of the model assume that the multiplier is a random variable, making the mean of λ_t the best estimate of the equilibrium relationship in Eq. (1). Deviations from the mean value of the multiplier represent abnormalities and mispricings. For example, Bodie, Kane, and Marcus (noted as BKM, 2014) make the following statement in their popular investments textbook:

> *The most popular approach to forecasting the overall stock market is the earnings multiplier approach applied at the aggregate level.* (*p. 429*)

As an illustration, if the long run average of the equity market P/E is 15 the long run average for the earnings yield (E/P) is 6.67%. If the long run average of the 10-year Treasury yield is 5% the long run average of the Fed model multiplier is 1.334 (0.0667 / 0.05 = 1.334).[5] If the current 10-year Treasury yield is 2.3%, the expected value of the E/P today is 3.068% (1.334 $\times$ 0.023). Based on this logic the current market value of equities should be 32.59 times aggregate earnings (1/0.03068 = 32.59 = P/E). If the current market P/E is below 32.59, the Fed model would predict undervaluation and a buy signal would be appropriate. The Fed model offers a benchmark for fair value but the time series properties of the multiplier plays a crucial role. The example only holds if the multiplier is a random variable, making the long run mean the best estimate of the expected multiple in the next period.

3.1. Why the fed model might work

The basic argument for using the Fed model as a measure of normal market relationships rests on the view that stocks and bonds are competing asset classes, prompting investors to make yield comparisons when allocating assets. When stock yields are high relative to bond yields ($E/P > YT_{10}$), investors buy stocks and funds flow away from bonds to stocks. The process will bring stock prices up and equity yields down back in line with bond yields. Critics point out that the earnings yield is a real return while the Treasury yield is in nominal terms, suggesting that the competing asset explanation is flawed (Asness, 2003). Nevertheless, investors may follow the Fed model because of money illusion, at least in the short run. Practitioners emphasize the descriptive validity of the Fed model rather than its theoretical validity.

Another justification for using the Fed model to evaluate market valuation builds on the discounted cash flow model for equity valuation. The discount rate in this valuation process is a risk free rate plus an equity risk premium. The long run Treasury yield is a proxy for the risk free rate in this calculation. As the Treasury yield falls the present value of equity cash flows (P) increases and the earnings yield (E/P) falls as the Fed model predicts. Critics point to the potential for time varying risk premiums, which are not in the Fed model. A counter to this argument is that risk premiums are very difficult to predict (Fernandez, Aguirremalloa, & Corres, 2011) and implementation of valuation theory in the real world uses a stable long run average risk premium rather than time varying forward estimates. Finally, the Fed model could be valid simply because practitioners use it. The market moves when the ratio of the earnings yield to the Treasury yield reaches an inflection point if investors move funds in responses to that ratio, for whatever reason.

3.2. Prior use of the fed model for asset allocation

The original version of the Fed model in Eq. (1) has been tested using monthly data by Koiva, Pennanen, and Ziemba (2005), Shen (2003), and Ziemba and Schwartz (1991). These studies find that timing based on extreme value switch points using the traditional Fed model adds value beyond a buy and hold strategy. Even so, the studies are subject to various criticisms such as data mining with multiple models, failure to adjust for taxes and transaction costs, and not covering the financial crisis period in the post-2008 period.

4. Time varying fed model

Rather than pick an arbitrary value of λ as the switch point for asset allocation or use the mean based on the assumption that λ_t is a random variable, we test for the time series properties of the Fed model. The strict version of the Fed model suggests that the multiplier λ_t is one, but there is no prediction of how deviations will adjust back to one over time. Less strict views of the Fed model would allow for persistent deviations from one because of differences in equity risk premiums or changes in growth. The time series for the multiplier is subject to empirical testing. The information content of the Fed multiplier (λ_t) may follow a random variable, random walk, or autoregressive series. Eq. (2) is the constant coefficient benchmark model in our empirical analysis.

$$(E/P)_t = \lambda(Y10)_t + \varepsilon_t \tag{2}$$

The specification of Eq. (2) implicitly places a restriction on the multiplier coefficient (λ) by assuming it is a constant. There is good reason to suspect that the multiplier (λ) may change over time. For example, Federal Reserve intervention may artificially keep the Treasury yield from adjusting when equity earnings yields are abnormally high or low. Other arguments for time variation in the multiple (λ) rest on the discount model approach to equity valuation if changing risk premiums or growth affect the relationship between equity earnings yields and Treasury yields.[6]

Kalman's (1960) estimation procedure, known as the Kalman filter, provides a flexible model for testing and estimating a model's time varying coefficients. In our context, Kalman's time varying parameter model relaxes the assumption that λ is constant and allows testing of the hypothesis that time variation occurs in the parameter (λ_t) versus the null hypothesis that the parameter is constant (λ_t). We modify Eq. (2) to create a measurement equation with a time-varying coefficient as Eq. (3).

$$(E/P)_t = \lambda_t (Y10)_t + \varepsilon_t \tag{3}$$

A state equation models the time variation of λ_t. In our empirical work, we test the following specification for time variation of the Fed multiple (λ):

$$\lambda_t = \phi_0 + \phi_1 \lambda_{t-1} + \mu_t \tag{4}$$

where the disturbance term in the state equation (μ_t) has a normal distribution with a mean of zero and a constant standard error (Eq. 5).

$$\mu_t \sim N(0, \sigma) \tag{5}$$

Time variation in the Fed multiplier (λ_t) may follow a random walk, random variable, or an autoregressive form. The constant coefficient model of Eq. (2) is a special case of the model in Eqs. (3) and (4). The coefficient (λ) is constant if the standard error (σ) from Eq. (4) is zero. The coefficient (λ_t) follows a random walk if the standard error is not zero and the intercept coefficient is zero ($\phi_0 = 0$) while the slope coefficient estimate is equal to one ($\phi_1 = 1$). If the standard error θ is not zero and the estimate of coefficient ϕ_1 is zero, the multiplier λ_t in Eq. (3) is a random variable with a mean of ϕ_0. The Fed multiplier λ_t is autoregressive if the standard error θ is not zero, the intercept coefficient is not zero ($\phi_0 \neq 0$), and the coefficient ϕ_1 is between zero and one.[7]

The model in Eqs. (3) and (4) represents a Kalman filter specification of the state equation following the Cooley-Prescott (1973) adaptive regression approach. Estimation of the model follows a recursive maximum likelihood process. The process uses an updating method that bases the regression estimates for each period on the last period's estimates plus data from the current period. Kahl and Ledolter (1983) show that a recursive Kalman filter approach obtains simultaneous maximum likelihood estimates of the parameters in Eqs. (3) and (4). A likelihood ratio test statistic with a χ^2 distribution provides a test of the null hypothesis ($\sigma = 0$), which implies that the coefficient of the model (l) is constant. In general, our empirical models allow us to first test for the time series model up to the holdout period and then implement the Fed model using the Vanguard fund indexes and the appropriate benchmark for a switch point (λ_t).

5. Test for time series properties of the fed multiplier

We use Shiller's monthly data for aggregate earnings, S&P 500 price, and the 10-year Treasury yield to first test time series models of the Fed multiplier over diverse markets.[8] We

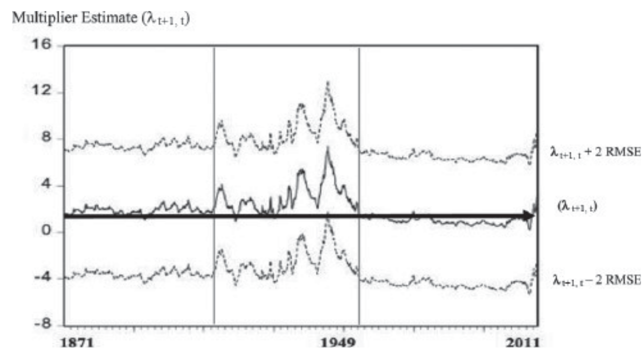

Fig. 1. Kalman filter estimates of the Fed multiplier ($\lambda_{t+1,\ t}$) and the 95% confidence interval ($\lambda_{t+1,\ t}$ + 2 RMSE) using Shiller's data from 1871 through 2011.

Notes:

- The dark arrow represents a multiplier value of 1, consistent with the strict version of the Fed model.
- The strict form of the Fed model multiplier ($\lambda = 1$) is contained in the 95% confidence interval throughout the long history of the Shiller data up to the investment holdout period. The RMSE notation represents the root mean square error.
- The vertical lines represent the period from 1912 to 1954 where the multipliers were higher and more volatile. This period contains the Great Depression, two world wars, and the Korean War.

end the test period analysis with Shiller's data in December 2011, because we later use the Vanguard index fund data from January 2012 through December 2016 as our out of sample investment period. Shiller computes monthly earnings data from the S&P four-quarter totals with linear interpolation to monthly figures over a very long time span starting in 1871. Stock price data are monthly averages of daily closing prices. One advantage of using the Shiller data source is that it is readily available and often used in academic studies, avoiding data construction as a source of different findings.

The center plots in Fig. 1 represent the Kalman filter estimates ($\lambda_{t+1,\ t}$) of the Fed multiplier in Eqs. (3) and (4) from 1871 through 2011. A 95% confidence interval around the center plots also appears in Fig. 1 with a dark arrow representing a multiplier of one, as predicted by the strict version of the Fed Model. The only time the 95% confidence interval does not contain the strict Fed multiplier value of one occurs briefly at the end of WWII. Fig. 1 illustrates time variation in the Fed multiplier but the multiplier is much more stable and consistent with the strict Fed model ($\lambda_{t+1,\ t} = 1$) before and after the period from 1912 to 1954. This period contains the Great Depression, WWI, WWII, and the Korean War. The multiplier is stable and close to the strict Fed model prediction in the modern era after 1954.

Table 1 provides specific tests for time variation in the multiplier and for the time series properties of the varying coefficients (multipliers). The test uses Shiller's data for the period from 1988 through 2011, leading up to our holdout investment period. The choice of the test period focused on modern markets while still allowing for a long time span. Four different models of the time series for the multiplier (λ_t) appear in the table to include constant coefficient, random variable, autoregressive, and random walk specifications. The χ^2 test statistic in the second column of Table 1 offers a test for time varying coefficients, based on the value of the standard error (σ) in Eq. (4). A statistically significant χ^2 value supports rejection of the hypothesis that the standard error is zero and the coefficient (λ_t) is

Table 1 Test results for alternative time varying Kalman filter coefficient models using Shiller's data from January 1988 through 2011

Coefficient test model	$\chi^2 = 2(LL_{constant} - LL_{variable})$	Log Likelihood (LL)	Akaike criterion
Constant	N/A	N/A	N/A
Random variable	2,516[a]	−5,986[b]	7.088[c]
Autoregressive	17,542[a]	−13,499	15.985
Random walk	2,030[a]	−5,743[b]	6.801[c]

Notes: [a]The χ^2 statistic is significant at the 0.001 level, supporting rejection of the constant coefficient specifications.

[b]The higher log-likelihood value corresponds to the model with the best fit to the data. The random walk offers the best fit but the random variable model is a close second.

[c]The lowest Akaike value corresponds to the model with the best fit to the data. The random walk is the best fit but the random variable is again a close second.

a constant in Eq. (3). The χ^2 values rest on differences in the log likelihood values of a constant coefficient specification in Eq. (4) versus a time varying specification. For every alternative time varying model, the χ^2 statistic is highly significant, supporting rejection of the hypothesis of a constant coefficient (multiplier).

Both the Log Likelihood values and Akaike (1974) goodness of fit measures in Table 1 support a Kalman filter model where the next month's expected multiplier is equal to the last month's multiplier. Because the random variable model also provides a good fit, the average multiplier is also close to the best estimate. The goodness of fit results suggest that the last observed multipliers remain close to the long run mean multiplier, but the multiplier is not a constant. Fig. 2 shows the estimated values of the Fed multiplier using the Kalman filter over the test period from 1988 through 2011. The multiplier is time varying but does not stray far from one, ranging from a high of 1.1 to a low of just over 0.85. The combined findings of Fig. 1, Table 1, and Table 2 support a stable, but not constant multiplier in the 24 years leading up to our investment holdout period. The best estimate of the next period's multiplier

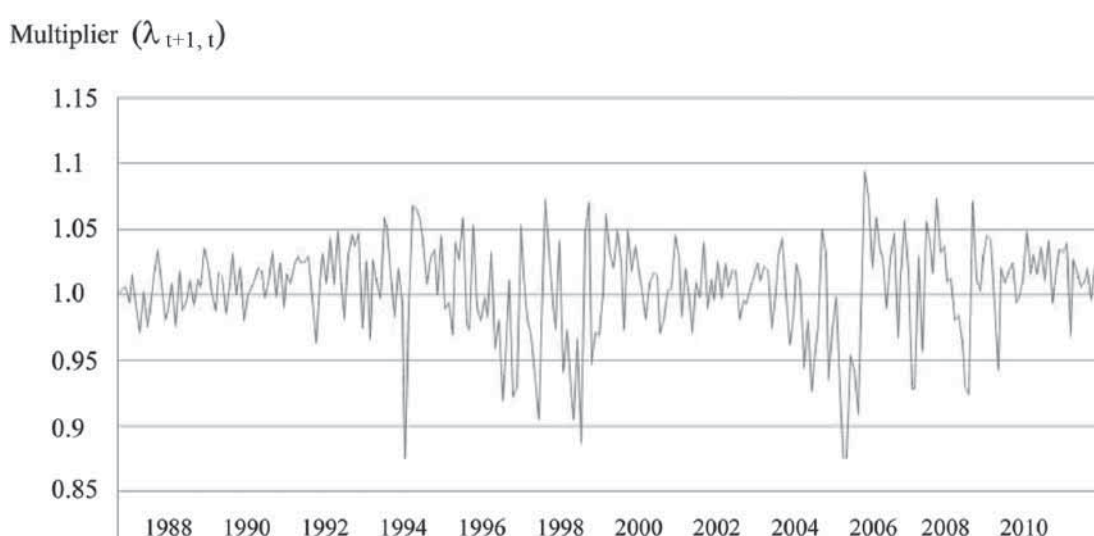

Fig. 2. Test period estimates of the Fed multiplier (1988 through 2011 period).

Table 2 Test results for the Kalman filter time varying coefficient models using Vanguard mutual fund data over the January 2012 through December 2016 out of sample investment period

Coefficient model	$\chi^2 = 2\,\lvert LL_{constant} - LL_{variable}\rvert$	Log Likelihood (LL)	Akaike criterion
Constant	N/A	N/A	N/A
Random variable	2,178[a]	−628[b]	4.5537[c]
Autoregressive	2,842[a]	−960	6.9568
Random walk	2,134[a]	−606[b]	4.3458[c]

Notes: [a]The χ^2 statistic is significant at the 0.001 level, supporting rejection of the constant coefficient specifications.

[b]The higher log-likelihood value corresponds to the model with the best fit to the data. The random walk offers the best fit but the random variable model is a close second.

[c]The lowest Akaike value corresponds to the model with the best fit to the data. The random walk offers the best fit but the random variable model is again a close second.

would be the last observed multiplier based on these findings but we would not expect it to deviate more than 0.15 from one. The caveat is that in Fig. 1 we see that periods of major global disruptions, unlike anything we have seen since the late 1940s and early 1950s, appear to affect the multiplier relationship with equity and bond yields.

6. Investment results in out-of-sample markets

A model that offers a good fit to the data in a test period may offer good investment performance over that same period, but may not offer good predictions or investment performance in another market period. This is a key criticism of studies that find a predictable relationship over a period and then report the investment performance from only that period. We first examine the robustness of the Kalman filter test findings from the long run test period in Table 1 by replicating the analysis in our investment period from January 2012 through December 2016 using the Vanguard mutual fund data. We then test the investment performance of the Kalman filter by creating a portfolio based on switches between Vanguard funds using estimated multipliers and the strict Fed model. Ultimately, the issue is whether the switching information from the Kalman filter model translates into better investment performance than buying and holding either the Vanguard equity or the bond Index mutual funds.

6.1. Robustness of Kalman filter tests

Table 2 reproduces the tests of time variation in the Fed model reported in Table 1 but with the Vanguard mutual fund data and our holdout investment period from January 2012 through December 2016. We now use the monthly holding period return relatives for each of the Vanguard funds over the recent holdout period rather than Shiller's data. Our findings in Table 2 mirror the findings from Table 1. The χ^2 tests support time varying coefficient models over a constant coefficient model. Both the Log Likelihood and Akaike goodness of fit measures support a random walk specification of the multiplier in the Kalman filter model closely followed by a random variable. The model performs consistently over different periods and with different data sources.

Table 3 Investment performance in the holdout period January 2012 through December 2016 for the Vanguard Index Fund portfolios and the active switching portfolio based on the strict fed model

Portfolio measure	VFINX portfolio	VFITX portfolio	Active switching portfolio
Average monthly return	.01074	.00093	0.0196[a]
Effective annual rate of return	.1368	.0112	.2623[b]
Standard deviation of monthly return	0.0298	0.0102[c]	0.0199
Average monthly return/standard deviation	0.360	0.0912	0.985[d]
Upside to downside monthly volatility	.902	1.113	1.291[e]

Notes: VFINX = Vanguard's S&P500 Index Fund; VFITX = Vanguard's Treasury Index Fund.
[a]The active switching portfolio has the highest average monthly return.
[b]The active switching portfolio has the highest effective annual rate of return.
[c]The Vanguard Index Intermediate Bond fund has the lowest monthly volatility of monthly returns.
[d]The switching portfolio provides the best return for risk tradeoff.
[e]The switching portfolio provides the best upside to downside volatility.

6.2. Investment performance results from the strict fed model

Our findings up to this point suggest that the Fed multiplier does not exhibit a trend and deviations of the multiplier from month to month are relatively small leading up to our investment holdout period. Our long run analysis of Kalman filter estimates of the Fed multiplier suggests that the strict version of the Fed model provides a reasonable benchmark for making switching decisions. The Kalman filter provided a robust prediction model for the Fed multiplier. The next step is to evaluate whether using the model to switch between Vanguard index funds in recent markets provides attractive investment performance.

We constructed an active switching portfolio by making asset allocation shifts to the VFINX when the expected multiplier from the Kalman filter model is greater than one ($\lambda_{t+1,\ t} > 1$). In this case, the expected aggregate equity yield, using the Vanguard S&P500 Index Fund as the price index, exceeds the expected yield on the VFITX. This position is held until the expected multiplier is less than one ($\lambda_{t+1,\ t} < 1$), calling for a switch from the Vanguard S&P500 Index Fund to the VFITX. There is potential for as many as 12 switches per year in this five-year period. However, movement of funds monthly within the Vanguard family does not carry a transaction cost for trading. Furthermore, any capital gains or losses would be irrelevant for retirement fund investments.

Table 3 summarizes the investment performance using the buy and hold Vanguard funds and the active switching portfolio over the holdout investment period. The switching portfolio has an average monthly rate of return of 1.96% (26.23% effective annual rate), which is higher than the average monthly returns for either of the Vanguard fund returns. The monthly standard deviation and monthly rate of return of the Vanguard Index Treasury bond fund is the lowest, as expected. However, on a reward for risk basis, the switching portfolio has the highest ratio of monthly returns to monthly standard deviation (0.985).

The switching portfolio also offers the best upside gain relative to the downside risk, providing favorable positive skewing of the return performance.[9] The ratio of upside monthly standard deviation to downside monthly standard deviation is 1.29 for the switching portfolio relative to 1.113 for the Vanguard Index Treasury Bond fund and only 0.902 for the Vanguard S&P 500

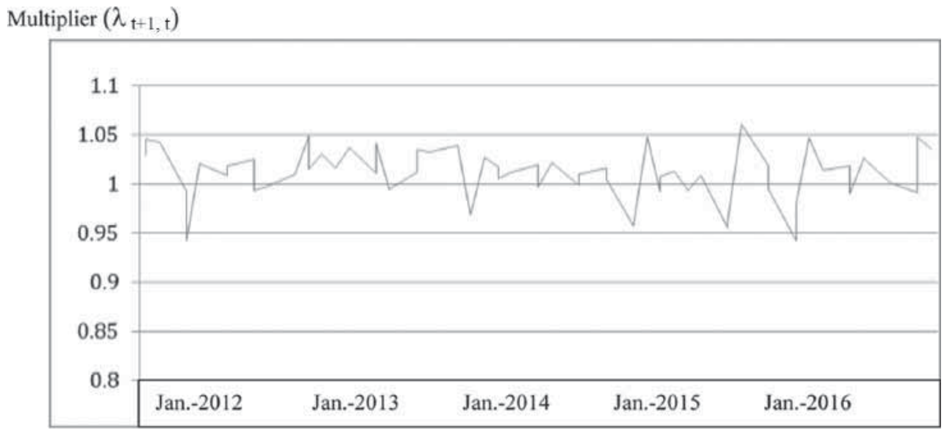

Fig. 3. Fed multiplier estimates ($\lambda_{t+1,\ t}$) using Vanguard Index Fund data over the January 2012 through December 2016 out of sample investment period.

Notes:

- Estimation of the Fed multiplier with the Kalman filter uses the Vanguard Treasury Index Fund (VFITX) and the Vanguard S&P 500 Index Fund (VFINX) data over the investment period.
- The multiplier has a lack of trend with volatility around a multiplier of $\lambda_{t+1,\ t}$ = 0 0.95 and a range of multiplier values from 1.05 to 0.95.

Index fund. For many investors, the favorable positive skewing of return performance from the switching portfolio is especially important. Pfeifer (1985) demonstrates how an investor's utility function with respect to loss aversion should be included in investment performance. Prospect theory (Kahneman & Tversky, 1979) suggests investors fear losses more than they enjoy gains, making a simple reward to risk metric insufficient for investment performance.

Investors who chase winners play a losing game by buying stocks when they are high and selling when stocks are low. The switching portfolio offers a counterbalance to the tendency to chase winners. When the earnings yield (E/P) is high, the market price is low relative to earnings. Rather than sell stocks in a falling market, the switching portfolio buys stocks. This contrarian aspect of investing with the Fed model is an attractive feature for investors subject to recency, herding, and regret aversion biases outlined in the behavioral finance literature (Nofsinger, 2013).

6.3. Switches in the strict fed model

Fig. 3 shows the variation in the Kalman filter estimates of the Fed multiplier ($\lambda_{t+1,\ t}$) over the investment performance period from January 2012 through December of 2016. The multiplier estimate moved within a tight range from 1.05 to 0.95. Each crossing of the estimate over the strict Fed multiplier of one represents a portfolio switch in Vanguard funds. We assumed *a priori* that the strict version of the Fed model would be an appropriate benchmark for our switching portfolio rather than mine the data to find an optimal switch benchmark. Our decision to use the strict Fed model is consistent with the long run performance of the Kalman filter found in the test period. We did not find that changing risk premiums, revisions of growth estimates, absence of money illusion, or other criticisms of the theoretical arguments invalidated the strict Fed model interpretation.

7. Conclusions and implications

The controversy over the potential for active asset allocation to enhance investment performance is likely to continue with a debate over methods, data, return adjustments and interpretations of findings. In this article, we first focused the debate on switching funds within a family of funds to bypass concerns over transaction costs and tax effects. This focus did not reduce the relevance of the study, given the large retirement fund universe. We used a simple "risk on" and "risk off" approach with a basic switch rule defined by the strict Fed model. Shiller's data allowed a very long run test period of the time varying properties of the Fed model rather than assuming mean reversion or other forms of moving averages. The flexible Kalman filter model offered time varying estimates of the relevant Fed model multiplier in the test period. In a holdout investment period of recent markets, investment performance from switching between index funds in the Vanguard family of funds resulted in attractive investment performance relative to a buy and hold of either index fund separately. The performance was especially attractive for investors seeking positively skewed investment performance consistent with prospect theory where the investor values gains less than avoidance of losses.

Added research could enhance the switching methods outlined here. We limited our analysis to a "risk on" and "risk off" approach, but switching at only extreme multiplier values may offer added enhancements to performance. However, such extreme value switch rules would need to be determined in out-of-sample test periods. We also know that our reported performance in the 2012 to 2016 period may not be representative of performance going forward. Even so, our analysis suggests that the Fed model is stable outside the 1912 to 1954 period where major global disruptions occurred.

We used monthly switch points that might be excessive for many individual investors, calling for additional work on quarterly or annual switch point analysis with the Kalman filter model. It is common to find changing time series patterns by changing the holding period of returns. This issue merits more attention in the context of the Fed model. While we used the Vanguard index funds in this analysis, it would be possible to use ETFs rather than mutual funds and gain added performance. The equivalent ETFs would be the Vanguard S&P500 ETF (VOO), for the VFINX mutual fund and the Vanguard Intermediate-Term Government Bond ETF (VGIT), for the VFITX mutual fund.

Notes

1 Vanguard (2015) allows an investor to buy or exchange back into the same fund, in the same account, every 30 calendar days. There is no limitation for ETFs. See https://personal.vanguard.com/us/whatweoffer/overview/redemptionpolicy

2 Kahneman and Tversky generated volumes of research that define behavioral finance. For a very readable reference to the totality of the work of Kahneman and Tversky, see Lewis (2016).

3 The original impetus for the Fed model came from the "Monetary Policy Report to Congress Pursuant to the Full Employment and Balanced Growth Act of 1978." The

Federal Reserve Bank never officially adopted the Fed model but Greenspan (2007) references the model in his writings.

4 Some applications of the Fed model use the spread between the earnings yield (E/P) and the Treasury yield (Y_{10}) rather than the ratio. In this case the Fed model is $[E/P - \lambda Y_{10}] = 0$. Again, when λ = one the strict Fed model holds.

5 The example in Bodie, Kane, and Marcus (2014) use the spread between the equity earnings yield and the Treasury bond yield in their example.

6 A manipulating of the dividend discount model shows that the equity earnings yield (E/P) is a function of the risk free rate, equity risk premium, and earnings growth rate. The Fed model focuses on the relationship between (E/P) and the risk free rate, assuming that variation in the risk premium and earnings growth either remain stable or investors do not consider them in short run monthly investment decisions.

7 The estimates of the slope and intercept coefficients determine the time series model at work with the data. If both the intercept and slope are significant, both the mean and the last observation determine the next period's multiplier. If the intercept is insignificant with a significant slope of about one, the last observation determines the next period's multiplier. With a significant intercept and insignificant slope coefficient, the mean is the best estimate of next period's multiplier.

8 To obtain Shiller's data see (http://www.econ.yale.edu/~shiller/data.htm).

9 See Sortino (1994) for a more in-depth treatment of the use of upside to downside standard deviation relationships.

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