Analyzing the impact of TFP news shocks on equity indexes & Fama-French 5-factor portfolios

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Abstract:

This paper further investigates "News Shocks and the Slope of the Term Structure of Interest Rates" by Andre Kurmann and Christ Otrok (2013) in which they explore the relationship between shocks to the slope of the term structure of interest rates and TFP news shocks. In our paper, we explore specifically TFP news shocks, repeating the same identification procedure as Kurmann-Otrok (2013) and continue this research by evaluating how these TFP news shocks affect equity indexes (i.e., S&P 500, NASDAQ) as well as how these shocks impact a selection of Fama-French 5-factor portfolios. Our VAR specification shows that 50-70% of the forecast error variance (FEV) in the S&P 500 and up to 40% of the long-run FEV of the NASDAQ composite can be explained by shocks to future TFP. Additionally, we find that portfolios built on cash-flow heavy (i.e., dividend-bearing) assets, such as the Conservative Minus Aggressive (CMA) Fama-French portfolio have up to 50% of the long-run FEV explained by these TFP news shocks. Unsurprisingly, in the long run, positive TFP news shocks increase the value of every portfolio, while the direction, timing, and magnitude of the short run response to TFP news shocks varies among the portfolios. We attribute these short-run discrepancies to differences in portfolios dividend distribution policies (i.e., the asset's cash flows). We argue TFP news shocks can be interpreted as shocks to the expectation of future cash flows of the underlying equities in the portfolios in a discounted cash flow framework.

I. Introduction:

A common interpretation of financial markets is that they are the market capitalization of discounted expected future cash flows. Provided that definition, we can represent the price of a risky asset (equity) as:

$$S_t = \sum_{k=1}^{\infty} \frac{\mathbb{E}_t[D_{t+k}]}{(1+r)^k}$$

Where S_t is the price of the asset today, $\mathbb{E}_t[D_{t+k}]$ represents the expectation in period t of future cash flows in period $t+k$, and r represents an appropriate discount rate. This definition is a common explanation for asset pricing phenomena and underpins the findings of this paper.[1]

Both practitioners and researchers of asset pricing models concern themselves with the implementation of this formula: investment bankers commonly use discounted cash flow (DCF) valuations to compute the value of an enterprise and economists use the formula across all fields of literature (macro, monetary, finance, etc.). When applying the discounted cash flow valuation formula to an asset, it is apparent that we must model two fundamental processes: future cash flows D_{t+k} and the discount rate r.

Projecting future cash flows of an asset is a dynamic field of study, as the future cash flows can be influenced by an uncountable number of correlated factors, each rendering some effect on how market participants value and trade equities. Many papers attempt to uncover how asset prices respond to various events, such as Lee (2012) where she investigates how stochastic jump diffusion models can be used to predict jumps in equity prices in response to both macro events and firm-specific information releases, such as FOMC meetings and dividend declarations.[2] Our paper focuses on macro factors, and specifically shocks to future

[1]See the appendix for the derivation of this model for the price of a risky asset.

[2]Lee (2012) investigates asset price jumps using a doubly stochastic Poisson model. In particular, she investigates how asset prices move in response to market and firm-specific events. She concludes that equity price jumps can be predicted accurately using a set of events as predictors for the model.

productivity (TFP); we treat TFP news as a proxy to the expectation of future economic productivity. Because we argue that the value of an asset is tied directly to the expected future cash flows, we hypothesize that these TFP news shocks carry significant predictive information about future firm performance, and thus their public valuation. We identify TFP news shocks as an innovation that explains the maximum amount of variance in future TFP while having no contemporaneous effect on TFP.[3] This is referred to as the 'zero-impact' restriction henceforth.

The discount rate can be represented in one of many ways. Practitioners may use the weighted-average cost of capital (WACC) to value securities in a professional setting, macroeconomists may use the federal funds rate or an appropriate T-bill yield, and financial economists may represent it in terms of the stochastic discount factor (SDF) in consumption-based asset pricing models. As this paper seeks to explore the effects of TFP news shocks on asset prices, we will use a treasury rate as described in Section III. We will leave further exploration of the discount rate models to future research.

II. Econometric Implementation:

This analysis focuses on the identification of one type of shock, the TFP news shock. To identify TFP news shocks, we adopt an identification scheme developed by Uhlig (2004) and implemented in Kurmann-Otrok (2013) that identifies these shocks by finding n orthogonal innovations that maximizes the FEV of a target variable over a given horizon.[4,5] Prerequisite to the identification procedure is selecting the target variable (i.e., the impulse we are studying) and the horizon $0 < \underline{k} < \overline{k}$ upon which we want to maximize the FEV. This

[3]Kurmann, André, and Otrok, Christopher. 2013 "News Shocks and the Slope of the Term Structure of Interest Rates," American *Economic Review,* 103 (6): 2612-32.
[4]Uhlig, Harald. 2004. "What moves GNP?," Econometric Society 2004 North American Winter Meetings 636, Econometric Society.
[5]Kurmann, André, and Otrok, Christopher. 2013 "News Shocks and the Slope of the Term Structure of Interest Rates," American *Economic Review*, 103 (6): 2612-32.

section intends to only give an overview of the methodology, and we will relegate much of the detail of the procedure to both the appendix and Kurmann-Otrok (2013). We begin with the standard moving average vector autoregression (VAR) specification,

$$Y_t = \Theta(L)u_t$$

where Y_t is the m x 1 vector of variables (yields, macro, financial) at time t. $\Theta(L)$ is a m x l lag polynomial matrix with l lags. u_t is defined as the VAR forecast error at $t+1$ with a variance-covariance matrix of $\Sigma = \mathbb{E}[u_t u_t']$. The goal of this procedure is to find a linear transformation $F\colon u_t \to \epsilon_t$ where ϵ_t is a vector of mutual orthogonal shocks and $FF' = \Sigma$. This mapping matrix F is non-unique (i.e., $\tilde{F}Q = F$) and thus we must find the orthonormal matrix Q which maximizes the FEV of Y_t from $\underline{k}$ to $\overline{k}$.[6] Substituting in $\tilde{F}$ and ϵ_t gives us a formula for the k-step ahead forecast error of the jth variable,

$$Y_{j,t+k} - \mathbb{E}_t\left[y_{j,t+k}\right] = i_j'[\sum_{l=0}^{k-l} \Theta_l\, \tilde{F}Q\epsilon_{t+k-l}]$$

where i_j is a column vector with all zeros except for the jth row. The problem we must then solve becomes,

$$Q_n^* = \underset{Q_n}{\text{argmax}}\{\, i_j'[\sum_{k=\underline{k}}^{\overline{k}} \sum_{l=0}^{k-l} \Theta_l\, \tilde{F}Q_n Q_n' \tilde{F}' C_l']\, i_j\} \quad \text{subject to } \; Q_n' Q_n = I_n$$

where Q_n represents the n columns of the most informative orthogonal shocks to $Y_{j,t}$. Clearly, we can reformulate this problem in terms of a principal component analysis solution in which Q_n^* is the n x m matrix with columns containing the n eigenvectors corresponding to the n eigenvalues of greatest magnitude from the appropriate objective function. Once we have

[6]Kurmann, André, and Otrok, Christopher. 2013 "News Shocks and the Slope of the Term Structure of Interest Rates," American *Economic Review*, 103 (6): 2612-32.

identified Q_n^*, we can then interpret the shocks through studying the impulse response functions (IRFs) of each $Y_{j,t}$ against a shock to the jth column of Q_n^*.

Next is the question of how to represent our ‘zero-impact’ restriction. In other words, we impose the additional restriction such that contemporaneous TFP shocks are orthogonal to TFP news shocks, separating TFP innovations today from innovations that impact TFP over our target horizon. We represent our exogenous TFP process with the moving average VAR,

$$A_t = \Phi(L)\epsilon_t^{current} + \Psi(L)\epsilon_t^{news}$$

where $A_t \equiv \log(TFP)$; $\Phi(L)$, $\Psi(L)$ are lag polynomial matrices; and $\epsilon_t^{current}$, ϵ_t^{news} are orthogonal shocks. We represent the ‘zero-impact’ restriction as $\Psi(0) = 0$.[7] With our previous Uhlig max-FEV shock identification protocol and assuming we place TFP first among all variables in our VAR, we find $\epsilon_t^{current}$ to be the first column of $\tilde{F}$, where $\tilde{F} = Chol(\Sigma)$. Thus, ϵ_t^{news} represents the shock spanning the remaining variation in TFP orthogonal to $\epsilon_t^{current}$. Additional to the assumption that TFP evolves exogenously, in Barsky-Sims (2011), there exists the assumption that TFP can be explained by two orthogonal shocks. The model is dependent on the validity of this assumption, and the assumption is consistent with much of the literature on business cycles.[8]

III. Data

The VAR is built using a selection of interest rates, macro variables, and Fama-French portfolios. The data used in our model spans 1963:Q3–2005:Q2, capturing several business cycles, the erratic inflation of the 1980’s, and the .com bubble of the late 90’s and early 2000’s. This sample ends before the Great Financial Crisis.[9]

[7] The ‘zero-impact’ restriction is a critical assumption that allows us to identify two orthogonal shocks that maximize TFP movements over the specified horizon. For more, see Kurmann-Otrok (2013).

[8] Barsky, Robert B. & Sims, Eric R. 2011. "News shocks and business cycles," *Journal of Monetary Economics*, Elsevier, vol. 58(3), pages 273-289.

[9] We chose this sample period to mimic the results of Kurmann-Otrok (2013) closely, and because the unique evolution of financial markets and the term structure during and after the Great Financial Crisis change the behavior of our model.

The interest rate data is pulled from FRED, and following Kurmann-Otrok (2013), we use the federal funds rate, 5-year treasury yield, and the spread calculated therein. Notably, for the 5-year yield, we do not use the Fama-Bliss unsmoothed rate and rather use the 5-year yield as quoted on an investment basis directly from the FRED database.[10] We made this decision for data availability and model accessibility. All yields are reported as annual rates and are representative of quarterly arithmetic averages for each daily observation in the quarter.

The macro variables used are real GDP, real consumption, real investment, TFP, and the personal consumption expenditures (PCE) chain-type price index. Real consumption and investment are calculated as personal consumption expenditures and gross private domestic investment, respectively, deflated by our PCE index. All macro data is taken from FRED directly. In testing the model with various measures of inflation, the major conclusions of the model remain consistent; PCE was selected to explore monetary policy responses to inflationary pressures and real output.[11] The TFP series used is the 2023 vintage of Fernald's utilization-adjusted TFP accumulated into a level, based on his model from Fernald (2014) which computes utilization-adjusted TFP from a firm's profit maximization condition.[12] All macroeconomic variables are reported in logs.

Two financial indexes are used in this paper to represent the overall response of market participants to a shock to future productivity. The indexes are the S&P 500 index and the NASDAQ composite. The S&P 500 data is from CRSP and NASDAQ data comes from FRED. The indexes are represented as quarterly average levels and reported in logs.

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[10] In rigorous testing, our model appears robust to the decision to use yields quoted on an investment basis versus Fama-Bliss unsmoothed zero-coupon yields, although at the sacrifice of model interpretability.

[11] The model was re-run with the consumer price index (CPI) and the GDP deflator; results remained qualitatively the same between all specifications.

[12] Fernald, John. 2012. "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity," *Federal Reserve Bank of San Francisco Working Paper Series* 2012-19, Updated April 2014.

We also decided to analyze the response of Fama-French 5-factor portfolios to a shock to TFP news. The 5-factor Fama-French portfolios originate from the Dartmouth Data Library. These portfolios are selected to gain deeper insight into how TFP news shocks impact portfolios representative of different market capitalizations and capital structures. The two portfolios included in this paper are small minus big (henceforth SMB) and conservative minus aggressive (henceforth CMA). SMB will show us how small-cap equities respond to TFP news impulses relative to large-cap equities and CMA will highlight how corporations with "conservative" capital structures (i.e., investment philosophies) perform relative to firms with "aggressive" investment strategies.[13] Furthermore, SMB is intended to highlight how volatility plays a role in returns. The data for these portfolios is representative of the quarterly average of the level of each portfolio. Each data series is reported in logs.

IV. How do News Shocks Move Financial Markets?

This section delves into the impact that TFP news shocks have on financial markets. We present two unique augmentations of the baseline macro-yields VAR: (a) with the S&P 500 and NASDAQ composite indexes and (b) with our selection of Fama-French 5-factor portfolios (SMB and CMA). For the model parameters, we set the lags in our VAR to $l = 4$ and the forecast horizon to $\underline{k} = 0$ up through $\overline{k} = 40$ quarters.[14] Additionally, we add an intercept term to each VAR. Using the methodology developed earlier, we will construct two separate VARs and then analyze the evolutions of both the forecast error variance decompositions (FEVDs) and the impulse response functions (IRFs) of each variable in the VAR to a 1% TFP news shock over the course of our horizon. While the figures depict the

[13]Fama, Eugene F. and French, Kenneth R. September 2014. "A Five-Factor Asset Pricing Model," Fama-Miller Working Paper.

[14]These are the same parameters used by Kumann-Otrok (2013), and in our analysis, they provide ample explanatory power without overparameterizing the model. These will be used for all specifications of VAR mentioned in this paper.

FEVDs and IRFs for every variable, we are focusing our attention on how the shock impacts the selected financial indexes. To estimate our FEVDs, IRFs, and their respective confidence intervals, we use a Bayesian estimation procedure, applying a Minnesota prior and calculating means and bounds by averaging 1000 draws taken from the posterior distribution.[15] The confidence bands shown are from 10% to 90%, and we identify $n = 2$ orthogonal TFP news shocks, following the procedure from Kumann-Otrok (2013).

Figure 1 shows the FEVDs for the variables in model (a) response to a TFP news shock. We can see that TFP news shocks have a significant amount of explanatory power in terms of generating both real business cycles and financial market fluctuations. These news shocks explain over 60% of the FEV in future TFP, and over 30% of the FEV in real GDP, consumption, and investment. Interestingly, this shock clearly does not sufficiently explain movements in the term structure of interest rates, although this is not a feature we are investigating closely.[16] However, in this specification, TFP news shocks explain approximately 50-70% of the FEV in the S&P 500 at all horizons. Additionally, it explains around 40% of the FEV in the NASDAQ in the medium term. Because TFP news shocks by definition impact only future productivity, in the S&P, where returns are driven more heavily by cash flows (i.e., dividends), we see that markets instantaneously price in this information as the expectation of future firm productivity increases. However, we hypothesize that because the NASDAQ is composed of primarily infotech stocks that do not pay shareholders meaningful dividends, it takes longer for this future productivity to be realized in the portfolio’s value. Figure 2 shows the impulse responses to a 1% shock to TFP news in model (a). We can see that the impulse generated the expected increases in TFP, GDP, investment, and consumption where they

[15]See: Doan, Thomas, Robert B. Litterman and Christopher A. Sims. 1984. "Forecasting and Conditional Projection Using Realistic Prior Distributions," *Econometric Reviews*, Vol. 3, No. 1 Jan. pp. 1-100.

[16]This is the central argument in Kurmann-Otrok (2013). In that paper, they use the 2007 vintage of the Fernald utilization-adjusted TFP series. In our analysis with experimenting with different TFP vintages from Fernald, we noted that using older TFP measures (i.e., 2007) yield in more explanatory power for the term structure at the expense of lower explanatory power in financial indexes. For more see Kurmann-Otrok (2016).

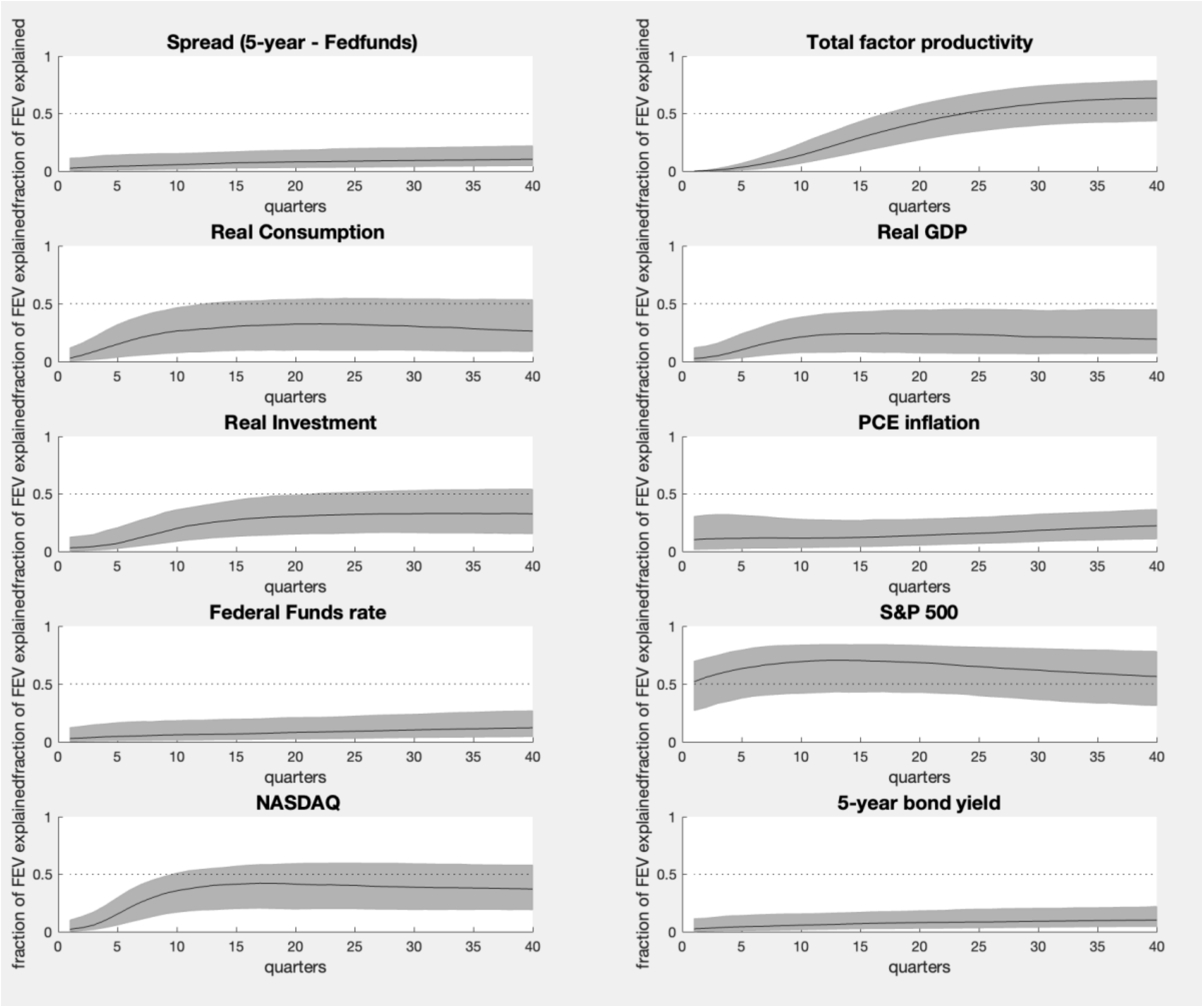

FIGURE 1. FRACTION OF FORECAST ERROR VARIANCE EXPLAINED BY TFP NEWS SHOCK

remain at a persistently higher level. We also see an instantaneous drop in inflation and long term growth. Innovations to TFP news drive up the 5-year yield temporarily. In combination with a drop in the federal funds rate, this pushes the spread up in the short term, and after 2 years it begins to fall slightly and then settle to a new level, although from our conclusions about the term structure from the FEVDs in Figure 1, see this is as not a significant force in moving yields. Notably, investment increases over 2 times as much as consumption. From this information, we can conclude that business cycle movements can be generated by innovations to TFP news. In the financial markets, the S&P 500 experiences an instantaneous jump where it continues to climb and then reaches a new stable level in the long run. The NASDAQ takes several quarters to experience the innovation where it increases to approximately the same peak

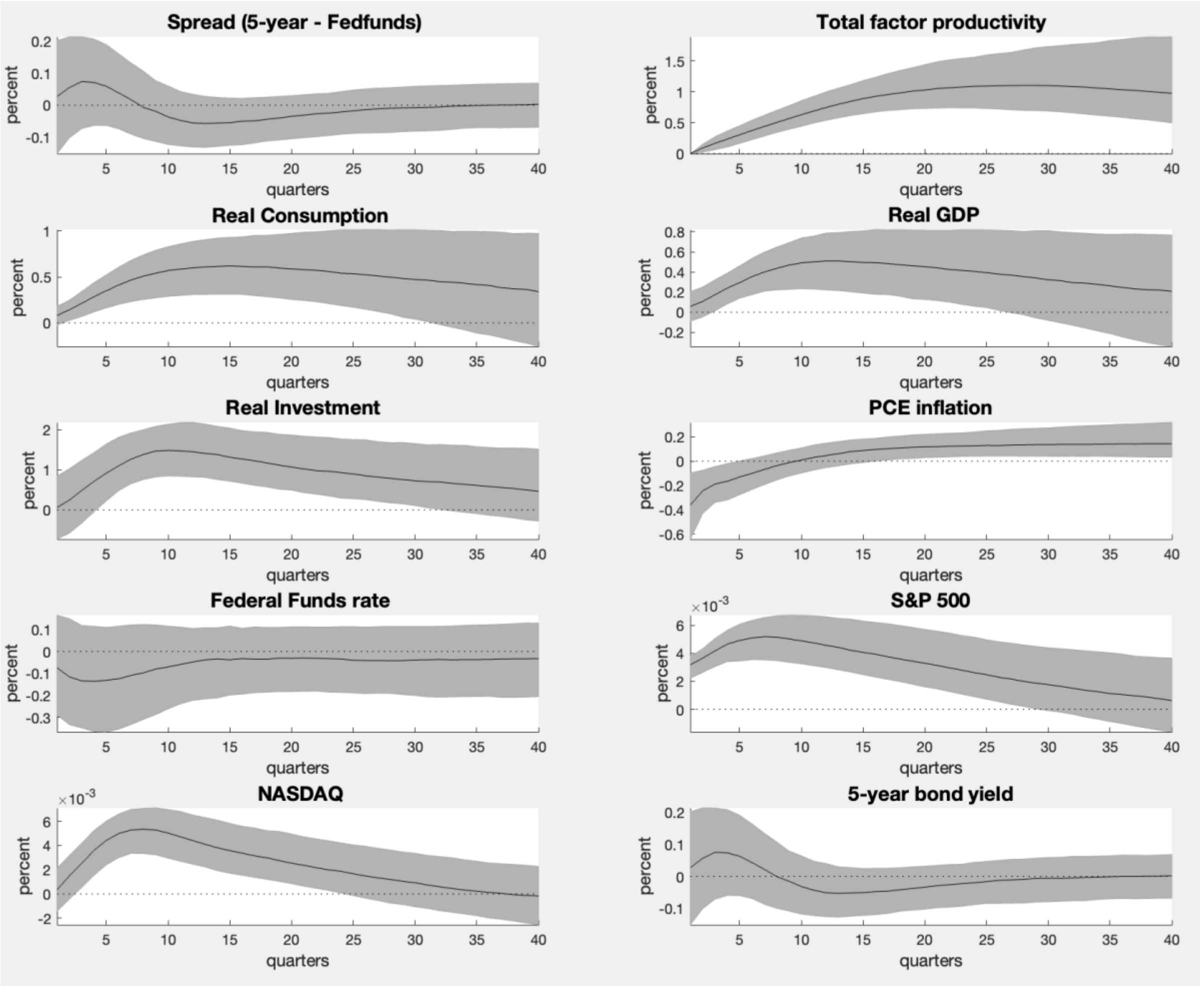

FIGURE 2. IMPULSE RESPONSE TO A 1 PERCENT INNOVATION TO THE TFP NEWS SHOCK

movement as the S&P 500; in the long run, it settles to a new higher level as well. This aligns with the hypothesis that the prospects of increases in future productivity will increase the price of financial assets defined in our discounted cash flow model. Over the course of our horizon, these information shocks become priced in per efficient market hypothsesis; as this information about future productivity diffuses among the agents trading the portfolios, the values start to stabilize.

Next, we analyzed the same VAR model but replaced the two indexes (S&P 500 and NASDAQ) with a complementary selection of Fama-French 5-factor portfolios: small minus big (SMB) and conservative minus aggressive (CMA). These portoflios were selected to investigate the response of one portfolio of highly-volatile ('growth') small-cap equities

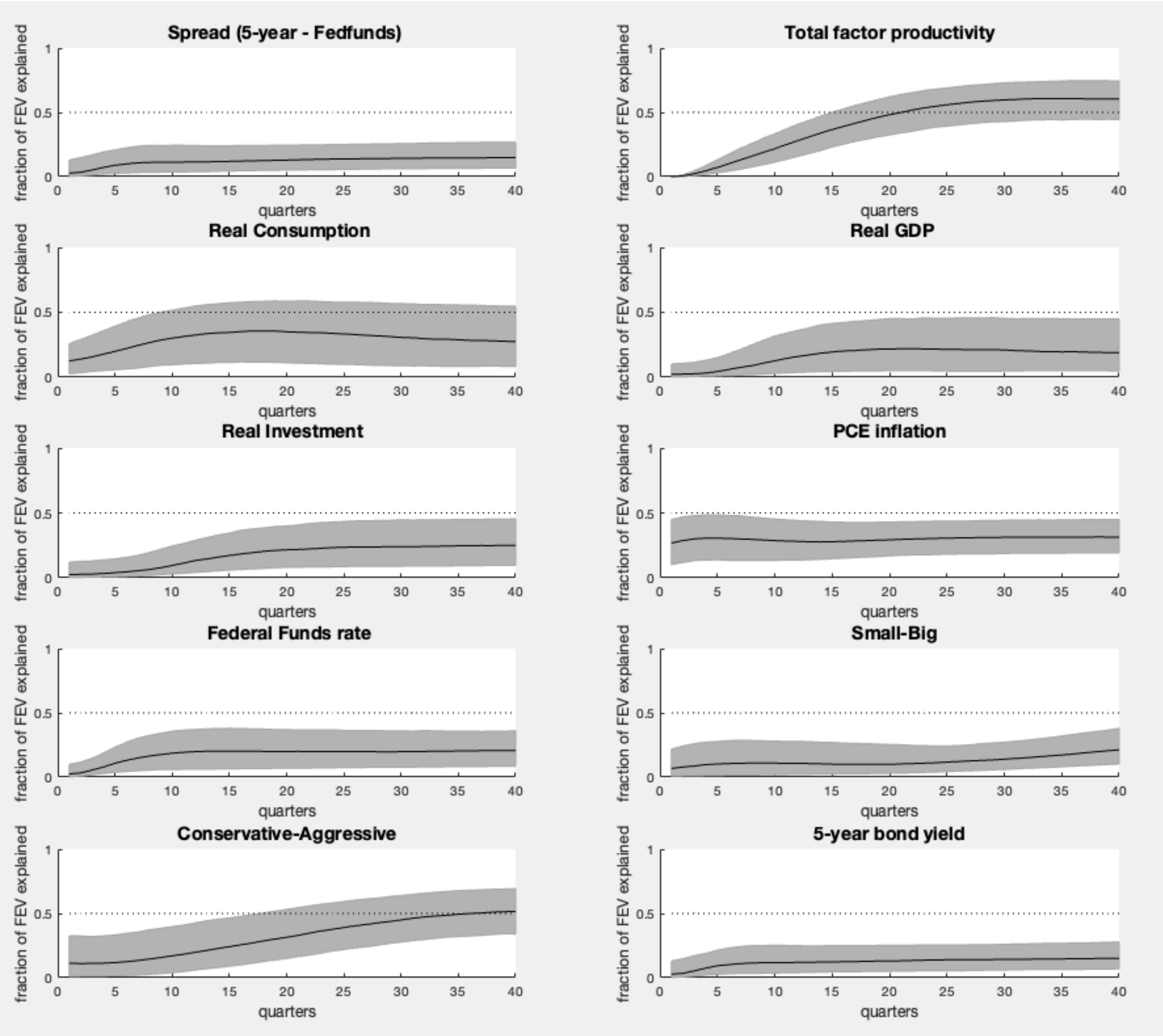

FIGURE 3. FRACTION OF FORECAST ERROR VARIANCE EXPLAINED BY TFP NEWS SHOCK

(SMB), and a portfolio of more stable ('value') assets that have a "conservative" approach to deploying capital (CMA). The FEVDs in Figure 3 show variance decomposition for model (b). From the FEVDs in Figure 3 we can see that the general conclusions made in Figure 1 still hold with regard to macro and yield curve variables. As for our Fama-French portfolios, we see that TFP news shocks capture 10-25% of the variance in the small-big portfolios and between 10% and 50% of the variance in the CMA portfolio. This illustrates how portfolios with relatively more "conservative" investment strategies respond strongly to shocks to future TFP, and, while not as significant, small-cap companies also see a noticable response in their value in response to a TFP news shock. This is evidence that small-cap equities are much less

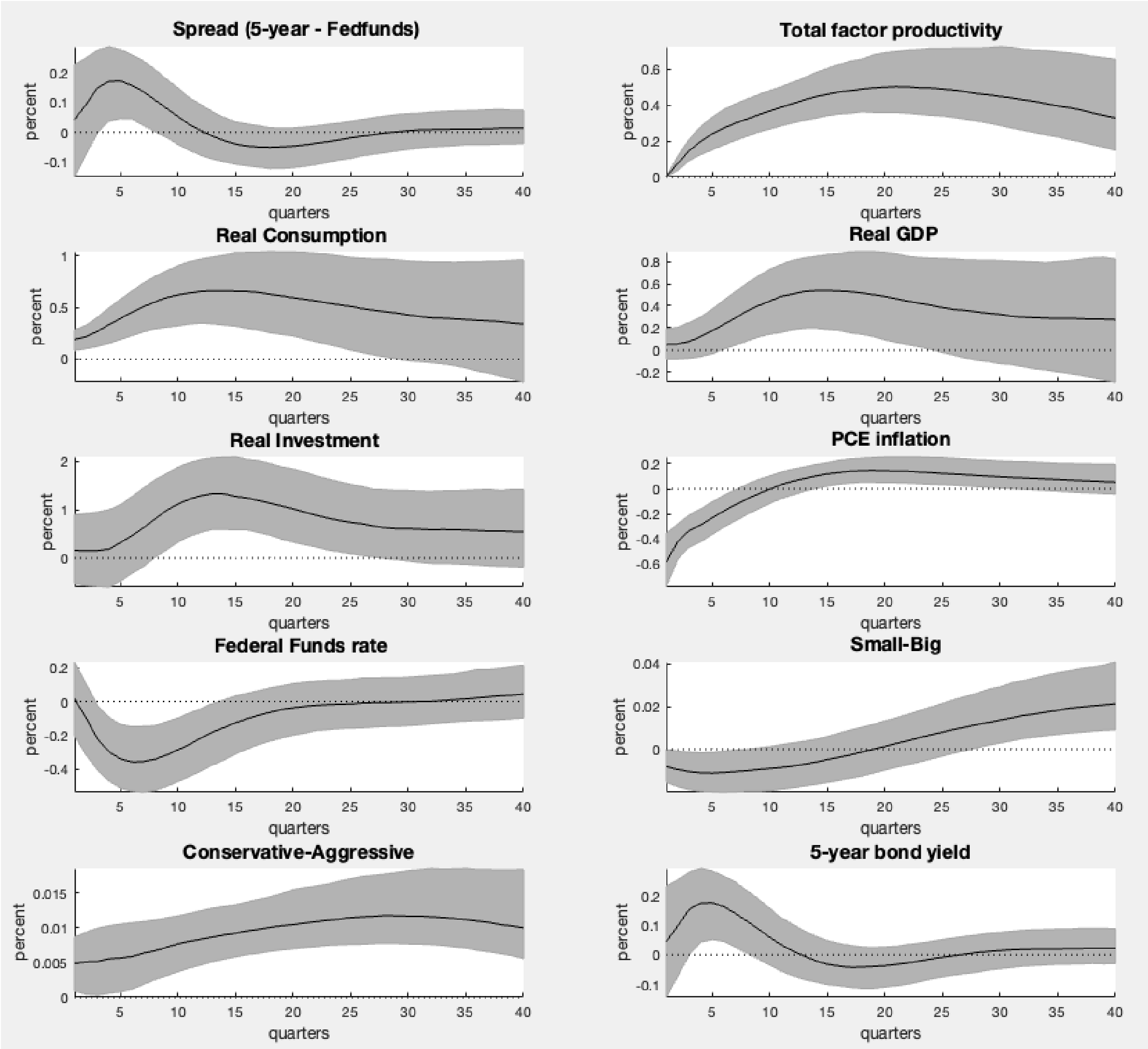

FIGURE 4. IMPULSE RESPONSE TO A 1 PERCENT INNOVATION TO THE TFP NEWS SHOCK

susceptible to systematic, macroeconomic shocks versus all other portfolios we analyzed in both models (a) and (b).

In the IRFs in Figure 4, we see that the responses of macro and yield curve variables are consistent with our first VAR. We also notice that on impact, the SMB portfolio decreases in value before breaking even at 20 quarters and experiencing a long-run increase. This is particularly interesting as one might expect SMB to see an increase in value on impact as the prospects of future cash flows increase, but in our VAR, we see a selloff in the short-run. We perceive this selloff to be at least partially induced by increase to market volatility that a TFP news shock brings. The future payoff for volatile assets such as the SMB portfolio is much more uncertain, and even though this future productivity bodes well for asset prices, the increase in uncertainty contributes to the early decline in the SMB's price. Additionally, as the shock to TFP is realized over our horizon, SMB starts to increase, implying that investors begin to allocate capital here once they identify that economic productivity is increasing. Contrarily, the CMA portfolio sees consistent increases in both the short- and long-run. We interpret this as robust assets such as the CMA portfolio have a larger portion of the portfolio's value tied to the distribution of dividends to their investors, and as real economic productivity increases, will distribute more capital these investors. Because we connect asset prices today to future cash flows, this shock increases the price today for CMA.

V. Conclusion

In our analysis, we uncover the hidden relationship between TFP news shocks and movements in financial market prices. In both models, we show that TFP news shocks capture a majority of FEV in TFP between 0 and 40 quarters, and how these shocks generate business cycles. Additionally, our study of the FEVDs of model (a) unveils how over 50% of the FEV in the value of the S&P 500 and up to 40% of the FEV in the NASDAQ composite can be explained by our TFP news shock identification. According to our IRFs, both indexes respond positively in the long run and remain at persistently higher levels, although these shocks are realized across different horizons among the portfolios due to how the portfolios provide financial value to investors. In model (b), FEVDs illustrate how movements in Fama-French 5-factor portfolios are also explained to a significant degree by news shocks. TFP news shocks explain 25% of the variance in the SMB portfolio and up to 50% of the variance of the CMA portfolio. On impact, we see a negative response from SMB, hypothesized to be due to higher volatility, although the portfolio's value increases in the long run as productivity is realized. The CMA portfolio responds positively at all horizons and maintains a higher growth rate in the long run. This corroborates our notion that portfolios that provide distributions to investors see instantaneous jumps in value in response to shocks to future productivity. In conclusion, we learn that TFP news shocks have different effects on various public equity portfolios, depending on what features of the instrument investors value (capital gains vs. income). This paper could be extended by adding measures of volatility, pursuing our hypothesis that volatility is a major force in instantaneous asset price movements in the presence of a TFP news shock.[17] Another potential continuation is to evaluate how shocks to the discount rate, the denominator of our asset-pricing formula, affect the value of these portfolios.

VI. Appendix

Derivation of Asset Pricing Formula (DCF)

For any risky asset, we can model the holding period return of the asset from time t to time $t+1$ as:

$$h_{t,t+1} = \frac{(S_{t+1} + D_{t+1}) - S_t}{S_t}$$

where D_{t+1} represents cash flow in the next period (i.e., dividend) and $S_t$is the price of the asset at time t. Next, assume $\mathbb{E}_t\left[h_{t,t+1}\right] = r$ where r is our discount rate. Rearranging, we get,

$$S_t = \frac{\mathbb{E}_t[S_{t+1} + D_{t+1}]}{(1+r)}$$

Substituting recursively for S_{t+1} yields,

$$S_t = \frac{\mathbb{E}_t[D_{t+1}]}{(1+r)} + \frac{\mathbb{E}_t[D_{t+2}]}{(1+r)^2} + \cdots$$

$$= \sum_{k=1}^{\infty} \frac{\mathbb{E}_t[D_{t+k}]}{(1+r)^k}$$

[17]Moench (2021) explores an extended VAR following the work done in Kurmann-Otrok (2013), studying yield news shocks, TFP news shocks and volatility shocks, using indexes such as VIX and MOVE to investigate volatility movements.

This formula results in the value of our risky asset being equal to the present discount value of the perpetual sum of expected cash flows.

Derivation of forecast error variance maximizing shock in a VAR

Following *Uhlig (2004)*, the goal is to find an impulse matrix F that explains the maximum possible variance of our target variable j for some specified horizons $k \in [\underline{k}, \overline{k}]$. Looking at a VAR containing only target variables, the variance can be written as:

$$\sigma^2(\underline{k}, \overline{k}) = \sum_{k=\underline{k}}^{\overline{k}} \Sigma(\mathrm{k})_{jj}$$

We wish to explain as much of this variance using a single impulse vector; equivalently, we need to find an orthonormal vector b_1 which maximizes this sum. Let $I_{(jj)}$ be a matrix with all zeros except for the jth row and jth column. We then calculate,

$$\sigma^2(\underline{k}, \overline{k}; b_1) = \sum_{k=\underline{k}}^{\overline{k}} \sum_{l=0}^{k} ((\tilde{R}_l b_1)(\tilde{R}_l b_1)')_{jj}$$

$$= f_1' S f_1$$

where

$$S = \sum_{k=\underline{k}}^{\overline{k}} \sum_{l=0}^{k} \tilde{R}_l' I_{(jj)} \tilde{R}_l$$

$$= \sum_{l=\underline{0}}^{\overline{k}} (\overline{k} + 1 - \max(\overline{k}, l)) \tilde{R}_{l,j}' \tilde{R}_{l,j}$$

where $\tilde{R}_{l,j}$ can be interpreted as the response of variable j to the impulse.[18]

[18]For more, see: Uhlig, Harald. 2004. "What moves GNP?," Econometric Society 2004 North American Winter Meetings 636, Econometric Society.

We can solve this problem by reframing it as a Lagrangian maximization with constraint $b_1' b_1 = 1$. This is equivalent to finding the first principal component of our objective function, solved by performing an eigenvalue decomposition on S. It follows that $\sigma^2(\underline{k}, \overline{k}; b_1) = \lambda$ (i.e., the eigenvalue corresponding to eigen vector b_1). The impulse vector can be found by,

$$f_1 = \tilde{F} b_1$$

where $\tilde{F}$ is the Cholesky decomposition of the variance-covariance matrix of the lag polynomial matrix of our VAR.

Construction of Fama-French 5-factor portfolios

Eugene Fama and Kenneth French publish the 3-factor model (1993) to help explain cross-sectional asset returns.[19] In 2013, they publish the 5-factor model to help explain returns on small stocks with high investment despite low profitability, extending their 3-factor model. The augmented 5-factor model is,

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}$$

where SMB_t is the difference in returns on diversified portfolios of equities with small and big market capitalizations, HML_t is the difference in returns on diversified portfolios with high and low book-to-market value, RMW_t is the difference in returns on diversified portfolios with robust and weak operating profitability, and CMA_t is the difference in returns on diversified portfolios with conservative and aggressive investment strategies. These portfolios are representative of the difference between the highest quintiles and lowest quintiles for each factor, respectively.[20]

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[19]For more, see: Fama, Eugene F. & French, Kenneth R. 1993. "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, Elsevier, vol. 33(1), pages 3-56, February.

[20]For more, see: Fama, Eugene F. and French, Kenneth R. September 2014. “A Five-Factor Asset Pricing. Model,” Fama-Miller Working Paper.

Measuring TFP

We can specify a traditional Cobb-Douglass aggregate production function with constant returns-to-scale as,

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}$$

where A_t is total factor productivity (TFP), K_t is the capital stock, and L_t is the labor supply at time t. Thus, we can compute the change in the traditional Solow residual TFP measure as,

$$\Delta \ln(A_t) \equiv \Delta \ln(Y_t) - \alpha \Delta \ln(K_t) - (1-\alpha) \Delta \ln{(L_t)}$$

Given this definition, we can define utilization-adjusted TFP growth as,

$$\Delta \ln(\text{TFP\_util}) = \Delta \ln(\text{TFP}) - \Delta \ln{(U)}$$

where $\Delta \ln{(U)}$ is the estimated contribution of utilization. Since utilization is unobserved, it must be measured through the solution to a firm's profit maximization condition. This second model of (utilization-adjusted) TFP is the one used in our paper.[21]

[21]For the full derivation and explanation, see: Fernald, John. 2012. "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity," *Federal Reserve Bank of San Francisco Working Paper Series* 2012-19, Updated April 2014.

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