Fearing the Fed: How Wall Street Reads Main Street*

Tzuo-Hann Law[†] Dongho Song[‡] Amir Yaron[§]

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Abstract

We document that the sensitivity of the stock market reaction to major macroeconomic news announcements (MNAs) is countercyclical and depends on the expectation of monetary policy. In particular, stock prices react more to announcement surprises when the economy is below its potential trend with the expectation of easing policy. Based on comprehensive regression analyses and a no-arbitrage asset pricing model with state-dependent dynamics of cash flows (dividends), interest rates (monetary policy), and risk premium, we argue that this cyclical pattern is driven by the procyclical nature of monetary policy expectation and countercyclical nature of market price of risk.

JEL Classification: G12, E30, E40, E50.

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[†]Boston College; tzuo.law@bc.edu

[‡]Carey Business School, Johns Hopkins University; dongho.song@jhu.edu

[§]Bank of Israel & Wharton School, University of Pennsylvania; yarona@wharton.upenn.edu

1 Introduction

There is a growing literature that identifies the impact of economic news, such as the Federal Open Market Committee (FOMC) meetings or pre-scheduled macroeconomic news announcements, on financial markets.[1] However, predicting the stock market's response to these news is challenging. For example, stock prices might not react to announcements that suggest improvement in future cash flows if market participants expect future interest rate to be elevated as a result of stabilization policy or there is change in compensation for risk. The perception about stabilization policy, in particular by Federal Reserve (henceforth Fed), depends on the phase of the business cycle and economic conditions. This interaction between economic conditions, perceptions about the Fed's possible response, and changes in risk compensation can lead to significant time variation in the stock market's reaction to news.[2] Motivated by these considerations, this paper examines the cyclicality in the reaction of the stock market to major macroeconomic news announcements surprises (MNAs).

We first estimate the time-varying sensitivity of stock returns to MNAs using the nonlinear regression proposed by Swanson and Williams (2014). We rely on intra-day S&P 500 futures prices and surveys of market expectations of upcoming 20 MNAs to construct announcement surprises from January 1998 to December 2017. We focus on the pre-scheduled macroeconomic data releases because they contain direct information about macroeconomic fundamentals. We show that the stock return sensitivity to MNAs increases by a factor greater than two coming out of recessions and remains above average for about one to two years. The reaction of stock returns gradually attenuates as the economy expands and it takes about four years to move from peak to trough sensitivity with the return to peak sensitivity taking about similar amount of time. At trough sensitivity, stock prices generally do not react to news. We confirm that our results persist when we stretch the estimation sample to early 1990s which encompasses three business cycle troughs.

We argue that the phase of business cycle and the expectation of monetary policy stabilization are key determinants of the cyclicality of the response of the stock market. The

[1] See Savor and Wilson (2013) and Lucca and Moench (2015) among others.

[2] See McQueen and Roley (1993), Flannery and Protopapadakis (2002), Boyd, Hu, and Jagannathan (2005) and Andersen, Bollerslev, Diebold, and Vega (2007) for early explorations relating MNAs and stock market responses.

empirical evidence supporting this claim is provided by connecting the cyclical stock response coefficients to business cycle and monetary policy-related variables. We construct proxies for the expected direction of the economy and monetary policy by comparing survey forecasts of interest and unemployment rates to their current (potential) values. We find muted response during periods in which the economy is above its potential trend (lower unemployment rate relative to trend) with tightening expectations. For example, the so called "Fearing the Fed" effect essentially nullifies better-than-expected macroeconomic news surprises and results in no response in the stock market. On the other end of spectrum, we find a much greater response of the stock market to news when the economy is significantly below its potential trend (larger unemployment rate relative to trend), and at the same time, there is an easing expectation.

To shed light on the mechanism at work, we assess the informational content of news. Depending on the phase of business cycle the economy might be more or less sensitive to growth opportunities with different level of risk tolerances. To understand this, we decompose the stock market sensitivity to components attributable to news about cash flows, risk-free rate, and risk premium following Campbell and Shiller (1988) and Campbell (1991). The time variation in the reaction of the stock prices must come from variations in these news primitives. We impose that the stock return sensitivity is the sum of the sensitivities associated with cash flows, risk-free rate, and risk premium with the latter two entering with a negative sign. For this, we re-estimate the benchmark nonlinear equation for stock futures returns jointly with the intra-day Eurodollar futures return and VIX returns, which serve as empirical proxies for capturing news about risk-free rate and risk premium, respectively.[3] It is intuitive to find that news about cash flows is the dominant force driving the cyclicality considering that we are zooming into times when news about fundamentals are released. That said, we find that news about risk-free rate and risk premium combined explain more than half portion of the cyclicality of the return responses, and their relative importance depends on the phase of business cycle. Our evidence suggests that while news about risk-free rate plays a more dominant role when the economy is above trend, news about risk premium is more important when the economy is below trend.

To guide the interpretation of our empirical findings, we propose a no-arbitrage asset pricing model that allows for state dependence in the dynamics of cash flows (dividends),

[3] As explained in Swanson and Williams (2014), Eurodollar futures are the most heavily traded futures contracts that are known to be closely related to market expectations about the federal funds rate.

interest rates (monetary policy), and risk premium.[4] We assume that the dynamics of dividends is forward looking, which is similar to a standard New Keynesian IS curve, where a higher real rate lowers dividends through expectation. Federal Reserve directly controls the real rate by choosing to respond to dividend gap, the distance between the actual dividends we model and the exogenously assumed potential level of dividends. We allow the level of dividends, target level of real rate, and the strength with which the Fed tries to pursue its goal—a stabilization policy—to differ across economic states. This way, the dynamics of cash flows and interest rates are interrelated and how much the Fed influences cash flow dynamics depends on the phase of business cycle. The log pricing kernel is affine conditional on state with regime-switching market price of risk dynamics.[5]

To achieve a certain level of sophistication yet maintaining parsimony, we assume that the economy evolves according to a four-state Markov chain. We label the states by the "above trend & tightening (AT)," "above trend & neutral (AN)," "near trend & neutral (NN)," and "below trend & easing (BE)," respectively. The first letter indicates the phase of business cycle and the second letter denotes the stance of monetary policy. Consistent with the labeling of states, we impose the highest dividends level in the above trend state, during which monetary policy can be tightening or neutral. It is lower in the near trend with neutral policy state. Finally, dividends level is negative in the below trend state which is accompanied with easing monetary policy. The target level of real rate is largest for the AT state. We impose identical target rate for the remaining states. We normalize the policy reaction coefficient to zero to indicate that the neutral monetary policy neither stimulates nor restrains growth. The policy reaction to dividend gap is more aggressive during the BE state compared with the AT state (larger easing than tightening action).[6]

We rely on empirical measure of risk-free rate, risk premium estimate from Schorfheide, Song, and Yaron (2018), and real-time measure of unemployment rate gap to estimate the model coefficients and latent economic states. We assume that dividend gap is proportional to unemployment rate gap, which directly corresponds to one of the statutory objectives for monetary policy. From the first two measures, we can learn about business cycle and

[4] Relatedly, Bikbov and Chernov (2013) consider a regime-switching no-arbitrage framework to study the Treasury bond yields.

[5] By relying on Campbell-Shiller log-linear approximation, we can preserve conditionally affine structure of log market return dynamics (with regime-switching coefficients). It is important to emphasize that this conditionally affine dynamics enables analytical characterization of the return variations.

[6] The asymmetric response of the Federal Reserve, e.g., more aggressive stimulation policy, is motivated by Cieslak and Vissing-Jorgensen (2017).

policy-related parameters as well as the economic states. The empirical proxy for the risk premium is necessary to learn about the market price of risks. All these measures are available from January 1990 to December 2017 in monthly frequency. We use a longer span of data to learn model dynamics. We highlight two key features of the estimation results: the identified regimes are broadly consistent with other existing evidence and the economy frequently switches across economic regimes; we find much larger market price of risk during the BE state compared to the other states,. e.g., roughly five times larger relative to that in the AN state. Thus, the BE state can be regarded the worst state in our economy.

Our model allows us to attribute stock return variations to variation in news about cash flows, risk-free rate, and risk premium, respectively. In our model, the innovation to dividends is interpreted as MNA surprise, which signals particular transition path of the economy. For example, a large positive innovation to dividends signals policy tightening. By designing several plausible transition paths, we aim to understand how the news primitives, and ultimately, stock returns are differentially affected by beliefs about transition of the economy. There are two key takeaways from this analysis. First, it is shown that the expectation for monetary policy stabilization can reduce or even nullify economic shocks. This happens commonly across different economic states although a rise (fall) in risk-free rate news can be smaller relative to cash flows news when the economic shock does not lead to an immediate monetary tightening (easing) in the below (above) trend state. Second, the model implies sizable negative comovement between news about cash flows and risk premium in the below trend state. Thus, even in the presence of monetary policy stabilization expectation (risk-free rate news partly offsets cash flows news), stock prices strongly react to the economic shock due to substantial movements in risk premium news. This does not materialize during the above trend state (due to close to zero movement in risk premium news) and we find muted stock return response as a consequence of the Fed's stabilization effect. As our evidence suggests, there is important compositional shifts in news primitives and our model nicely reconciles this fact.

To better understand the role of monetary policy stabilization on return variations, we conduct a counterfactual experiment of fixing the real rate constant, removing risk-free rate news variation while keeping all else identical. Since monetary policy does not smooth out cash flow fluctuations any more, the economic shock leads to substantial negative comovement between cash flows news and risk premium news even in the above trend state where the market price of risk is low. Therefore, the reaction of the stock return is large both during the above and below trend states, which is inconsistent with our evidence. Next, we instead fix the market price of risk to be constant while keeping all else identical to isolate the role of risk premium in the overall return variations. We find that the reaction of stock returns to economic shocks are muted due to monetary policy stabilization effect notably in the below trend state. Again, the implication is inconsistent with the strong countercyclicality in the return response that we document in the data.

Our work is related to papers that argue stock market's reactions to announcement surprises may depend on the state of the economy. McQueen and Roley (1993) first demonstrate that the link between MNAs and stock prices is much stronger after accounting for different stages of the business cycle. Boyd, Hu, and Jagannathan (2005) use model-based forecasts of the unemployment rate and Andersen, Bollerslev, Diebold, and Vega (2007) rely on survey forecasts of major MNAs to emphasize the importance of measuring the impact of MNAs on stock prices over different phases of the business cycle. While insightful, the findings of the previous literature were concentrated on comparing the stock market's reactions in recessions to those in expansions. We contribute to the literature by improving on the measurement of the stock market response to news with a broader set of macroeconomic news announcements and high-frequency returns, but most importantly, by providing a realistic asset pricing model that highlights how beliefs about transitioning into and out of business cycle and monetary policy stabilization regimes can generate cyclicality in the response of the stock market.

Our paper can be linked to a large literature that studies asset market and monetary policy, for example, Pearce and Roley (1985), Thorbecke (1997), Cochrane and Piazzesi (2002), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Gurkaynak, Sack, and Swanson (2005a), Bekaert, Hoerova, and Lo Duca (2013), Neuhierl and Weber (2016), and Tang (2017) among others. Recently, Cieslak and Vissing-Jorgensen (2017) focus on a related and complementary channel by relating stock market movements to subsequent monetary policy action by the Fed. Nakamura and Steinsson (2017) estimate monetary non-neutrality based on evidence from yield curve and claim the FOMC announcements affect beliefs not only about monetary policy but also about other economic fundamentals. Paul (2019) estimates the time-varying responses of stock and house prices to changes in monetary policy and finds that asset prices have been less responsive to monetary policy shocks during periods of high and rising asset prices.

Broadly speaking, we are related to a literature exploring the relationship between various news announcements including the FOMC announcements and asset prices. Faust and Wright (2018) and Savor and Wilson (2013) find positive risk premia in bond markets for macroeconomic announcements. Lucca and Moench (2015) find the stock market on average does extremely well during the 24 hours before the FOMC announcement. Ai and Bansal (2018) explore the macro announcement premium in the context of generalized risk preferences.

Our paper also analyzes the relative importance of cash flows versus discount rates, a central discussion in finance. Campbell and Shiller (1988), Campbell (1991), Campbell and Ammer (1993), Cochrane (2011) among others claim variations in discount rate news account for most of the variations in asset prices. Other papers ascribe a significant role to cashflow news in variations of asset prices, such as Bansal and Yaron (2004), Bansal, Dittmar, and Lundblad (2005), Lettau and Ludvigson (2005), Schorfheide, Song, and Yaron (2018) among others. We show that at high frequency around the time of macroeconomic news announcements, while variations in stock prices are mostly accounted for by cash flows news, the role of news about risk-free rate is elevated when the economy is above its potential trend while news about risk premium becomes more important during below trend periods. A recent paper by Diercks and Waller (2017) provide complementary evidence to our findings that the Fed plays a key role in how equity markets interpret news about cash flows and discount rate, but their focus is on the effect of changes in personal taxes.

2 The Reaction of the Stock Market to News

2.1 Data

Macroeconomic news announcements (MNAs). MNAs are officially released by government bodies and private institutions at regular prescheduled intervals. In this paper, we use the MNAs from the Bureau of Labor Statistics, Bureau of the Census, Bureau of Economic Analysis, Federal Reserve Board, Conference Board, Employment and Training Administration, and Institute for Supply Management. We use the MNAs as tabulated by Bloomberg Financial Services. Bloomberg also surveys professional economists on their expectations of these macroeconomic announcements. Forecasters can submit or update their predictions up to the night before the official release of the MNAs. Thus, Bloomberg forecasts could in principle reflect all available information until the publication of the MNAs. Most announcements are monthly except initial jobless claims (weekly) and GDP annualized QoQ (quarterly). With the exception of industrial production MoM which is released at 9:15am, all announcements are released at either 8:30am or 10:00am. We consider all announcements released in between January 1998 to December 2017. Details are provided in the appendix. For robustness, we also consider Money Market Services (MMS) real-time data on expected U.S. macroeconomic fundamentals to measure MNA surprises. None of our results are affected.

Standardization of the MNA surprises. Denote MNA i at time t by $\text{MNA}_{i,t}$ and let $E_{t-\Delta}(\text{MNA}_{i,t})$ be proxied by median surveyed forecast made at time $t-\Delta$. The individual MNA surprises (after normalization) are collected in a vector X_t whose ith component is

$$X_{i,t} = \frac{\text{MNA}_{i,t} - E_{t-\Delta}(\text{MNA}_{i,t})}{\text{Normalization}}.$$

The units of measurement differ across macroeconomic indicators. To allow for meaningful comparisons of the estimated surprise response coefficients, we consider two normalizations. The first normalization scales the individual MNA surprise by the cross-sectional standard deviation of the individual forecasters' forecasts for each announcement. The key feature of this standardization is that the normalization constant differs across time for each MNA surprise. The second normalization scales each MNA surprise by its standard deviation taken over the entire sample period.[7] The key feature of the second approach is that for each MNA surprise, the normalization constant is identical across time. Thus, this normalization cannot affect the statistical significance of sensitivity coefficient. We find that the two different approaches yield highly correlated surprise measures. We use the first normalization as our benchmark approach because it scales the surprises by the disagreement making them economically interpretable. Our results are robust across both methods. Details are provided in the appendix.

Financial data. We consider futures contracts for the asset prices in our analysis: S&P 500 E-Mini Futures (ES), S&P 500 Futures (SP), and Eurodollar futures (ED). Futures contracts allow us to capture the effect of announcements that take place at 8:30am Eastern time before the equity market opens. This exercise would not be possible if we relied solely

[7] This standardization was proposed by Balduzzi, Elton, and Green (2001) and is widely used in the literature.

on assets traded during regular trading hours. We use the first transaction in each minute as our measure of price and fill forward if there is no transaction in an entire minute. We also consider SPDR S&P 500 Exchange Traded Funds (SPY) to examine robustness of our findings. Asset prices are obtained from TickData. We use S&P 500 Volatility (VIX) index from the Chicago Board Options Exchange (CBOE). We use survey forecasts from the Blue Chip Financial Forecasts. We take the price-to-dividend ratio from Robert Shiller's webpage.

Macroeconomic data. All macroeconomic data are from the Federal Reserve Bank of St. Louis. We also use survey forecasts from the Survey of Professional Forecasters. For the purpose of capturing the episodes in which the economy is significantly above (below) its potential level, we use the real-time civilian unemployment rate and natural rate of unemployment (NROU) data from Federal Reserve Bank of St. Louis and Federal Reserve Bank of Philadelphia to construct unemployment rate gap. We also use the Baker-Bloom-Davis Economic Policy Uncertainty Index.

2.2 Regression analysis

To measure the effect of the MNA surprises on stock prices, we take the intra-day future prices and compute returns r_t in a Δ-minute window around the release time. For our benchmark results, we use the ES contract to measure stock returns because it is most actively traded during the MNA release times. To determine which MNAs impact returns, we estimate the following nonlinear regression over τ-subperiod suggested by Swanson and Williams (2014)

$$r_{t-\Delta_l}^{t+\Delta_h} = \alpha^\tau + \beta^\tau \gamma' X_t + \epsilon_t \tag{1}$$

where the vector X_t contains various MNA surprises; γ measures the sample average responses; ϵ_t is a residual representing the influence of other factors on stock returns at time t; and α^τ and β^τ are scalars that capture the variation in the return response to announcement during subperiod τ. For the empirical analysis, τ indexes the calendar year. As discussed in Swanson and Williams (2014), the primary advantage of this approach is that it substantially reduces the small sample problem by bringing more data into the estimation of β^τ. The underlying assumption is that while the relative magnitude of γ is constant, the return responsiveness to all MNA surprises shifts by a proportionate amount over the τ subperiod. The identification restriction is that β^τ is on average equal to one. This implies that the sample average of $\beta^\tau\gamma' X_t$ is identical to $\gamma' X_t$. When β^τ is always one, then (1) becomes the OLS regression motivated by Gurkaynak, Sack, and Swanson (2005b) and others.

We proceed by first determining the most impactful announcements across various window intervals, selecting the return window, and then focusing on the cyclicality of the return response.

Selection of the MNA surprises and return window interval. We now turn to the selection of the MNAs. We find that change in nonfarm payrolls, initial jobless claims, ISM manufacturing, and consumer confidence index are, broadly speaking, the most influential MNAs for the stock market.[8] This choice of four announcements is consistent with findings in the literature.[9] The details are explained in the appendix.

As our results can depend on the size of the return window, we consider all combinations of Δ_l and Δ_h between 10 minutes and 90 minutes in the increments of 10 minutes (81 regressions in total) and find that results are robust across various return window intervals.[10] For ease of exposition, we present the regression results with $\Delta = \Delta_l = \Delta_h = 30$min in the main body of the paper. Having fixed $\Delta = 30$min and restricted the set of MNAs to the top four most influential MNAs, we now turn our attention to measuring the time-varying sensitivity of the returns to macroeconomic announcements.

Cyclicality of the return response. Figure 1 provides the main focus of our study, that is, the estimate of the time-varying sensitivity coefficient $\hat{\beta}^\tau$ (black-solid line). The coefficients that measure the average sensitivity, i.e., $\hat{\gamma}$, are significant at the 1% level, which are reported in the footnote of Figure 1. We find strong evidence of persistent cyclical variation in the stock market's responses to the MNAs.[11] The evidence suggests

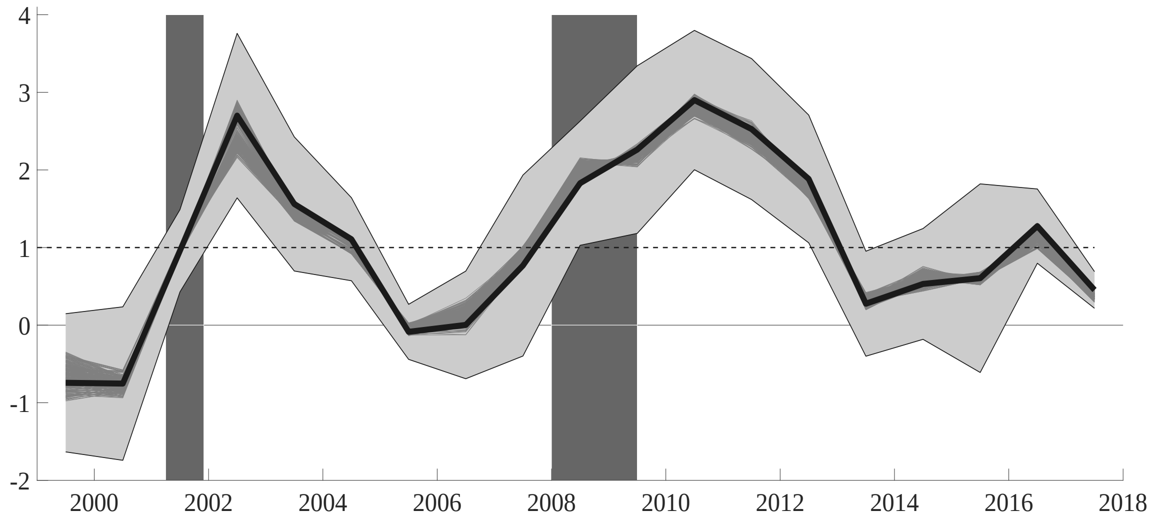
[8]This is consistent with Gilbert, Scotti, Strasser, and Vega (2017) who claim that investors care about certain macro announcements more than others based on evidence from Treasury yields.

[9]For example, Andersen, Bollerslev, Diebold, and Vega (2007) analyze the impact of announcement surprises of 20 monthly macroeconomic announcements on the high-frequency S&P 500 futures returns. They argue that change in nonfarm payrolls is among the most significant of the announcements for all of the markets and it is often referred to as the "king" of announcements by market participants. Bartolini, Goldberg, and Sacarny (2008) discuss the significance of change in nonfarm payrolls as well as the other three announcements which are also significant in our regressions.

[10]Bollerslev, Law, and Tauchen (2008) show that sampling too finely introduces micro-structure noise while sampling too infrequently confounds the effects of the MNA surprise with all other factors aggregated into stock prices over the time interval.

[11]For robustness, we also plot the results from additionally including every possible combination of the next eight influential MNAs. All these regressions yield the light-gray-solid lines that are very close to

Figure 1: The time-variation in the stock return sensitivity to macroeconomic news



Notes: The benchmark MNAs are change in nonfarm payrolls (CNP), initial jobless claims (IJC), ISM manufacturing (ISM), and consumer confidence index (CCI). We set $\Delta = 30$min. We impose that β^τ (black-solid line) is on average equal to one. We provide ± 2-standard-error bands (light-shaded area) around β^τ. The shape is robust to all possible combinations (light-gray-solid lines) of the next eight influential MNAs. We overlay the NBER recession bars. The individual estimates and standard errors (in parenthesis) for γ are below

CNP	IJC	ISM	CCI
0.088	-0.021	0.070	0.051
(0.011)	(0.003)	(0.011)	(0.008)

The sample period is from January 1998 through December 2017.

that the sensitivity of stock returns to the MNAs can increase by a factor greater than two coming out of recessions and remains above average for about one to two years. It is important to understand that the peak is obtained at the early stage of expansions. We find that the stock market's prolonged above-average reaction (three to four years) is unique to the recovery from the Great Recession during which interest rates were bounded. The reaction of stock returns gradually attenuates as the economy expands and it takes about four years to move from peak to trough sensitivity. During these periods, stock returns hardly reacted to news.

This evidence is consistent with existing papers that argue stock market's reactions to announcement surprises may depend on the state of the economy (e.g., McQueen and

each other and hence, appear as a gray band when viewed from a distance.

Roley (1993), Boyd, Hu, and Jagannathan (2005), and Andersen, Bollerslev, Diebold, and Vega (2007)). While insightful, the findings of the previous literature were concentrated on comparing the stock market's reactions in recessions to those in expansions. Our evidence provides a new perspective to the literature because it clearly presents the cyclical nature of the responses of the stock market to macroeconomic announcements.

Robustness. Before we provide any interpretation, we want to be sure that our results survive a variety of robustness checks. To save space, we select a few and briefly explain what we did here. We refer to the appendix for detailed discussions.

We first consider the possibility that the changing sensitivity of the stock return is merely tracking volatility changes because the magnitudes of news surprises can be larger during downturns. We do not find any supporting evidence for this claim. We create two dummy variables locating the below trend and above trend periods and regress the raw and absolute MNA surprises on these dummy variables. We find that coefficients for these two dummy variables are largely insignficant. To be fully robust, we estimate (1) by using the residuals from this regression as "clean" measure of surprises. We find that the estimated time-varying sensitivity of the stock return did not change much from Figure 1.

Next, we check if our results persist when we extend the analysis to early 1990s which encompass last three business cycle troughs. Because we are investigating the cyclical variation of the responses of stock returns to MNAs, it is important to confirm results from a longer span of data. For this exercise, we estimate (1) with daily returns. This choice is inevitable considering the illiquidity in the futures market in the 1990s. The bright side of this exercise is that we can find out if the impact of the MNAs on the stock market is not short-lived and economically important. The estimate of the time-varying sensitivity coefficient looks qualitatively similar which is estimated with larger standard errors as expected.

2.3 Identifying the economic drivers

Having confirmed the robustness of the evidence, we aim to identify the economic drivers behind the cyclicality of the responses of the stock market. We rely on the same regression (1) as before but with the following parametric assumption on the sensitivity coefficient

$$r_{t-\Delta}^{t+\Delta} = \alpha^{\tau} + \beta^{\tau}\gamma' X_t + \epsilon_t, \quad \beta^{\tau} = \beta_0 + \beta_1' Z_{\tau-1}. \tag{2}$$

We examine if the time variation in the stock return sensitivity, β^τ, can be explained by key economic observables, $Z_{\tau-1}$. We consider unemployment rate gap, inflation, interest rates, price-dividend (PD) ratio, VIX, and uncertainty index (collected by Scott Baker, Nicholas Bloom and Steven J. Davis) as potential predictors of the stock return sensitivity under the assumption that cyclical return variations are rooted in economic fundamentals. We also consider the NBER recession dummy variable as one of the potential predictors.

Note that we set τ to index a quarter to bring more data into the estimation which alleviates the short sample problem substantially. We avoid the endogeneity problem by lagging the predictor variables by a quarter. By standardizing the predictor vector $Z_{\tau-1}$ and assuming $\beta_0 = 1$, we maintain the identification restriction, i.e., $E(\beta^\tau) = 1$.

The estimation results are provided in Table 1. Consistent with the previous results, all MNAs are significant at 1% level, i.e., $\hat{\gamma}$s are estimated to be statistically significant which are not reported here to save space. We rather discuss the estimation results regarding the stock return sensitivity $\hat{\beta}_1$. We first discuss the results from a univariate specification which are summarized in Panel (A). We document that an increase in each of interest rate (either level or annual change) and PD ratio significantly predicts lower stock return sensitivity. On the other hand, unemployment rate gap, VIX index, and recession indicators significantly predict larger stock return sensitivity. It is only inflation that turns out to be insignificant in this regression. In sum, our intrepretation of the results is that stock returns respond more aggressively when there is a greater slack in the economy and interest rate has been previously low or decreasing.

Panel (B) of Table 1 provides the estimation results from multivariate specifications of the stock return sensitivity. In particular, we estimate various versions in which empirical approximation of monetary policy rules are considered. The idea is to test if the cyclical return variations are rooted in variables recognized as connected to monetary policy. Column (1) examines the simplest case where unemployment rate gap and inflation are included. We find that the coefficient associated with unemployment rate gap is estimated to be significantly positive while that associated with inflation turns out to be insignificant and changed sign from negative to positive. Column (2) to (4) provide the results when interest rates in various forms are additionally included. This is because interest rates cannot be fully spanned by unemployment rate gap and inflation series, for example, due to the presence of monetary policy shocks. We also include a longer maturity interest rate (5-year Treasury yields) to proxy the market's expectation of the future short rate

Table 1: The economic drivers behind the cyclicality of the return responses

	(A) Univariate regression								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unrate gap	0.67***								
	(0.18)								
Inflation		-0.25							
		(0.16)							
FFR			-0.40***						
			(0.14)						
ΔFFR				-0.65***					
				(0.16)					
T-bond (5y)					-0.39***				
					(0.10)				
ΔT-bond (5y)						-0.59***			
						(0.18)			
PD ratio							-0.40***		
							(0.14)		
VIX								0.47***	
								(0.15)	
Recession									0.69***
									(0.18)
R^2 adjusted	0.12	0.08	0.09	0.11	0.10	0.10	0.09	0.09	0.11
	(B) Multivariate regression								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unrate gap	0.73***	1.40***	1.28***	1.37***	0.86***	0.96***	1.23***	1.37***	1.26**
	(0.19)	(0.46)	(0.39)	(0.44)	(0.28)	(0.35)	(0.43)	(0.49)	(0.50)
Inflation	0.16	0.51*	0.33	0.49*	0.24	0.30	0.43*	0.50*	0.43*
	(0.17)	(0.26)	(0.23)	(0.25)	(0.18)	(0.20)	(0.25)	(0.26)	(0.26)
FFR		0.73**		0.99*			0.76	0.99*	0.79
		(0.35)		(0.53)			(0.55)	(0.57)	(0.61)
ΔFFR		-0.81***		-0.88***			-0.64**	-0.88***	-0.66**
		(0.25)		(0.27)			(0.32)	(0.29)	(0.33)
T-bond (5y)			0.59*	-0.30			-0.28	-0.32	-0.33
			(0.31)	(0.46)			(0.49)	(0.54)	(0.69)
ΔT-bond (5y)			-0.46**	0.12			0.12	0.12	0.12
			(0.19)	(0.19)			(0.19)	(0.21)	(0.20)
PD ratio					0.31	0.31	0.14		0.16
					(0.22)	(0.23)	(0.28)		(0.36)
Recession					0.71***	0.67***	0.35		0.35
					(0.21)	(0.22)	(0.27)		(0.27)
VIX						0.19		0.03	0.02
						(0.18)		(0.22)	(0.26)
EPU index						-0.09		-0.03	-0.05
						(0.23)		(0.32)	(0.35)
R^2 adjusted	0.11	0.14	0.12	0.14	0.13	0.13	0.14	0.14	0.14

Notes: The estimation sample period is from 1998 to 2017. We only report the estimates associated with β in the regression. Unemployment rate gap is the difference between the actual unemployment rate and the natural rate of unemployment rate. Inflation is GDP deflator and FFR is the effective federal funds rate. We also consider the 5-year Treasury yields. PD ratio is the price to dividend ratio and VIX is CBOE volatility index. Economic Policy Uncertainty (EPU) index is collected by Scott Baker, Nicholas Bloom and Steven J. Davis. All variables are standardized. "Δ" indicates annual change. These predictor variables are lagged one quarter. We use the benchmark macroeconomic announcements. We report the Newey-West adjusted standard errors. Notation: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 2: The role of expectations in the cyclicality of the return responses

Periods		(1)	(2)	(3)	(4)	(5)	(6)
Baseline		1.09***	0.97***	0.93***	1.12*	0.84***	0.96*
		(0.02)	(0.06)	(0.04)	(0.02)	(0.05)	(0.05)
Expected	tightening	-1.22***			-0.91***		-0.65**
		(0.22)			(0.28)		(0.29)
	neutral		0.16				
			(0.30)				
	easing			0.99*		0.95*	1.04**
				(0.49)		(0.49)	(0.45)
Expected	above trend				-0.78**		-0.94***
					(0.28)		(0.24)
	near trend						
	below trend					1.30**	1.08**
						(0.47)	(0.43)
R^2 adjusted		0.09	0.08	0.08	0.09	0.09	0.10

Notes: We construct dummy variables as follows. First, we subtract the current federal funds (FF) rate and the real-time natural rate of unemployment from the one-quarter ahead survey mean forecast of the FF rate and unemployment rate, respectively. Both measures the expected direction of the next quarter interest rate and unemployment rate relative to the current (potential) level. Second, we set the threshold to the fourth (first) quintile and define the expected tightening (above trend) period if the FF (unemployment rate gap) direction is above (below) that threshold. The expected easing (below trend) period is when the FF (unemployment rate gap) direction is below (above) the first (fourth) quintile. The expected neutral (near trend) periods are the remaining case. The results are not to sensitive to the choices of the cutoff points. The estimation sample period is from 1998 to 2017. We only report the estimates associated with β in the regression. We report the Newey-West adjusted standard errors. Notation: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

that is not contained in the short-term interest rate. Across various permutations, we find that the estimates for unemployment rate gap and annual change in the FF rate are always statistically significant and have signs consistent with Panel (A). The estimate for inflation, on the other hand, is positive and marginally significant. Column (5) to (9) additionally include financial variables and recession indicators. It is interesting to see that they lose significance after controlling for monetary policy-related variables, which are shown in column (7), (8), and (9). We highlight that the fitted $\hat{\beta}^{\tau}$s based on the estimates in Panel (B) look very similar to our benchmark stock return sensitivity estimate in Figure 1. This indirect evidence suggests that the cyclical return variations are indeed rooted in monetary-policy related variables.

One may argue that our analysis thus far is limited because it does not explicitly account for forward-looking expectations of key variables. To address this, we repeat the regression exercise by relying on survey forecasts of unemployment rate and the FF rate. We create dummy observations based on these surveys for ease of interpretation. First, we subtract the current FF rate and the real-time natural rate of unemployment from the one-quarter ahead survey mean forecast of the FF rate and unemployment rate, respectively. Both measures the expected direction of the next quarter interest rate and unemployment rate relative to the current (potential) level. Second, we set the threshold to the fourth (first) quintile and define the expected tightening (above trend) period if the FF (unemployment rate gap) direction is above (below) that threshold. The expected easing (below trend) period is when the FF (unemployment rate gap) direction is below (above) the first (fourth) quintile. The expected neutral (near trend) periods are the remaining case. The results are not sensitive to the choices of the cutoff points.

We rely on the estimation specification in (2), but assume that $Z_{\tau-1}$ are comprised of dummy observations. Table 2 provides the estimation results. We show in column (4) that when the economy is expected to be above trend with tightening expectation, the stock returns' response to news is close to zero (marginally negative). In contrast, in column (5) we find that when the economy is expected to be below trend, and at the same time, there is an easing expectation, the stock returns' response to news is about three times greater than the average response. Taken together, our evidence strongly suggests that expectations about the phase of the business cycle and future interest rate are key determinants of the cyclicality of the response of the stock market.

3 Assessing the Informational Content of News

To shed light on the mechanism at work, we assess the informational content of the MNAs and decompose the stock market sensitivity to components attributable to news about cash flows (CF), risk-free rate (RF), and risk premium (RP) following Campbell and Shiller (1988) and Campbell (1991). This is of interest in its own right in terms of understanding the contribution of the news components to the sensitivity of the return response at the impact of the announcement. Furthermore, such decomposition has a long tradition in the finance literature and our analysis provides a new perspective using high-frequency data around announcements.

For this exercise, we rely on the 12-month Eurodollar futures (ED) and VIX index (VX) as empirical proxies for capturing news about risk-free rate and risk premium, respectively. As explained in Swanson and Williams (2014), Eurodollar futures are the most heavily traded futures contracts that are known to be closely related to market expectations about the FF rate. VIX index proxies the premium associated with the volatility of volatility. Our results will obviously depend on how valid and informative the empirical proxies are with respect to news about risk-free rate and risk premium. We acknowledge the shortcomings of our proxies since they do not reflect changes in expectations over long-run horizons. For example, VIX index only measures the market's expectation of 30-day volatility. Similarly, while we believe that news about risk-free rate can only be reflected in Eurodollar future contracts with much longer maturity dates, these contracts suffer from liquidity problems and are only available for relatively short period of time. In addition, there is very little fluctuation in short-maturity Eurodollar futures return during the zero-lower bound periods which contrasts starkly with the pre-crisis periods.[12] With these caveats in mind, we proceed with discussion of the evidence.

3.1 Decomposing the cyclicality of the return response

We verify that there are indeed substantial variations in Eurodollar futures and VIX Index around the announcement events. Here, we use them as instruments for decomposing the stock return sensitivity coefficient, our object of interest. To be specific, we jointly estimate the following three equation system

$$\begin{bmatrix} r_{t-\Delta}^{t+\Delta} \\ r_{t-\Delta,ED}^{t+\Delta} \\ r_{t-\Delta,VX}^{t+\Delta} \end{bmatrix} = \begin{bmatrix} \alpha^{\tau} \\ \alpha_{ED}^{\tau} \\ \alpha_{VX}^{\tau} \end{bmatrix} + \begin{bmatrix} \left(\beta_{CF}^{\tau} - \beta_{RF}^{\tau} - \beta_{RP}^{\tau}\right)(\gamma' X_t) \\ \beta_{RF}^{\tau}(\gamma_{ED}' X_t) \\ \beta_{RP}^{\tau}(\gamma_{VX}' X_t) \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ \epsilon_{t,ED} \\ \epsilon_{t,VX} \end{bmatrix} \tag{3}$$

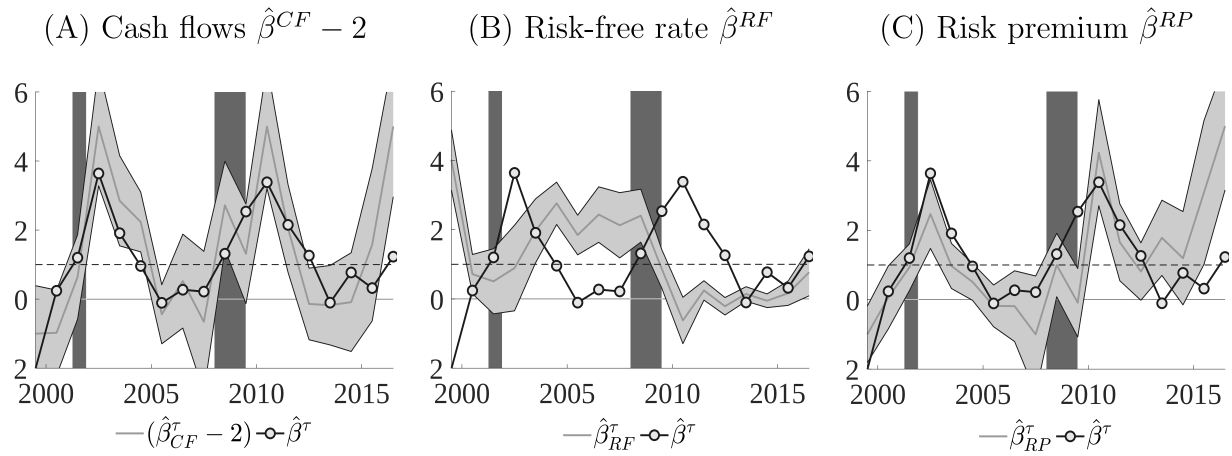
where we have the following identity

$$\beta^{\tau} = \beta_{CF}^{\tau} - \beta_{RF}^{\tau} - \beta_{RP}^{\tau}. \tag{4}$$

Note that the top equation in (3) is identical to our benchmark regression of (1). The purpose of the joint estimation is to separately identify β_{CF}^{τ}, β_{RF}^{τ}, and β_{RP}^{τ} by bringing in

[12] In the appendix, we show that our results are robust to using the 5-year T-Note futures (FV).

Figure 2: Decomposing stock return sensitivity



Notes: We focus on the macroeconomic announcements released at 10am, which are consumer confidence index (CCI), durable goods orders (DGO), and ISM manufacturing (ISM). This is because we do not have intraday VIX index before the trading hours. The identification assumption is that the individual average of $\beta^{\tau}_{CF} - \beta^{\tau}_{RF} - \beta^{\tau}_{RP}$ and β^{τ}_{RF} and β^{τ}_{RP} is equal to one. We provide the 1-standard-error bands (light-shaded area) around the mean estimates. Because we are estimating a large number of parameters, we do not allow for time variation in $\alpha^{\tau}_{(\cdot)}$ in the estimation. For ease of comparison, we provide the benchmark return sensitivity estimate $\hat{\beta}^{\tau}$ (black-circled lines). The individual estimates for $\hat{\gamma}$ are

	S&P 500 E-mini			Eurodollar 12m			VIX		
	CCI	DGO	ISM	CCI	DGO	ISM	CCI	DGO	ISM
$\hat{\gamma}$	0.15	0.07	0.15	-0.0052	-0.0034	-0.0086	-0.74	-0.02	-0.94
(s.e.)	(0.02)	(0.02)	(0.03)	(0.0016)	(0.0017)	(0.0020)	(0.27)	(0.03)	(0.28)

The sample period is from January 1998 through December 2017.

more observations. The identification assumption is that each of $\beta^{\tau}_{CF} - \beta^{\tau}_{RF} - \beta^{\tau}_{RP}$, β^{τ}_{RF}, and β^{τ}_{RP} averages one.

We provide the sensitivity estimates in Figure 2. For ease of comparison, we plot them against the benchmark stock return sensitivity estimate $\hat{\beta}^{\tau} = \hat{\beta}^{\tau}_{CF} - \hat{\beta}^{\tau}_{RF} - \hat{\beta}^{\tau}_{RP}$. There is an important level difference amongst the sensitivity estimates. Note that $E(\hat{\beta}^{\tau}_{CF} - \hat{\beta}^{\tau}_{RF} - \hat{\beta}^{\tau}_{RP}) = E(\hat{\beta}^{\tau}_{RF}) = E(\hat{\beta}^{\tau}_{RP}) = 1$ imply $E(\hat{\beta}^{\tau}_{CF}) = 3$. For ease of comparison across other estimates, we provide $\hat{\beta}^{\tau}_{CF} - 2$ instead of $\hat{\beta}^{\tau}_{CF}$. According to our decomposition, both news about risk-free rate and risk premiums explain more than half portion of the cyclicality of the return responses, but serve very different roles in different periods. What appears to be happening is that while it is the above trend periods when news about risk-free rate plays a more important role, the opposite holds true for the news about risk premiums.

We find that our results are broadly consistent with other existing evidence. For example, in periods of tightening expectation, say from mid-2004 to mid-2006 during which Federal Reserve increased the FF rate by more than 4 percentage points, the role of news about risk-free rate was much elevated. At that time, news about risk premiums hardly moved. We observe that these are also periods in which fluctuations in news about cash flows were smallest compared to other periods. Consistent with our explanation, the stock market hardly reacted to the MNAs during those periods. Similar to Swanson and Williams (2014), we find that news about risk-free rate were nearly zero during the ZLB periods. On the other hand, news about cash flows and risk premiums were at peaks. Our interpretation is that during downturns, the economy is quite sensitive to growth opportunities and the stock market strongly respond to news. Because of the elevated uncertainty, this effect can be amplified by risk premium news.

4 A Model with Regime-Switching Monetary Policy

In this section, we propose a no-arbitrage framework that jointly models the dynamics of cash flows (dividends), interest rates (monetary policy), and risk premia enabling both qualitative and quantitative assessment of the framework specifically tailored to help the reader interpret our empirical findings.

4.1 Framework

Real dividends and monetary policy. We first assume that dividends, d_t, dynamics resemble the standard New Keynesian IS curve (see Gali (2008) for textbook treatment). That is, dividends dynamics are forward looking, which are affected by the real rate (a higher rate lowers dividends). Next, we assume that Federal Reserve directly controls the real rate, r_t, by choosing to respond to dividend gap, $d_t - d_t^*$.[13] Here, d_t^* indicates the potential level of dividends in the economy, which follows a random walk with drift. Put

[13]The underlying assumption from the perspective of the New Keynesian model is that prices are infinitely sticky and thus changing the nominal rate is equivalent to changing the real rate. See Nakamura and Steinsson (2017) for similar representation. We make this assumption because we find that inflation does not have a first-order impact at least in the last two decades. Moreover, both the realized inflation and expected inflation were stable during the periods.

together,

$$\begin{aligned} d_t &= \bar{d}(S_t) + \gamma d_{t-1} + (1-\gamma) E_t d_{t+1} - \xi r_t + u_{d,t} \\ i_t - E_t \pi_{t+1} \equiv r_t &= \bar{r}(S_t) + \phi(S_t)(d_t - d_t^*) \\ d_t^* &= \mu + d_{t-1}^* + u_{\tau,t}, \quad u_{\tau,t} \sim N(0, \sigma_\tau^2). \end{aligned} \tag{5}$$

Note that we are introducing two shocks in this economy. One is real dividends shock, $u_{d,t}$, and the other is trend shock, $u_{\tau,t}$, both of which follow an AR(1) process, respectively

$$u_{l,t+1} = \rho_l u_{l,t} + \sigma_l \epsilon_{l,t+1}, \quad \epsilon_{l,t+1} \sim N(0,1), \quad l \in \{d, \tau\}. \tag{6}$$

For ease of exposition, we described them with a VAR(1) process

$$u_t = \Phi u_{t-1} + \Sigma \varepsilon_t, \quad \varepsilon \sim N(0, I_2). \tag{7}$$

According to our model, since dividends do not react directly to the trend shock, we take the stance of interpreting the macroeconomic news announcement surprise as $\epsilon_{d,t+1}$.

Finally, certain coefficients are allowed to switch over time. For example, the level of dividends, $\bar{d}(S_t)$, and target interest rate, $\bar{r}(S_t)$, depend on the state and the strength with which the Federal Reserve tries to pursue its goal—a stabilization policy—also changes over time. The stabilization policy is "aggressive" or "loose" depending on its responsiveness. We capture this time variation with a regime-switching policy coefficient, $\phi(S_t)$. Here, S_t denotes the state (regime) indicator variable $S_t \in \{1, ..., K\}$. We define the Markov transition probability p_{ij}, i.e., the probability of changing from regime i to regime j, $\forall i, j \in \{1, ..., K\}$. We refer to Π as the transition probability matrix.

Solution. We can re-express (5) in terms of deviation from potential level, i.e., $\hat{r}_t = r_t - \bar{r}(S_t)$ and $\hat{d}_t = d_t - d_t^*$,

$$\begin{aligned} \hat{d}_t &= c(S_t) + \gamma \hat{d}_{t-1} + (1-\gamma) E_t \hat{d}_{t+1} - \xi \hat{r}_t - \gamma u_{\tau,t} + u_{d,t} \\ \hat{r}_t &= \phi(S_t) \hat{d}_t \end{aligned} \tag{8}$$

where we conveniently re-express $c(S_t) = \bar{d}(S_t) - \xi \bar{r}(S_t) + (1-2\gamma)\mu$. By plugging the second equation to the first equation in (8), the system reduces to a single regime-dependent equation

$$\chi(S_t)\hat{d}_t = c(S_t) + \gamma \hat{d}_{t-1} + (1-\gamma)E_t\hat{d}_{t+1} + \omega' u_t \tag{9}$$

where $\chi(S_t) = 1 + \xi\phi(S_t)$ and $\omega = [1, -\gamma]'$. There exists a unique bounded regime-dependent linear solution of the form (see Davig and Leeper (2007) and Song (2017) for discussion)

$$\hat{d}_t = \psi_0(S_t) + \psi_1(S_t)\hat{d}_{t-1} + \psi_2(S_t)' u_t \tag{10}$$

for $p_{ij} \in [0, 1)$. We refer to the appendix for details.

Expected dividend growth. Having derived the expression for dividends, we are now in a position to understand the model-implied expected dividend growth dynamics, which is a key element in asset pricing. Similar to (10), we can express the expected n-period-ahead dividend growth rate by

$$E_t\Delta d_{t+n} \;=\; \psi^e_{n,0}(S_t) + \psi^e_{n,1}(S_t)\hat{d}_{t-1} + \psi^e_{n,2}(S_t)' u_t. \tag{11}$$

The details of the expression are provided in the appendix. We emphasize that these coefficients depend on the transition paths of business cycle and monetary policy states. Therefore, beliefs about future economic states shape the expected dividend growth dynamics.

Since our model in (5) imposes stationarity in dividends level, one might conjecture that a positive shock to the level of dividends $u_{d,t}$ is associated with a decrease in the growth rate going forward. There are two polar cases to consider

$$(i) \quad \lim_{\gamma\to 0} \psi^e_{n,2,d}(\gamma) < 0 \qquad\qquad (ii) \quad \lim_{\gamma\to 1} \psi^e_{n,2,d}(\gamma) > 0.$$

When there is no backward-looking term in (5), that is, $\gamma \to 0$, this is going to be true. To the contrary, when there is no forward-looking term, a positive shock to the level of dividends $u_{d,t}$ can lead to increase in both the level and growth rates. For the empirical exercise, we select γ to be sufficiently close to but less than one so that we have both backward- and forward-looking terms in (5) and that expected growth rates increase upon a positive level shock.[14]

[14]We acknowledge that depending on the value of γ, it is possible to change sign for large n

Stochastic discount factor, market return, and price to dividend ratio. The log pricing kernel is assumed as

$$m_{t+1} = -r_t - \frac{1}{2}\lambda(S_t)'\Sigma\Sigma'\lambda(S_t) - \lambda(S_t)'\Sigma\varepsilon_{t+1} \tag{12}$$

where the market price of risk $\lambda(S_t)$ follows a Markov process similar to (10)

$$\lambda(S_t) = \lambda_0(S_t) + \lambda_1(S_t)\hat{d}_t + \lambda_2(S_t)'u_t. \tag{13}$$

Note that the real rate r_t is given in (5). In our empirical illustration, we impose that $\lambda_1(S_t) = 0$ and $\lambda_2(S_t) = 0$ to be conservative. The conditional covariance of the one-period pricing kernel and the state is zero, so there is no one-period risk premium associated with S_{t+1}. Their multi-period counterparts covary, thereby generating risk premiums.

We now introduce market return. We rely on Campbell-Shiller log-linear approximation to preserve (conditionally) linear log market return dynamics

$$r_{d,t+1} = \kappa_0 + \kappa_1 z_{t+1} - z_t + \Delta d_{t+1}. \tag{14}$$

We conjecture that the log price to dividend ratio has the following expression

$$z_t = z_0(S_t) + z_1(S_t)\hat{d}_{t-1} + z_2(S_t)'u_t. \tag{15}$$

We then solve for $z_0(S_t)$, $z_1(S_t)$, and $z_2(S_t)$ from combining (12) and (14) below

$$E\left[E(m_{t+1} + r_{d,t+1}|S_{t+1}) + \frac{1}{2}Var(m_{t+1} + r_{d,t+1}|S_{t+1})|S_t\right] = 0. \tag{16}$$

This is based on the approximate analytical solution proposed by Bansal and Zhou (2002).

News decomposition. Our model links the stock market to both the state of the economy and to the Federal Reserve's reaction function. We now tie the analysis to the main types of news that arise in asset pricing models. We denote the unexpected stock return by sum of news about cash flows, risk-free rate, and risk premium:

$$r_{d,t+1} - E_t r_{d,t+1} = N_{CF,t+1} - N_{RF,t+1} - N_{RP,t+1}. \tag{17}$$

$\lim_{\gamma\to 1}\psi^e_{n,2,d}(\gamma) \leq 0$.

We provide the expressions for the coefficients below in the appendix

$$N_{CF,t+1} = (E_{t+1} - E_t)\Big(\sum_{j=0}^{\infty} \kappa_1^j \Delta d_{t+1+j} \Big) = \sum_{j=0}^{\infty} \Big(N_{j,0}^{CF} + N_{j,1}^{CF} \hat{d}_{t-1} + N_{j,2}^{CF} u_t + N_{j,3}^{CF} \Sigma \varepsilon_{t+1} \Big)$$

$$N_{RF,t+1} = (E_{t+1} - E_t)\Big(\sum_{j=1}^{\infty} \kappa_1^j r_{t+1+j} \Big) = \sum_{j=1}^{\infty} \Big(N_{j,0}^{RF} + N_{j,1}^{RF} \hat{d}_{t-1} + N_{j,2}^{RF} u_t + N_{j,3}^{RF} \Sigma \varepsilon_{t+1} \Big)$$

$$N_{RP,t+1} = (E_{t+1} - E_t)\Big(\sum_{j=1}^{\infty} \kappa_1^j (r_{d,t+1+j} - r_{t+1+j}) \Big) = \sum_{j=1}^{\infty} \Big(N_{j,0}^{RP} + N_{j,1}^{RP} \hat{d}_{t-1} + N_{j,2}^{RP} u_t + N_{j,3}^{RP} \Sigma \varepsilon_{t+1} \Big).$$

It is important to understand that when regime switching is not allowed, $N_{j,0}^g = 0, N_{j,1}^g = 0, N_{j,2}^g = 0$ and $N_{g,t+1}$ is only function of innovation $\Sigma \varepsilon_{t+1}$ for $g \in \{CF, RF, RP\}$. The key takeaway is that regime switching enables richer characterization of news decomposition. Because of the regime-switching feature of our model, the relative magnitudes of news about cash flows, risk-free rate, and risk premiums critically depend on the perceived transition paths of business cycle and monetary policy states.

4.2 Estimation

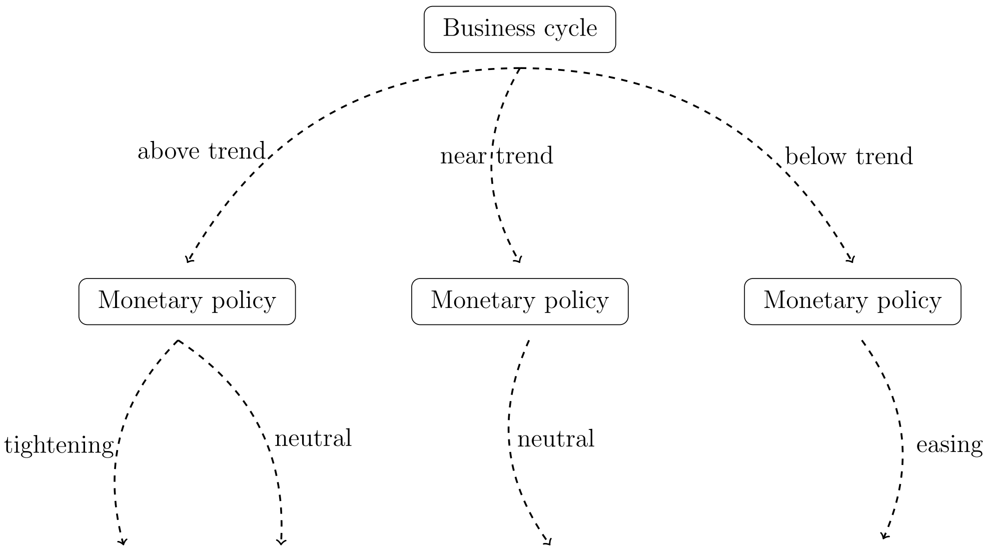
Identification of states. In order to achieve flexibility while maintaining parsimony, we assume that the economy evolves according to a four-state Markov chain. We label the states by the "above trend & tightening (AT)," "above trend & neutral (AN)," "near trend & neutral (NN)," and "below trend & easing (BE)," respectively. Here, monetary policy is usually "neutral" in that it neither stimulates or restrains growth. It only does so when the economy is either below or above trend. This is shown in Figure 3.

To respect the labeling of states, we need several parameteric restrictions. First, we impose that the constant term associated with dividends follows

$$\bar{d}(AT) = \bar{d}(AN) > \bar{d}(NN) > 0 > \bar{d}(BE). \tag{18}$$

This implies that dividends level is largest in the above trend state, during which monetary policy can be tightening or neutral. It is lower in the near trend with neutral policy state. It is actually negative during the below trend state which is accompanied with easing policy.

Figure 3: Economic states



Notes: The economy evolves according to a four-state Markov chain, which is denoted by "above trend & tightening, above trend & neutral, near trend & neutral, below trend & easing" regime, respectively.

The monetary policy parameters are restricted to be

$$\bar{r}(AT) > \bar{r}(AN) = \bar{r}(NN) = \bar{r}(BE) \quad (19)$$
$$\phi(BE) > \phi(AT) > \phi(AN) = \phi(NN) = 0.$$

We allow for minimalistic variation across states for parsimony. Note that the target interest rate levels are identical across states except for the above trend & tightening state which is higher. The policy reaction to business cycle gap is more aggressive during the below trend & easing state compared with the above trend & tightening state. The asymmetric response of the Federal Reserve, e.g., more aggressive stimulation policy, is motivated by Cieslak and Vissing-Jorgensen (2017). We normalize the reaction coefficient to zero during the neutral policy state which occurs either in the above trend or near trend state.

Finally, we impose that the ranking of the market price of risk follows

$$\lambda(BE) > \lambda(NN) > \lambda(AT) \geq \lambda(AN). \quad (20)$$

It is reasonable to think that the value is largest (smallest) during the below (above) trend states. We allow for the possibility that the market price of risk can be higher with the tightening policy than the neutral policy within the above trend state.

Data for the estimation. To learn about the model coefficients, we seek for empirical measures of dividend gap, real rate, and risk premiums. From the first two measures, we can learn about business cycle- and policy-related parameters as well as the economic states. The empirical proxy for the risk premium is necessary to learn about the market price of risks.

We construct the ex ante real risk-free rate as a fitted value from a projection of the ex post real rate on the current nominal yield and inflation over the previous year. We take the estimated risk premiums from Schorfheide, Song, and Yaron (2018) as an empirical proxy for risk premium. However, finding or constructing empirical proxy for dividend gap measure is especially challenging because of the difficulty in measuring the potential level of dividends in addition to the seasonality issues. We overcome this by assuming that dividend gap is proportional to the unemployment rate gap

$$\hat{d}_t = \delta_u \hat{u}_t, \quad \delta_u < 0. \tag{21}$$

The key advantages of this approach are that (1) one can easily measure the unemployment rate gap in real time to facilitate the estimation; and (2) the unemployment rate gap directly corresponds to one of the statutory objectives for monetary policy, which enables learning about the policy reaction rule as well. This assumption is reasonable to the extent that there is significant comovement across macroeconomic variables. All these measures are available from January 1990 to December 2017 in monthly frequency. We rely on a longer span of data to learn model parameters and states.

4.3 Estimation results

We transform parameters such that the identification restrictions can be easily incorporated. We use the Hamilton filter (see Hamilton (1989) and Kim and Nelson (1999) for details) to evaluate the likelihood function. The estimated parameter values are reported in the appendix which we transform back to match the model coefficients in (5), which are provided in Table 3. Rather than explaining the parameter estimates directly, we discuss the model-implied regime probabilities and expected dynamics of various components below.

Table 3: Parameters

Interest rate		Dividends		Market price of risk	
$\bar{r}(AT)$	0.0024	$\bar{d}(AT)$	0.0052	$\lambda_0(AT)$	28,300
$\bar{r}(AN)$	0.0009	$\bar{d}(AN)$	0.0052	$\lambda_0(AN)$	23,600
$\bar{r}(NN)$	0.0009	$\bar{d}(NN)$	0.0031	$\lambda_0(NN)$	39,500
$\bar{r}(BE)$	0.0009	$\bar{d}(BE)$	-0.0039	$\lambda_0(BE)$	118,000
$\phi(AT)$	0.0140	σ_d	0.00015	λ_1	0
$\phi(AN)$	0	σ_e	0.00036	$\lambda_{2,\tau}$	0
$\phi(NN)$	0	ρ	0.98	$\lambda_{2,d}$	0
$\phi(BE)$	0.0561	γ	0.99		
		ξ	0.28		
		μ	0		

Notes: We assume that the economy evolves according to a four-state Markov chain, which is denoted by "above trend & tightening, above trend & neutral, near trend & neutral, below trend & easing" regime, respectively. The transition probability matrix is given by

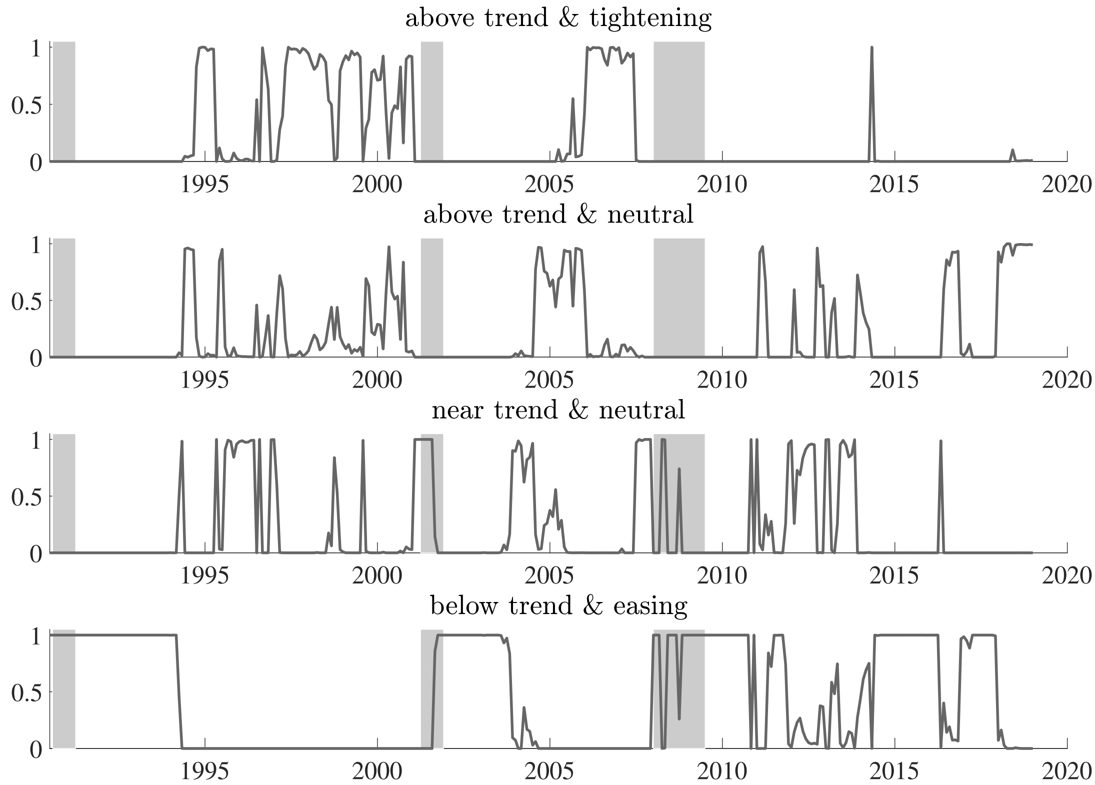
$$\Pi = \begin{bmatrix} 0.57 & 0.03 & 0.36 & 0.04 \\ 0.39 & 0.51 & 0.00 & 0.10 \\ 0.09 & 0.07 & 0.78 & 0.06 \\ 0.00 & 0.00 & 0.48 & 0.52 \end{bmatrix}$$

where each row sums to one. While we allow for any transition into the "below trend & easing" state, we prohibit the transition from the "below trend & easing" state to "above trend & neutral" or "above trend & tightening" state directly. This is imposed in the estimation.

Regime probabilities. Figure 4 provides the estimated regime probabilites. Consistent with the estimated transition matrix (which is not persistent), the economy switches across states quite often. As intended, the economy goes in and out from the near trend & neutral state when switching. For example, just before the NBER recession started, we find that the economy was in the near trend & neutral state. Then, it switched to the below trend & easing state and remained a few years even after the NBER recession ended. Thus, our bad (or worst) state does not coincide with the NBER recession dates. This is an important departure from the previous literature in characterizing economic states. Interestingly, note that the identified above trend states roughly coincide with periods in which our estimated stock return sensitivity coefficient was low (see Figure 1).

Expected dynamics. Figure 5 provides the expected dynamics of dividend growth, risk-free rate, and log return in excess of risk-free rate upto the horizon of one year. Because the estimated persistence of transition matrix is not high, the speed of mean reversion is quite fast. That being said, there is a large variation in the expected dynamics at shorter

Figure 4: The estimated regime probabilities



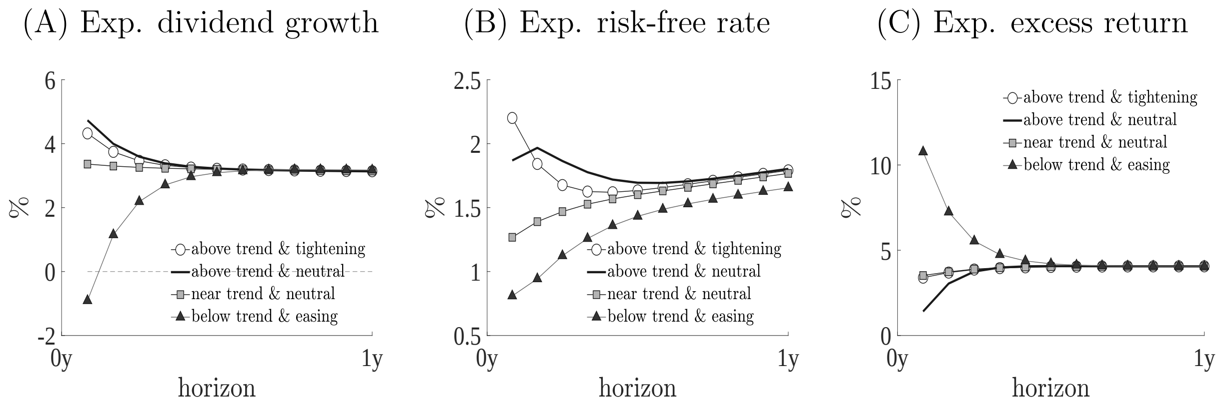
Notes: We assume that the economy evolves according to a four-state Markov chain, which is denoted by "above trend & tightening, above trend & neutral, near trend & neutral, below trend & easing" regime, respectively. We indicate the NBER recession dates with light-gray bars.

horizons. For example, our model can generate a downward-sloping, flat, or upward-sloping term structure of expected dividend growth rates and expected excess return.

In our model, a upward-sloping term structure of expected dividend growth rates is intimately related to the downward-sloping term structure of expected excess return. Intuitively, the short-term risk shoots up in the below trend & easing state due to negative growth and largest risk premium but starts to decline going forward due to mean reversion. The other extreme case is the above trend & neutral state during which the short-term risk is lowest initially but climbs up due to the risk of falling into the below trend & easing state, which is considered the worst state in our economy.

Note that the slopes of the term structure of expected dividend growth and excess return would have been steeper if it weren't for monetary policy. Here, monetary policy plays the role of smoothing out business cycle fluctuations, thus narrowing the gap between two

Figure 5: Expected dividend growth, risk-free rate, and excess return



Notes: We assume that the economy evolves according to a four-state Markov chain, which is denoted by "above trend & tightening, above trend & neutral, near trend & neutral, below trend & easing" regime, respectively. y-axis is expressed in annualized percentage terms.

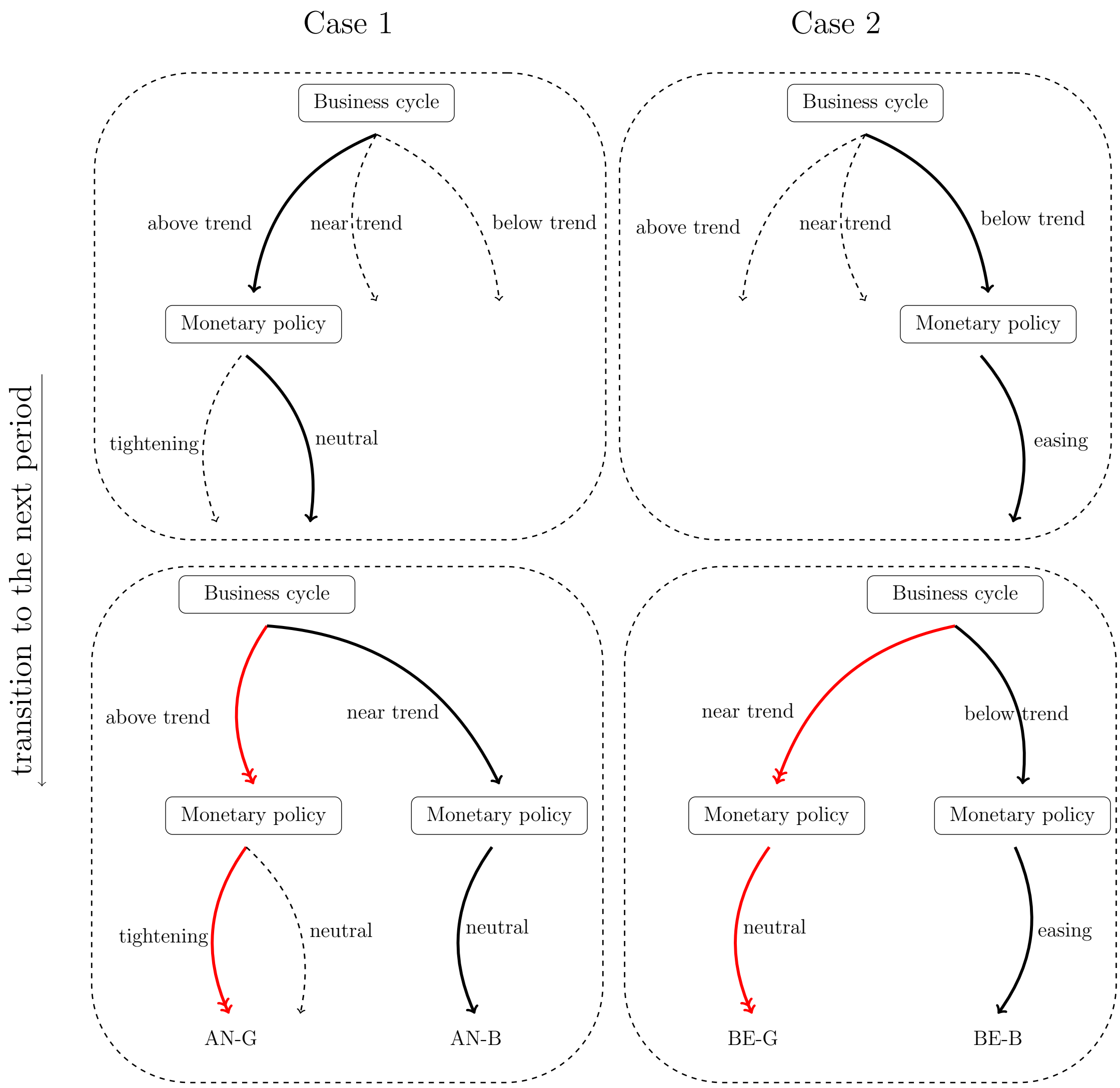
extreme states, i.e., above trend and below trend states. One way to see this is to look at the expected dividend growth rates under the above trend & tightening state which are uniformly lower than those under the above trend & neutral state. If we were to counterfactually allow for the below trend & neutral state, the corresponding expected dividend growth rates would be disastrous (much more negative).

Decomposing stock returns. We now move to the main part of the empirical exercise. We aim to understand how the perceived transition into and out of these economic states would lead to movements in stock returns. Our model allows us to attribute stock return variations to variation in news about cash flows, risk-free rate, and risk premiums, respectively. For clear presentation, we design particular transition paths to highlight the role of business cycle and monetary policy expectations in shaping return fluctuations. Specifically, we illustrate the idea with the following four cases in Figure 6. For ease of understanding Figure 6, one can imagine that the innovation in (6), e.g., $\epsilon_{d,t+1}$, contains news about the economic state S_{t+1}.[15] We refer a one-standard-deviation (or larger) positive (negative) $\epsilon_{d,t+1}$ innovation to "good (bad) news" for the economy.[16]

[15] Here, we assume that the innovation contains perfect information about the state. However, this assumption is for ease of exposition which can be easily relaxed. Any expectation that assigns a larger mass to this future state, but still allows for entering into other states would work as well.

[16] To minimize confusion, we emphasize that these transition paths should be perceived as ex post illustrations. The model assumes that the state transition is not influenced by the shock to dividends. We pick particular transition paths to clearly showcase how returns are affected.

Figure 6: An illustration of possible transition paths



Notes: We assume that the economy evolves according to a four-state Markov chain, which is denoted by "above trend & tightening, above trend & neutral, near trend & neutral, below trend & easing" regime, respectively. The boxes in the first (second) row indicate the regime in the current (next) period. We consider two different starting conditions, which are illustrated by the Case 1 and 2. Within each case, we allow two different transition paths, which can be triggered by good (red-double-arrowed line) or bad (black-arrowed line) economic shocks.

The first case assumes that the economy is in the above trend & neutral state which is the best state in our economy, e.g., highest short-horizon dividend growth expectation and lowest risk premium. Upon good news, the economy transits to the above trend & tightening state in which the short-horizon expected risk-free rate is largest. This is the "fearing the Fed" state where the rate hike is materialized. But, the economy remains in the above trend state. We label this example by "AN-G." The first letter indicates the starting state and the second letter denotes the type of news that signals state transition. Alternatively, upon bad news, the economy transits to the near trend & neutral state in which the short-horizon dividend growth expectation is lower than before with slightly larger risk premium. This implies that the pace of economic growth cooled a bit, yet recession is not likely to be around the corner. We labeled this example by “AN-B.”

The second case starts from the below trend & easing state, which is the worst state in our economy, e.g., lowest short-horizon dividend growth expectation and highest risk premium. Upon good news, the economy transits to the near trend & neutral state with considerably higher dividend growth expectation and lower risk premium. Because the economy departs from the easing to neutral policy state, this leads to higher interest rate expectation. We refer to this example by “BE-G.” Lastly, upon bad news, the economy remains in the below trend & easing state, which is the worst state in the economy. The economy failed to escape from the worst state. This is referred to as “BE-B.”

We provide the model-implied news about cash flows, risk-free rate, and risk premium expressed in (17) which is reproduced below

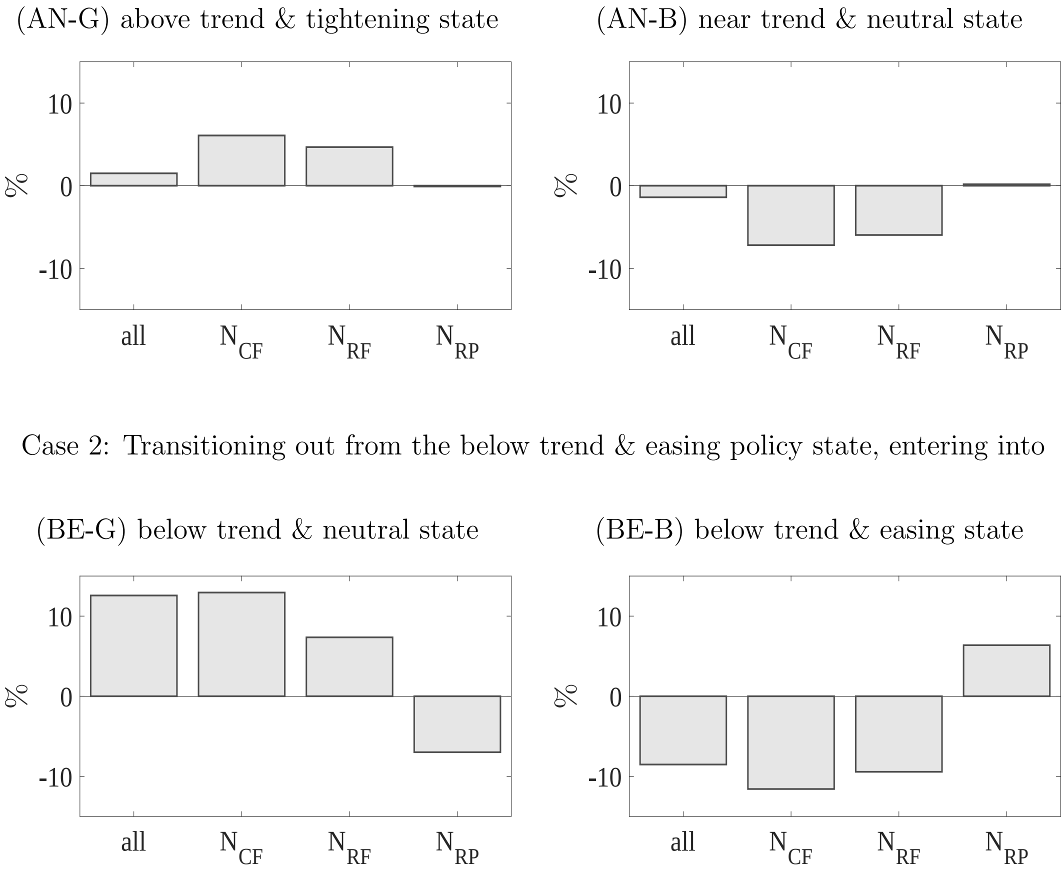
$$N_{g,t+1} = \sum_{j=0}^{\infty} \left(N^g_{j,0} + N^g_{j,1}\hat{d}_{t-1} + N^g_{j,2}u_t + N^g_{j,3}\Sigma\varepsilon_{t+1} \right), \quad g \in \{CF, RF, RP\} \tag{22}$$

under these four scenarios. Each news component is history-dependent according to our model since it depends on $\hat{d}_{t-1}$ and u_t. Therefore, our model can generate extremely rich news variations. However, because we want to be conservative in explaining our findings and for ease of illustration, we assume that the economy was at balance in the previous period, i.e., $\hat{d}_{t-1} = 0$ and $u_t = 0$. We now present our findings in Figure 7.

Perhaps, it is interesting to explain the BE-B case first. Because the economy failed to escape from the worst state, news about cash flows is significantly negative. But, monetary easing leads to negative news about risk-free rate, thereby canceling most of negative cash flows news. However, news about risk premium remains high leading to a significantly negative return response. This is reversed in the BE-G case. There is significant reduction in risk premium news because the economy escapes the worst state. News about risk-free rate does not fully nullify positive news about cash flows because the good news does not lead to an immediate monetary tightening. The overall return variations are above $\pm 10\%$ (annualized) for both BE-G and BE-B cases. However, when things were good before, that is, if the economy was in the above trend & neutral state, the patterns look quite

Figure 7: News decomposition of returns

Case 1: Transitioning out from the above trend & neutral policy state, entering into



Notes: We consider the following four cases: Transitioning out from the above trend & neutral policy state, entering into the above trend & tightening state (AN-G) and the near trend & neutral state (AN-B); Transitioning out from the below trend & easing policy state, entering into the below trend & neutral state (BE-G) and the below trend & easing state (BE-B). The first letter indicates the starting state and the second letter denotes the type of news that signals state transition. We are computing $r_{d,t+1} - E_t r_{d,t+1} = N_{CF,t+1} - N_{RF,t+1} - N_{RP,t+1}$. We are conditioning on $\hat{d}_{t-1} = 0$ and $u_t = 0$. Numbers are in annualized percentage terms.

different. The overall return variations are close to zero for both AN-G and AN-B cases. Note that news about risk premium hardly plays any role. Most of return variations are explained by news about cash flows and risk-free rate. Interestingly, news about cash flows are nearly offset by news about risk-free rate for both cases.

We summarize two key takeaways from this exercise. First, we find that the presence of monetary policy stabilization can reduce or even nullify economic shocks. This is hap-

Table 4: News decomposition of returns: Counterfactual experiments

	N_{CF}-N_{RF}-N_{RP}	N_{CF}	N_{RF}	N_{RP}	$\lvert N_{RF}\rvert/\sum\lvert N_j\rvert$	$\lvert N_{RP}\rvert/\sum\lvert N_j\rvert$
Panel A: The benchmark case						
AN-G	2.00	6.38	4.93	-0.55	42%	5%
AN-B	-2.00	-7.35	-5.86	0.51	43%	4%
BE-G	14.83	13.70	7.51	-8.65	25%	29%
BE-B	-10.35	-12.22	-9.76	7.89	33%	26%
Panel B: A constant risk-free rate case						
AN-G	23.36	8.13	0.00	-15.23	0%	65%
AN-B	-18.00	-9.23	0.00	8.77	0%	49%
BE-G	91.57	15.93	0.00	-75.65	0%	83%
BE-B	-87.36	-15.09	0.00	69.27	0%	82%
Panel C: A constant market price of risk case						
AN-G	0.23	6.38	4.93	1.22	39%	10%
AN-B	-0.91	-7.35	-5.86	-0.58	42%	4%
BE-G	5.95	13.70	7.51	0.24	35%	1%
BE-B	-2.21	-12.22	-9.76	-0.24	44%	1%

Notes: We consider the following four cases: Transitioning out from the above trend & neutral policy state, entering into the above trend & tightening state (AN-G) and the near trend & neutral state (AN-B); Transitioning out from the below trend & easing policy state, entering into the below trend & neutral state (BE-G) and the below trend & easing state (BE-B). The first letter indicates the starting state and the second letter denotes the type of news that signals state transition. We are computing $r_{d,t+1} - E_t r_{d,t+1} = N_{CF,t+1} - N_{RF,t+1} - N_{RP,t+1}$. We are conditioning on $\hat{d}_{t-1} = 0$ and $u_t = 0$. Numbers are in annualized percentage terms.

pening commonly across different economic states. Second, there is large swings in risk premium news mostly during bad times which serves as an important factor explaining return variations. News about risk premium does not seem to play an important role during good times.[17] Our model produces a high degree of realism when we compare with the evidence in Figure 2.

In our model, monetary policy stabilization affects news about cash flows and risk premiums as well. In order to cleanly understand the role played by monetary policy, we fix the interest rate to be constant and repeat the same exercise keeping all else identical to

[17]This is consistent with the explanation in Cochrane (2007). There are many papers providing evidence that stock returns are highly predictable (unpredictable) during bad (good) times, e.g., Rapach, Strass, and Zhou (2010) and Henkel, Martin, and Nardari (2011) among others.

before. This is shown in Panel (B) of Table 4. By construction, news about risk-free rate is zero. What is interesting to observe is that removing policy stabilization effect amplifies economic shocks substantially. Notable examples are AN-G and AN-B where we find substantial movements in both news about cash flows and risk premium. The combined effect leads to nearly ±20% (annualized) stock return variations, which are counterfactual and inconsistent with our previous evidence. In Panel (C) of Table 4, we instead fix the market price of risk to be constant while keeping all else identical. This time, we seek to understand the role of risk premium news by reducing their variations. A notable example is BE-B where we find inconsequential movements in returns due to monetary policy stabilization effect, which essentially nullifies negative cash flow news. Again, this is inconsistent with our evidence in the previous section.

5 Conclusion

This paper examines the cyclicality in the reaction of the stock market to macroeconomic news announcements. We establish that the cyclical response of stock returns to news is consistently documented across a wide range of macroecononic news announcements. We argue that this pattern is driven by the procyclical nature of monetary policy expectation and countercyclical nature of market price of risk (risk premium). Our interpretation is based on comprehensive regression analyses and a no-arbitrage framework that allows state-dependent dynamics of cash flows (dividends), interest rates (monetary policy), and risk premia enabling both qualitative and quantitative assessment of the framework. Our study highlights the importance of understanding the interplay between economic conditions, the expectations about monetary policy given these conditions, and their joint effect on the stock market.

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Appendix

Fearing the Fed: How Wall Street Reads Main Street

Tzuo-Hann Law, Dongho Song, Amir Yaron

A High-Frequency Regression

A.1 Data

Table A.1: Macroeconomic news announcements

Name	Obs.	Release Time	Source	Start Date	End Date
Capacity Utilization	231	9:15	FRB	16-Jun-1998	15-Dec-2017
Change in Nonfarm Payrolls	236	8:30	BLS	05-Jun-1998	08-Dec-2017
Construction Spending MoM	220	10:00	BC	02-Nov-1998	01-Dec-2017
Consumer Confidence Index	233	10:00	CB	30-Jun-1998	27-Dec-2017
CPI MoM	234	8:30	BLS	16-Jun-1998	13-Dec-2017
Durable Goods Orders	255	8:30	BC	24-Jun-1998	22-Dec-2017
Factory Orders	231	10:00	BC	04-Jun-1998	04-Dec-2017
GDP Annualized QoQ	237	8:30	BEA	26-Mar-1998	21-Dec-2017
Housing Starts	231	8:30	BC	16-Jun-1998	19-Dec-2017
Industrial Production MoM	231	9:15	FRB	16-Jun-1998	15-Dec-2017
Initial Jobless Claims	1006	8:30	ETA	04-Jun-1998	28-Dec-2017
ISM Manufacturing	233	10:00	ISM	01-Jun-1998	01-Dec-2017
ISM Non-Manf. Composite	223	10:00	ISM	05-Apr-1999	05-Dec-2017
Leading Index	233	10:00	CB	02-Jun-1998	21-Dec-2017
New Home Sales	232	10:00	BC	02-Jun-1998	22-Dec-2017
Personal Income	235	8:30	BEA	26-Jun-1998	22-Dec-2017
PPI Final Demand MoM	233	8:30	BLS	12-Jun-1998	12-Dec-2017
Retail Sales Advance MoM	231	8:30	BC	14-Jul-1998	14-Dec-2017
Trade Balance	233	8:30	BEA	18-Jun-1998	05-Dec-2017
Unemployment Rate	235	8:30	BLS	02-Jul-1998	08-Dec-2017

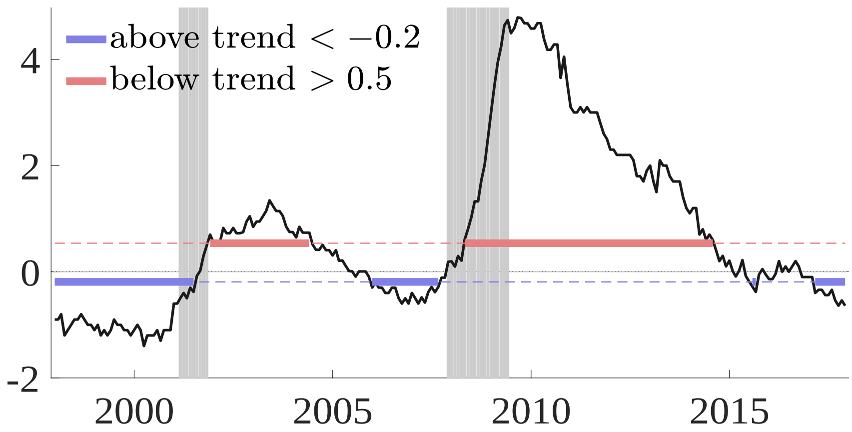
Notes: Bureau of Labor Statistics (BLS), Bureau of the Census (BC), Bureau of Economic Analysis (BEA), Federal Reserve Board (FRB), Conference Board (CB), Employment and Training Administration (ETA), Institute for Supply Management (ISM), National Association of Realtors (NAR). We use the most up-to-date names for the series, e.g., GDP Price Index was previously known as GDP Price Deflator, Construction Spending MoM was previously labeled as Construction Spending, PPI Final Demand MoM was labeled as PPI MoM, Retail Sales Advance MoM was labeled as Advance Retail Sales, ISM Non-Manf. Composite was labeled as ISM Non-Manufacturing. Observations (across all the MNAs) with nonstandard release times were dropped.

Table A.2: Descriptive statistics for the standardized MNA surprises

	(1) Across Surveys		(2) Across Time		Correlation b/w
MNAs	mean	std.dev.	mean	std.dev.	(1) and (2)
Change in Nonfarm Payrolls	-0.46	2.45	-0.20	0.94	0.95
Consumer Confidence Index	0.00	3.16	0.00	1.04	0.96
Initial Jobless Claims	0.08	2.44	0.04	1.03	0.90
ISM Manufacturing	0.12	2.28	0.06	1.02	0.97

Notes: We divide the individual surprise by a normalization factor. Normalization factor (1,"Across Surveys") is the standard deviation of all analyst forecasts for a particular MNA at a point in time. Normalization factor (2,"Across Time") is the standard deviation of all the raw surprises in the sample for a particular macroeconomic announcement.

Figure A.1: Unemployment rate gap



Notes: We use the real-time civilian unemployment rate and natural rate of unemployment (NROU) data from Federal Reserve Bank of St. Louis and Federal Reserve Bank of Philadelphia to construct unemployment rate gap. Because of the apparent asymmetry in the data, we set the threshold to 75% (25%) of negative (positive) unemployment rate gap and define the "above trend (below trend)" periods whenever unemployment rate gap is below (above) that threshold.

A.2 Nonlinear regression in Swanson and Williams (2014)

For macroeconomic indicator $y_{i,t}$, the standardized news variable at time t is

$$X_{i,t} = \frac{y_{i,t} - E_{t-\Delta}(y_{i,t})}{\sigma(y_{i,t} - E_{t-\Delta}(y_{i,t}))}$$

where $E_{t-\Delta}(y_{i,t})$ is the mean survey expectation which was taken at $t-\Delta$. For illustrative purpose, assume (1) two macroeconomic variables; (2) quarterly announcements (4 per a year); (3) 3 years of announcement data. We represent the quarterly time subscript t as $t = 12(a-1) + q$, where $q = 1, ..., 4$. We consider the following nonlinear least squares specification

$$R_{a,q} \quad = \quad \alpha_a + \beta_a \Big(\gamma_1 X_{1,a,q} + \gamma_2 X_{2,a,q} \Big) + \epsilon_{a,q},$$

where q is the quarterly time subscript and a the annual time subscript. This nonlinear regression can be expressed as

$$\begin{bmatrix} R_{1,1} \\ R_{1,2} \\ R_{1,3} \\ R_{1,4} \\ R_{2,1} \\ R_{2,2} \\ R_{2,3} \\ R_{2,4} \\ R_{3,1} \\ R_{3,2} \\ R_{3,3} \\ R_{3,4} \end{bmatrix} = \begin{bmatrix} X_{1,1,1} & X_{2,1,1} & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ X_{1,1,2} & X_{2,1,2} & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ X_{1,1,3} & X_{2,1,3} & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ X_{1,1,4} & X_{2,1,4} & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & X_{1,2,1} & X_{2,2,1} & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & X_{1,2,2} & X_{2,2,2} & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & X_{1,2,3} & X_{2,2,3} & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & X_{1,2,4} & X_{2,2,4} & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & X_{1,3,1} & X_{2,3,1} & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & X_{1,3,2} & X_{2,3,2} & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & X_{1,3,3} & X_{2,3,3} & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & X_{1,3,4} & X_{2,3,4} & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \beta_1\gamma_1 \\ \beta_1\gamma_2 \\ \beta_2\gamma_1 \\ \beta_2\gamma_2 \\ \beta_3\gamma_1 \\ \beta_3\gamma_2 \\ \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \epsilon_{1,1} \\ \epsilon_{1,2} \\ \epsilon_{1,3} \\ \epsilon_{1,4} \\ \epsilon_{2,1} \\ \epsilon_{2,2} \\ \epsilon_{2,3} \\ \epsilon_{2,4} \\ \epsilon_{3,1} \\ \epsilon_{3,2} \\ \epsilon_{3,3} \\ \epsilon_{3,4} \end{bmatrix}.$$

Table A.3: Selection of the MNA surprises based on average p-values

MNAs			Intra-day return				Daily return	
	Percent	p-val	Percent	p-val	Percent	p-val	p-val	p-val
Change in Nonfarm Payrolls	100.0 %	0.0000	100.0 %	0.0000	100.0 %	0.0000	0.5073	0.6077
ISM Manufacturing	100.0 %	0.0000	100.0 %	0.0000	100.0 %	0.0000	0.3299	0.4333
Consumer Confidence Index	100.0 %	0.0000	100.0 %	0.0000	100.0 %	0.0000	0.3607	0.3703
Initial Jobless Claims	100.0 %	0.0005	100.0 %	0.0000	100.0 %	0.0000	0.0927	0.0693
Durable Goods Orders	98.8 %	0.0011	81.5 %	0.0138	92.6 %	0.0031	0.4124	0.4032
Retail Sales Advance MoM	100.0 %	0.0011	79.0 %	0.0164	77.8 %	0.0161	0.1476	0.1239
Unemployment Rate	82.7 %	0.0226	23.5 %	0.1797	0.0 %	0.4359	0.8033	0.8817
Construction Spending MoM	34.6 %	0.0359	9.9 %	0.1215	0.0 %	0.3129	0.2155	0.2605
GDP Annualized QoQ	76.5 %	0.0477	72.8 %	0.0417	77.8 %	0.0203	0.3387	0.4266
Industrial Production MoM	16.0 %	0.0856	33.3 %	0.1855	45.7 %	0.0497	0.8363	0.9288
ISM Non-Manf. Composite	44.4 %	0.1076	56.8 %	0.0553	42.0 %	0.1189	0.0117	0.0214
Housing Starts	32.1 %	0.1678	1.2 %	0.5879	7.4 %	0.4324	0.8247	0.9425
CPI MoM	9.9 %	0.2206	100.0 %	0.0012	100.0 %	0.0006	0.2051	0.2228
New Home Sales	27.2 %	0.2221	2.5 %	0.5660	1.2 %	0.5946	0.9259	0.9442
Personal Income	2.5 %	0.2744	0.0 %	0.6717	0.0 %	0.5386	0.5103	0.5654
Leading Index	0.0 %	0.3226	0.0 %	0.7019	0.0 %	0.7393	0.4113	0.5079
Trade Balance	0.0 %	0.4007	0.0 %	0.1987	4.9 %	0.1718	0.0153	0.0125
Factory Orders	1.2 %	0.4563	1.2 %	0.2858	0.0 %	0.3721	0.0939	0.0923
Capacity Utilization	0.0 %	0.6591	0.0 %	0.6113	14.8 %	0.1244	0.7658	0.8442
PPI Final Demand MoM	0.0 %	0.7860	0.0 %	0.2763	0.0 %	0.2911	0.4420	0.3245
Nonlinear regression		✓						
Multivariate regression		✓		✓			✓	
Univariate regression						✓		✓

Notes: The sample is from January 1998 to December 2017 for the 81 regressions described in the main text. "Percent" refers to the percentage (number significant/81) of regressions in which returns significantly responds the MNA at the 99% confidence interval. Average p-value is the average two-sided p-value across all 81 regressions. We consider "multivariate" and "univariate" regressions. Daily return refers to using returns from 8am to 3.30pm. It is important to note that we remove all the days when there are the FOMC related news in constructing daily returns. We refer to the non-linear regression when β^{τ} is estimated; all the rest assume β^{τ} is set to one.

A.3 Selection of the MNA surprises and return window interval

We estimate various versions of (A.1)

$$r_{t-\Delta_l}^{t+\Delta_h} \;=\; \alpha^{\tau} + \beta^{\tau}\gamma' X_t + \epsilon_t \tag{A.1}$$

by considering all combinations of Δ_l and Δ_h between 10 minutes and 90 minutes in the increments of 10 minutes (81 regressions in total). We use many combinations of the return window precisely because the significance of the MNAs depends on the size of

Table A.4: Selection of the MNA surprises based on the magnitude of coefficient

MNAs	Intra-day return			Daily return	
Change in Nonfarm Payrolls	25.64	10.49	10.77	2.64	2.61
Initial Jobless Claims	23.58	16.05	16.22	14.26	16.25
ISM Manufacturing	21.75	10.77	10.61	4.11	3.86
Consumer Confidence Index	14.44	7.13	7.14	2.79	2.90
Retail Sales Advance MoM	14.13	5.45	5.30	6.53	7.33
Industrial Production MoM	10.99	6.07	5.69	1.67	0.54
Durable Goods Orders	9.71	4.70	4.68	3.47	3.42
GDP Annualized QoQ	8.52	6.11	6.20	4.71	4.40
Leading Index	8.13	1.30	1.39	6.70	6.08
CPI MoM	7.20	10.57	10.68	7.95	8.37
ISM Non-Manf. Composite	6.84	4.16	3.82	8.92	8.96
Unemployment Rate	6.72	2.59	1.72	0.98	0.76
Construction Spending MoM	6.42	2.39	2.02	4.11	4.17
Factory Orders	4.13	3.85	3.52	12.12	11.87
New Home Sales	3.71	0.78	0.86	0.24	0.19
Personal Income	3.07	1.12	1.12	3.87	3.47
Capacity Utilization	2.99	1.71	3.76	2.37	1.17
Housing Starts	2.53	0.77	0.96	0.69	0.25
Trade Balance	2.30	2.07	1.88	8.80	9.25
PPI Final Demand MoM	0.66	1.91	1.65	3.06	4.15
Nonlinear regression	✓				
Multivariate regression	✓	✓		✓	
Univariate regression			✓		✓

Notes: The sample is from January 1998 to December 2017 for the 81 intra-day regressions described in the main text. We consider multivariate and univariate OLS regressions with both daily and intra-day returns. Daily return refers to using returns from 8am to 3.30pm. We exclude all the days containing FOMC related news in constructing daily returns. In the non-linear regression, β^{τ} is estimated; all the rest assume β^{τ} is set to one. We sort the macro announcements by how much an individual MNA explains variation in stock market returns. More precisely, we compute $100 \times |\hat{\gamma}_i \#_i| / \sum_i |\hat{\gamma}_i \#_i|$ where $\#_i$ is the number of observations where MNA_i features in the regression (Column 2 in Table A.1) for each regression specification. Since our measure of surprises are normalized by either variation in time, or variation in the prediction of forecasters, this statistic will measure the relative importance of MNAs in a manner comparable across different regressions. When the regression is multivariate, $\hat{\gamma}_i$ refers to the i^{th} entry of vector $\hat{\gamma}$. When the regression is univariate, $\hat{\gamma}_i$ is the factor loading on MNA_i from the i^{th} regression. We average this statistic across all 81 intra-day regressions for the first 3 columns.

the return window, see for example, Andersen, Bollerslev, Diebold, and Vega (2003) and Bartolini, Goldberg, and Sacarny (2008). For robustness, we also examine both cases of multivariate and univariate regressions in which β^{τ} is fixed at one. Table A.3 tabulates the number of regressions in which stock returns significantly respond to a specific MNA at the 1% significance level. We can also order the MNAs by their economic impact instead of statistical significance. More precisely, we compute $100 \times |\hat{\gamma}_i \#_i| / \sum_i |\hat{\gamma}_i \#_i|$ where $\#_i$ is the number of observations for MNA_i. The results are provided in Table A.4. By and large, the ordering is similar to Table A.3. In sum, based on two approaches we select the top fours MNAs as our benchmark MNAs. We find that the range of R^2 values from these regressions are from 5% to 20%. For ease of presentation, we set $\Delta_l = \Delta_h = 30min$ (which yields an R^2 value of 0.13 which is representative of the distribution) for the remaining empirical exercises.

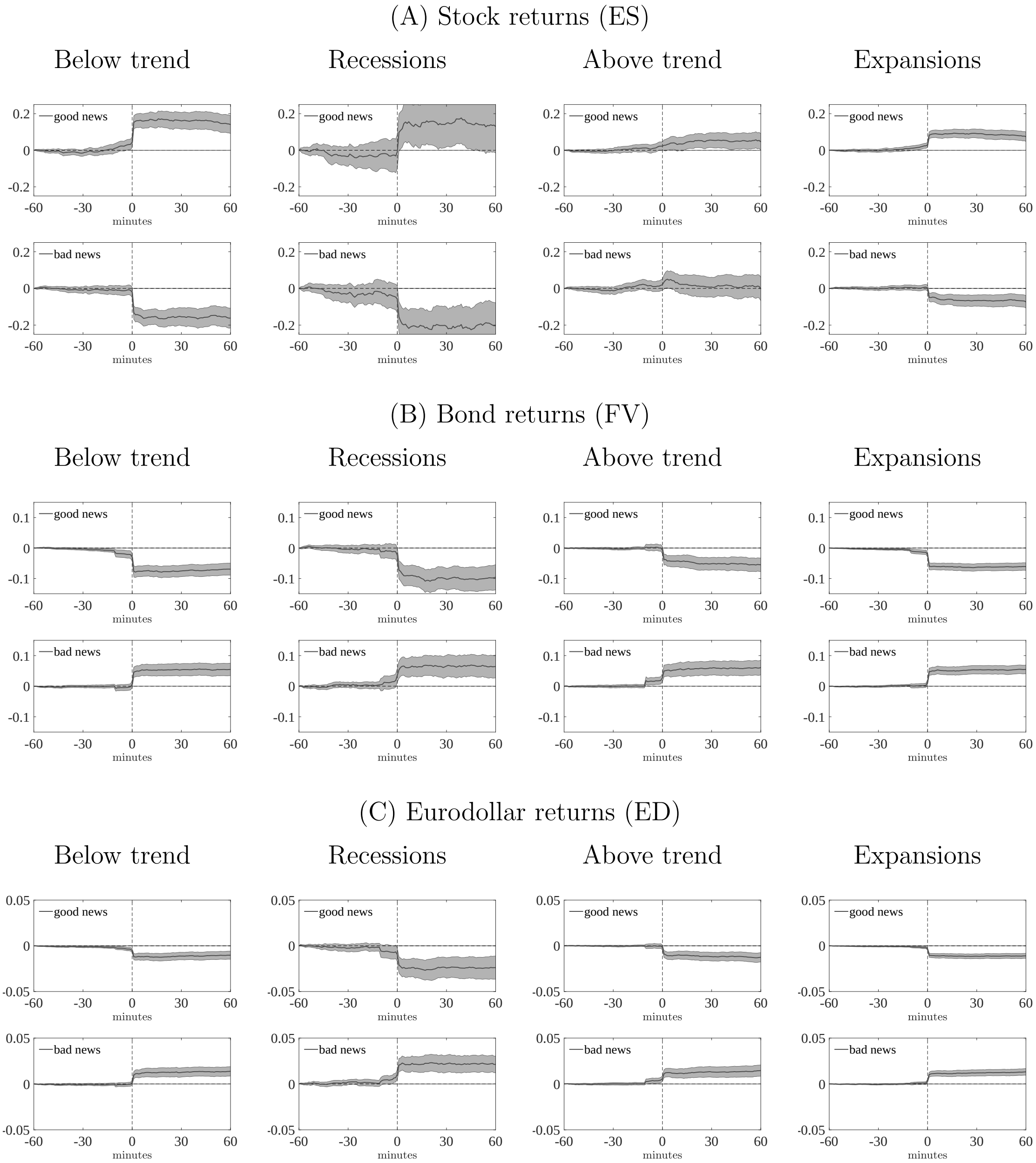
A.4 Revisiting Boyd, Hu, and Jagannathan (2005)

Our work is closely related to Boyd, Hu, and Jagannathan (2005) (BHJ) in many ways. Here, we explain the similarities and key differences between the two papers. For ease of exposition, we first summarize BHJ and explain our differences below.

BHJ investigates the short-run response of stock prices to the arrival of macro news (unemployment rate). To do this, they measure the anticipated and unanticipated component of unemployment rate using regressions with the change in the unemployment rate, monthly industrial production, and the 3-month T-bill rate, the change in the default yield spread between Baa and Aaa corporate bonds as predictor variables for the current unemployment rate. Then, they regress daily returns on bonds and stocks on the unanticipated component of unemployment rate. They find that stock market's response depends on whether the economy is expanding or contracting. To summarize, rising unemployment rate (bad news) is good (bad) for stock market during expansions (recessions); and because the economy is usually in expansions, rising unemployment rate is good for stock market.

BHJ examine the informational content of unemployment rate announcement. If unemployment rate news has an effect on stock prices, it must be because it conveys information about cash flows, interest rate, and risk premium. To understand how these three primitive factors influence stock prices, they consider the Gordon growth constant model for conceptual device of security valuation. For it to have information about future interest rates, stock and bond prices would respond in the same way. They don't. Instead, they find that stock prices react negatively to rising unemployment rate in recessions, but bond prices do not react. Therefore, unemployment rate news is about cash flows or risk premiums in recessions. They provide the evidence that rising unemployment rate is always followed by slower growth especially during recessions. In contrast, both stock and bond prices rise on rising unemployment rate during expansions. This suggests that bad labor news leads to decline in future interest rate expectation. Also, they find evidence that an

Figure A.2: The cumulative stock returns around the benchmark announcements



Notes: We plot the average cumulative returns in percentage points around scheduled announcements. Macroeconomic announcements are change in nonfarm payrolls, consumer confidence index, ISM manufacturing, and initial jobless claims. The black solid lines are the average cumulative return on E-mini S&P 500 futures (ES), US 5-Year T-Note Futures (FV), and Eurodollar Futures CME (ED) of maturity 12 month 60 minutes prior to scheduled announcements to 60 minutes after scheduled announcements. The light-gray shaded areas are ±2-standard-error bands around the average returns. The sample period is from January 1998 through December 2017. The vertical line indicates the time at which announcements are released in this sample period. y-axis expressed in percentage terms.

unanticipated increase in unemployment rate (bad news) may lead to an increase in the risk premium during expansions, but not during recessions.

From a technical point of view, our work extends BHJ by exploring a broader set of macroeconomic announcements with survey-based measure of announcement surprises and high-frequency returns. Our comprehensive data allow us to investigates how the "unanticipated surprises" of most influential announcements impact various financial market returns including stocks and bonds. Figure A.2 summarizes our findings. Consistent with BHJ, in Panel (A) we find that bad news, i.e., negative CNP, CCI, ISM and positive IJC surprises, significantly lowers stock returns during the below trend periods, but not during the above trend periods (for ease of comparison with BHJ, we also partition the sample with respect to the NBER recessions and expansions). However, we find that the same bad news leads to significant increase in bond futures returns during the below trend periods (indicating lower interest rates) in Panel (B) and (C). In addition, the magnitudes of increase in bond futures returns upon bad news are similar across the below and above trend periods. This is clearly different from BHJ.

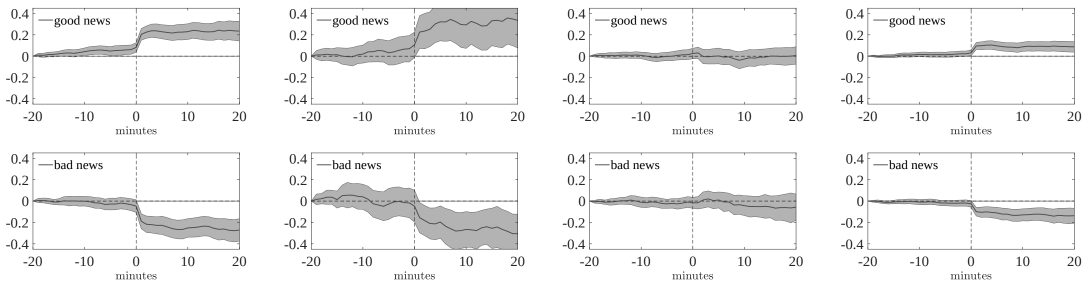
To precisely investigate the informational content, we focus on the announcements released during trading hours (CCI and ISM released at 10am), which allows us to use the intra-day VIX Index as our empirical proxy for equity premium. Figure A.3 provides the cumulative returns of stocks, bonds, and VIX Index around the 10am announcements. The reactions of both stock and bond returns are similar to Figure A.2. What is interesting is the reaction of the VIX returns. We find an opposite conclusion from BHJ that bad news, i.e., negative CCI and ISM surprises, leads to a significant increase in the risk premium during the below trend periods, but not during the above trend periods. We expect our new stylized facts to be valuable to the readers because our evidence leads to a different characterization of the informational content of announcement surprises.

We provide a framework that models the dynamics of cash flows, interest rate (monetary policy), and risk premium jointly enabling both qualitative and quantitative assessment of the framework specifically tailored to help the reader interpret our empirical findings. There are two key takeaways from our model. First, we find that the presence of monetary policy stabilization can reduce or even nullify economic shocks. This is commonly happening across different phases of business cycles. Second, there is large swings in risk premium news mostly during the below trend periods which serves as an important factor understanding return variations. News about risk premium does not seem to play an im-

Figure A.3: The cumulative stock returns around the 10am announcements (CCI,ISM)

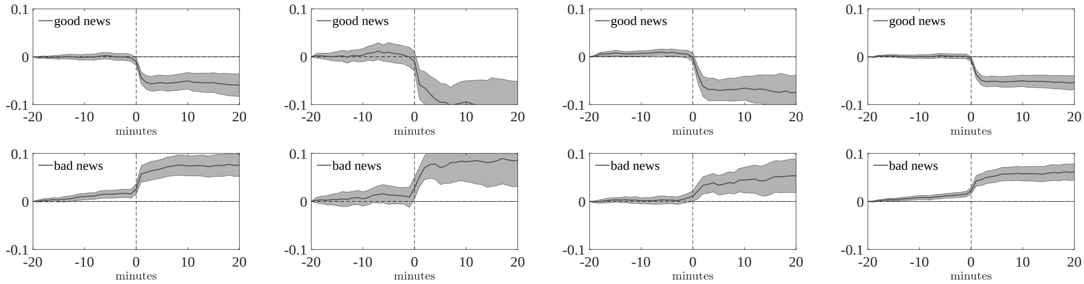
(A) Stock returns

Below trend Recessions Above trend Expansions



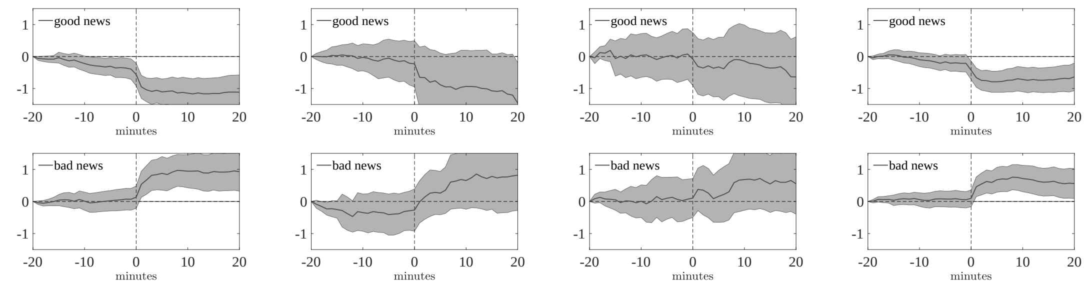
(B) Bond returns (5y)

Below trend Recessions Above trend Expansions



(C) VIX returns

Below trend Recessions Above trend Expansions



Notes: We plot the average cumulative returns in percentage points around scheduled announcements. Macroeconomic announcements are consumer confidence index and ISM manufacturing both of which are released at 10am. The black solid lines are the average cumulative return on E-mini S&P 500 futures (ES), US 5-Year T-Note Futures (FV), and CBOE VIX Index (VIX) 20 minutes prior to scheduled announcements to 20 minutes after scheduled announcements. The light-gray shaded areas are ±2-standard-error bands around the average returns. The sample period is from January 1998 through December 2017. The vertical line indicates the time at which announcements are released in this sample period. y-axis expressed in percentage terms.

portant role during the above trend periods. Put together, we believe the new empirical stylized facts as well as the modeling framework are our two fundamental contributions which goes beyond the existing works including BHJ.

A.5 Robustness checks

Stock return sensitivity before and after the announcements. To better understand how information contained in the MNAs is conveyed in the stock market, we decompose $\hat{\beta}^{\tau}$ to sensitivity attributable to periods before and after the announcements.

To recap, the estimates from the benchmark regression are provided below

$$\hat{r}_{t-30m}^{t+30m} = \hat{\alpha}^{\tau} + \hat{\beta}^{\tau}(\hat{\gamma}^{\top} X_t) = \hat{\alpha}^{\tau} + \hat{\beta}^{\tau}\hat{X}_t. \tag{A.2}$$

We estimate the modified (restricted) regression in which we regress return $r_{t-\Delta_l}^{t+\Delta_h}$ on $\hat{X}_t$

$$r_{t-\Delta_l}^{t+\Delta_h} = \alpha^{\tau} + \beta^{\tau}\hat{X}_t + \epsilon_t \tag{A.3}$$

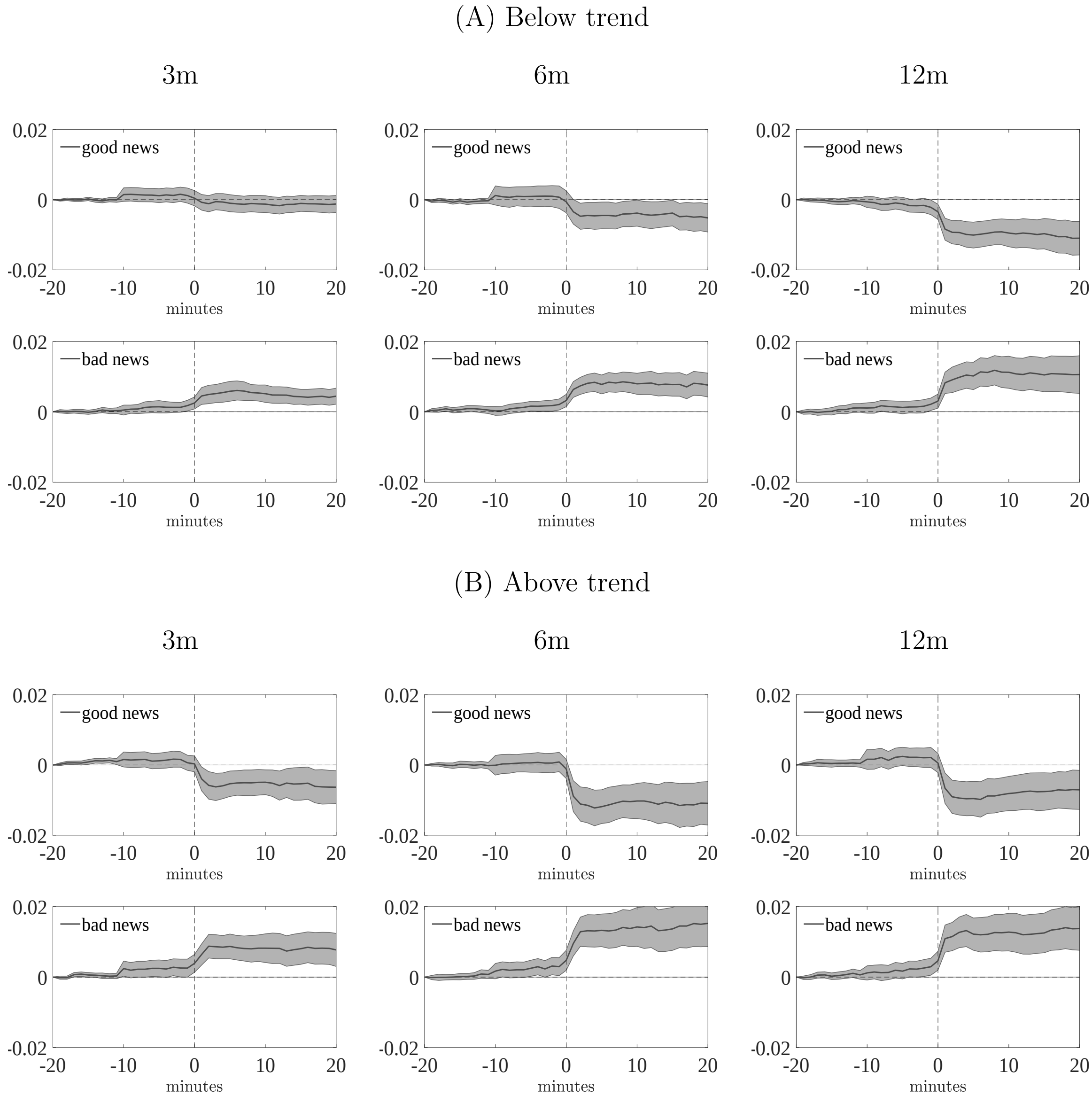
and obtain estimate of $\hat{\beta}^{\tau}$ for each combination of $(\Delta_h, \Delta_l) \in \{-5m, 0m, 5m, 30m\}$, which we denote by $\hat{\beta}^{\tau}(t - \Delta_l \to t + \Delta_h)$. See Figure A.5. It follows that $\hat{\beta}^{\tau}$ in (A.2) by construction equals

$$\begin{aligned} \hat{\beta}^{\tau}(t-30m \to t+30m) &= \hat{\beta}^{\tau}(t-30m \to t-5m) + \hat{\beta}^{\tau}(t-5m \to t) \\ &+ \hat{\beta}^{\tau}(t \to t+5m) + \hat{\beta}^{\tau}(t+5m \to t+30m). \end{aligned} \tag{A.4}$$

The sensitivity is with respect to the linearly transformed MNA surprises, $\hat{X}_t$. Since $\hat{X}_t$ is a generated regressor from (A.2), asymptotic standard errors are constructed using generalized methods of moments.

We do not find any evidence of pre-announcement phenomenon which is different from Lucca and Moench (2015); stock prices on impact react significantly to the MNA surprises, but there is no statistically significant movement five minutes after the announcements. This is important as it shows there is no immediate mean reversion in the reaction of the stock market. We extend our analysis to daily data and further confirm that the market reactions are not reflecting temporary noise.

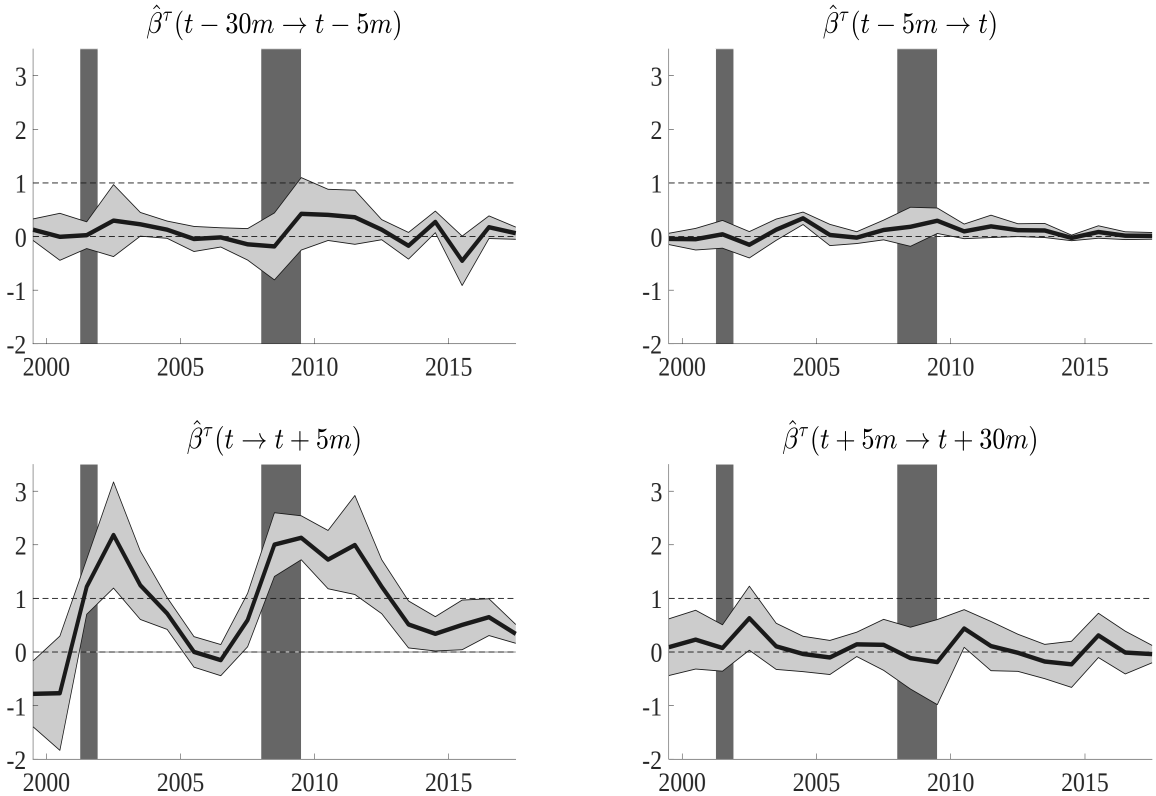
Figure A.4: The cumulative Eurodollar returns around the 10am announcements



Notes: We plot the average cumulative returns in percentage points around scheduled announcements. Macroeconomic announcements are consumer confidence index, durable goods orders, and ISM manufacturing which are released at 10am. The black solid lines are the average cumulative return on the Eurodollar futures of maturity 3, 6, 9, 12 months 20 minutes prior to scheduled announcements to 20 minutes after scheduled announcements. The light-gray shaded areas are ± 2-standard-error bands around the average returns. The sample period is from January 1998 through December 2017. The vertical line indicates the time at which announcements are released in this sample period. y-axis expressed in percentage terms.

Stock return sensitivity with lower-frequency data. To show that the impact of the MNA surprises on the stock market is not short-lived, we estimate the restricted

Figure A.5: The stock return sensitivity before and after the news announcements

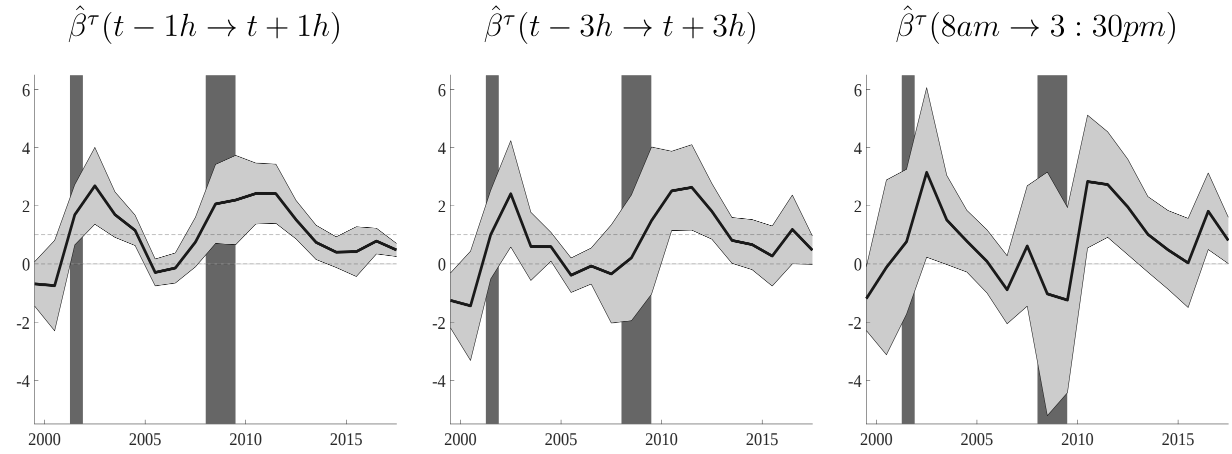


Notes: The individual $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ are shown with ± 2 standard-error bands. Here, we do not impose the restriction that the average of $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ is equal to one. This is because the regressor is already restricted to $\hat{X}_t$. By construction, the sum of individual $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ equals $\hat{\beta}^{\tau}$ shown in Figure 1.

regression (A.3) with larger window intervals in Figure A.6. Since we aim to compare the precision of the sensitivity coefficient estimates when we replace the dependent variable with lower-frequency returns, we fix the unconditional impact of the MNA surprises to be *ex ante* identical across various cases. Thus, the coefficient $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ can only be interpreted with respect to $\hat{X}_t$. It is important to note that we remove all the days when there are the FOMC related news in constructing daily returns. We find that the mean estimates are broadly similar across various window intervals. As expected, the standard-error bands increase moving from the case of hourly returns to daily returns. We emphasize that the results from the unrestricted regression are qualitatively similar.

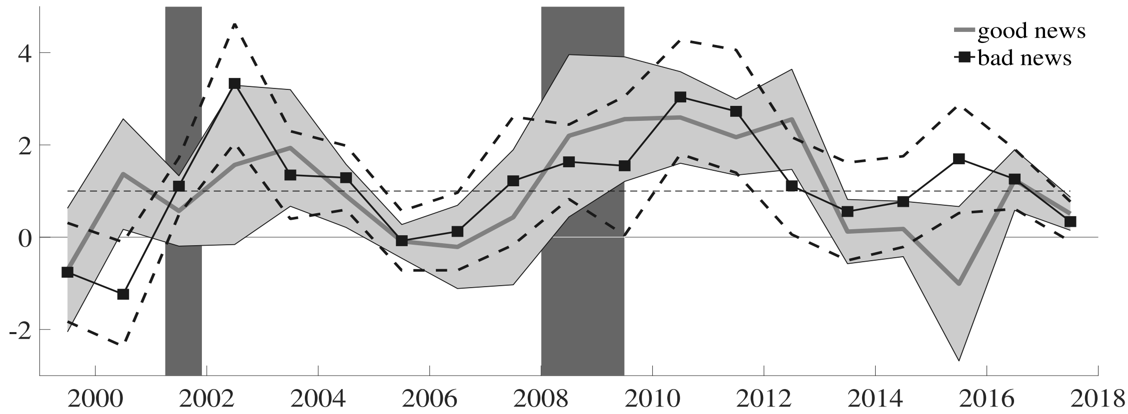
Evidence for asymmetry. We decompose the macroeconomic news announcements into "good" (better-than-expected or positive) and "bad" (worse-than-expected or negative)

Figure A.6: The stock return sensitivity: Evidence from lower-frequency data



Notes: The individual $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ are shown with ± 2 standard-error bands. Here, we do not impose the restriction that the average of $\hat{\beta}^{\tau}(t-\Delta_l \to t+\Delta_h)$ is equal to one. This is because the regressor is already restricted to $\hat{X}_t$.

Figure A.7: The stock return sensitivity to good and bad surprises



Notes: We decompose the macroeconomic news announcements into "good" (better-than-expected or positive) and "bad" (worse-than-expected or negative) announcements. Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We flip the sign of Initial Jobless Claims surprises for ease of comparison across other "good" surprises. We set $\Delta = 30$min. We impose that β_j^{τ} is on average equal to one. We provide ± 2-standard-error bands around β_j^{τ}, $j \in \{\text{good,bad}\}$.

announcements and examine if the stock return responses to good and bad MNA surprises are different from each other.[18] Here, we flip the sign of Initial Jobless Claim surprises for

[18] We also repeat this exercise using only the better half of good news (the most positive) and the worse

Table A.5: Distributions of the MNA surprises: Kolmogorov-Smirnov test

Surprises pair	CNP	CCI	IJC	ISM	RSA	DGO
(above trend, near trend)	0.997	0.953	0.233	0.707	1.000	0.546
(near trend, below trend)	0.734	0.125	0.920	0.479	0.519	0.752
(above trend, below trend)	0.912	0.081	0.050	0.063	0.900	0.473

Notes: We consider change in nonfarm payrolls (CNP), initial jobless claims (IJC), ISM manufacturing (ISM), consumer confidence index (CCI), retail sales advance (RSA), and durable goods orders (DGO). We partition the MNA surprise into three different subsamples and compute a test decision for the null hypothesis that the surprises in different subsamples are from the same distribution. We report the corresponding asymptotic p-values.

Table A.6: Distributions of the MNA surprises: Regression test

	MNA surprises (level)				MNA surprises (absolute level)			
	CNP	CCI	IJC	ISM-M	CNP	CCI	IJC	ISM-M
constant	-0.12	0.01	-0.10	0.09	0.70	0.90	0.72	0.74
(t-stat)	(-1.11)	(0.04)	(-1.54)	(0.66)	(11.58)	(11.85)	(16.64)	(8.28)
dummy aboveT	-0.15	0.13	0.07	-0.13	0.15	-0.29	-0.08	-0.01
(t-stat)	(-0.84)	(0.78)	(0.84)	(-0.78)	(1.39)	(-3.04)	(-1.47)	(-0.10)
dummy belowT	-0.07	-0.01	0.18	0.06	0.03	-0.06	0.05	0.08
(t-stat)	(-0.48)	(-0.04)	(2.24)	(0.36)	(0.29)	(-0.58)	(0.99)	(0.70)
R2	0.00	0.00	0.01	0.01	0.01	0.04	0.01	0.00

Notes: The benchmark MNAs are change in nonfarm payrolls (CNP), initial jobless claims (IJC), ISM manufacturing (ISM), and consumer confidence index (CCI). Distributions of the MNA surprises do not seem to differ much across different phases of business cycle during 1998-2017.

ease of comparison across other "good" surprises. We then run the following regression

$$r_{t-\Delta}^{t+\Delta} = \alpha^\tau + \beta^\tau_{\text{good}}\gamma' X_{\text{good},t} + \beta^\tau_{\text{bad}}\gamma' X_{\text{bad},t} + \epsilon_t. \tag{A.5}$$

Note that if β^τ_{good} and β^τ_{bad} are identical, this equation becomes (A.1). Figure A.7 displays the corresponding estimates of $\hat\beta^\tau_{\text{good}}$ and $\hat\beta^\tau_{\text{bad}}$. Surprisingly, the standard error bands on $\hat\beta^\tau_{\text{good}}$ and $\hat\beta^\tau_{\text{bad}}$ overlap almost always, and thus the sensitivity estimates are statistically indifferent from one another. In sum, there is no evidence for asymmetry in the response to good and bad MNA surprises during 1998 to 2017.

Distribution of the MNA surprises. One might suspect that time variation in the stock market sensitivity is primarily driven by time variation in MNA surprises. To test the hypothesis formally, we partition the sample into the above, near, and below trend periods

half of bad news (the most negative) and find that the results do not change.

(see Figure A.1) and perform the two sample Kolmogorov-Smirnov test in Table A.5. We compute a test decision for the null hypothesis that the surprises in different subsamples are from the same distribution. None of the test reject the null hypothesis at the 5% significance level. We then create two dummy variables locating the below trend and above trend periods and regress the raw and absolute MNA surprises on these dummy variables. We find that coefficients for these two dummy variables are largely insignficant as shown by Table A.6.

To be fully robust, we also modify the estimation specification in (A.1) and allow for the mean and variance of X_t to vary over time. Specifically, we estimate

$$\begin{aligned} r_{t-\Delta}^{t+\Delta} &= \alpha(S_t) + \beta(S_t)\gamma'(X_t - \mu(S_t)) + \epsilon_t \\ X_t &= \mu(S_t) + U_t, \quad U_t \sim N(0, \Sigma(S_t)). \end{aligned}$$

We allow for three states $S_t \in \{1, 2, 3\}$ with the identification restrictions

- $\beta(S_t = 1) > 1$ and $\Sigma(S_t = 1) = \delta(S_t = 1)\Sigma$
- $\beta(S_t = 2) = 1$ and $\Sigma(S_t = 2) = \Sigma$
- $\beta(S_t = 3) < 1$ and $\Sigma(S_t = 3) = \delta(S_t = 3)\Sigma$

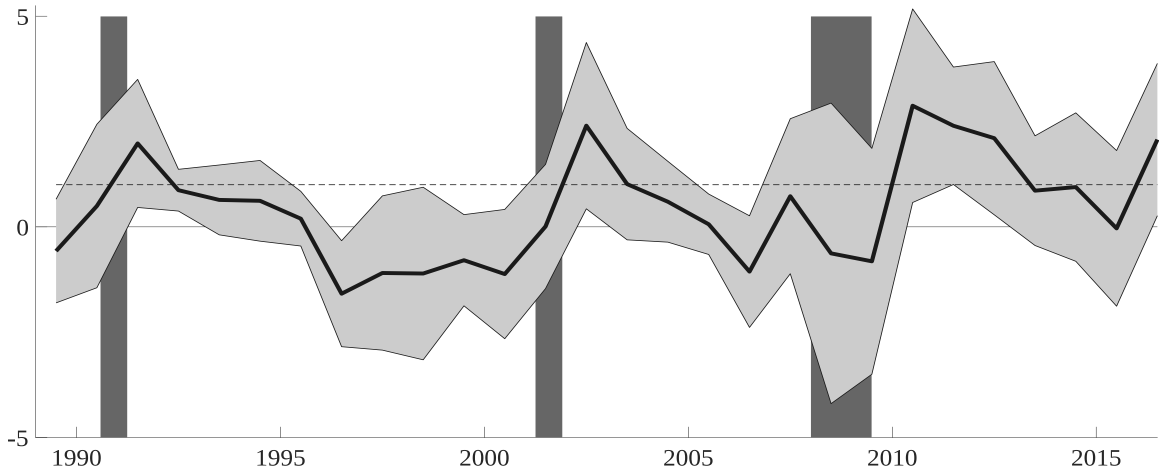
where $\beta(\cdot)$ and $\delta(\cdot)$ are scalar variables. We impose tight priors on the transition matrix such that persistence of each regime is close to one. We find that the estimated time-varying sensitivity of the stock return did not change much. The results are available upon request.

Controlling for possible omitted variable problems. It is possible that our benchmark specification may suffer from omitted variable problems. We augment the regression with other predictor variables $Z_{t-\Delta_z}$ which are known before the announcements

$$r_{t-\Delta}^{t+\Delta} = \alpha^{\tau} + \beta^{\tau}\gamma' X_t + \delta' Z_{t-\Delta_z} + \epsilon_t. \tag{A.6}$$

We consider three forms of $Z_{t-\Delta_z}$. The first one is spread between 10-Year Treasury Constant Maturity and 3-Month Treasury Constant Maturity and the second one is the change in spread both of which are available in daily frequency. The third one is the Aruoba-Diebold-Scotti business conditions index which is designed to track real business

Figure A.8: The stock return sensitivity: longer sample evidence with daily returns



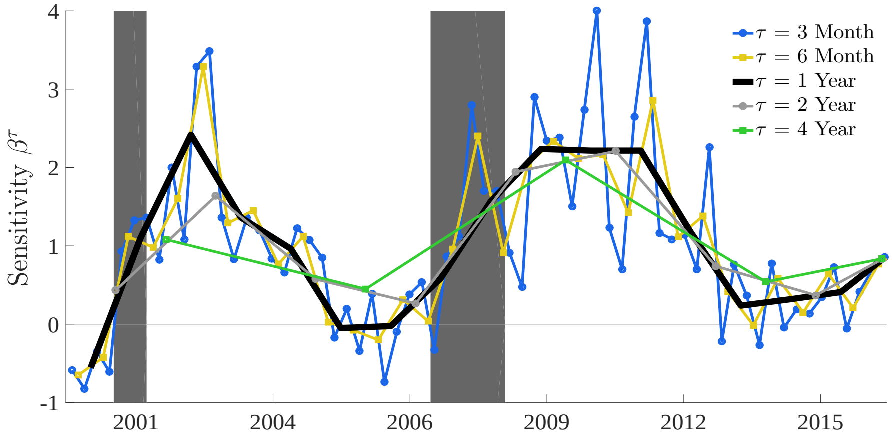
Notes: We use S&P 500 futures (SP) which are available from 1988 to 2017. We use daily returns to incorporate the following macroeconomic announcements, which are change in nonfarm payrolls, consumer confidence index, initial jobless claims, ISM manufacturing, new home sales, unemployment rate, GDP annualized QoQ. We first run (A.1) with ES from 1998 to 2017 in which the return window is set to $\Delta = 30$ min to obtain the estimate of $\hat{\gamma}$. Then, conditional on $\hat{\gamma}$, we run (A.1) with daily SP from 1988 to 2017 to obtain the estimates of $\hat{\beta}^{\tau}$. We do this to sharpen the inference on β^{τ}. We impose that β^{τ} (black-solid line) is on average equal to one. We provide $\pm$2-standard-error bands (light-shaded area) around β^{τ}.

conditions at daily frequency. We set Δ_z to be a day to reflect that most up-to-date information is included in the regression. We find that the coefficient loading on change in spread and the ADS index are estimated to be significant at 1% and 5% level of significance, respectively. Nonetheless, the resulting estimates for $\hat{\beta}^{\tau}$ from these regressions are essentially unchanged. We also tried to control for volatility changes, if any, in stock returns by dividing the return by VIX. Our results are not affected.

Longer-sample evidence. We extend the sample to the 1990s and examine if a similar pattern emerges. Before 2000, the futures market was very illiquid outside the trading hours. This restriction excludes the use of all announcements released at 8:30am. To tackle this issue, we use daily returns to incorporate a wider range of macroeconomic announcements which include change in nonfarm payrolls, consumer confidence index, initial jobless claims, ISM manufacturing, new home sales, unemployment rate, GDP annualized QoQ. We use the survey data from Money Market Service (MMS) to construct surprises. We do it because survey forecasts are available from early 1980s in MMS while they are only available after 1997 in Bloomberg. By changing both left-hand side and right-hand side variables in the regression, we aim to provide further robustness to our main finding.

We first run (A.1) with intra-day returns from 1998 to 2017 in which the return window is set to $\Delta = 30$ min to obtain the estimate of $\hat{\gamma}$. Then, conditional on $\hat{\gamma}$, we work with daily returns from 1988 to 2017 to obtain the estimates of $\hat{\beta}^{\tau}$ by running (A.3). It is important to note that we remove all the days when there are the FOMC related news in constructing daily returns. We do this to sharpen the inference on $\hat{\beta}^{\tau}$ which is provided in Figure A.8. The mean estimates are qualitatively similar, but estimated with larger standard errors. Overall, we conclude that our results are robust across various return measures, surprise measures, and different periods.

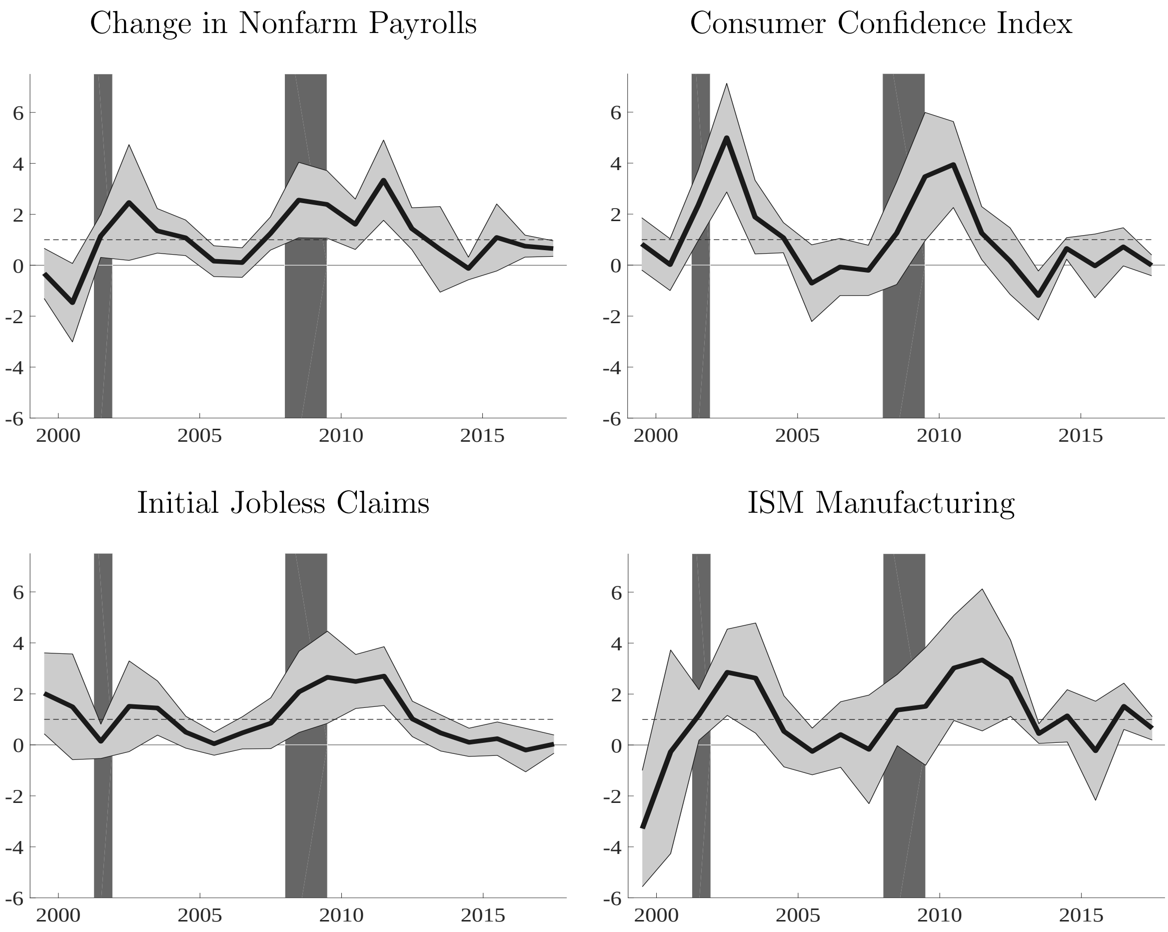
Figure A.9: The smoothing parameter τ



Notes: We repeat the estimation by varying the values of smoothing parameter τ. The highest frequency considered in this picture is 3 months and the lowest is 4 years.

Other robustness checks. We improve the econometric power in identifying the cyclical variation in stock return responses by pooling information within τ subperiod, that is, a year. Yet, it requires us to assume that the responses move proportionally within τ period. Figure A.9 show that our results are robust to different smoothing parameter values τ. We also relax the assumption that the stock return responsiveness to all MNA surprises shifts by a roughly proportionate amount. This amounts to removing the common β^{τ} structure in (A.1) and replacing with individual γ^{τ}. See Figure A.10. We also show that the stock return responsiveness is qualitatively similar across individual MNAs.

Figure A.10: The stock return sensitivity: Evidence from individual regression



Notes: Macroeconomic announcements are Change in Nonfarm Payrolls, Consumer Confidence Index, Initial Jobless Claims, and ISM Manufacturing. We set $\Delta = 30$min. We impose that γ^{τ} (black-solid line) is on average equal to one. We provide ± 2-standard-error bands (light-shaded area)

B Solving the Regime-Switching No-Arbitrage Model

Real dividends and monetary policy. We assume that the Federal Reserve can directly control the real rate, r_t. The monetary policy rule responds to dividend gap. To generate monetary non-neutrality, we assume that dividends dynamics resemble the standard New Keynesian IS curve. Put together,

$$\begin{aligned} d_t &= \bar{d}(S_t) + \gamma d_{t-1} + (1-\gamma)E_t d_{t+1} - \xi r_t + u_{d,t} \\ r_t &= \bar{r}(S_t) + \phi(S_t)(d_t - d_t^*) \\ d_t^* &= \mu + d_{t-1}^* + u_{\tau,t}, \quad u_{\tau,t} \sim N(0, \sigma_\tau^2). \end{aligned} \tag{A.7}$$

Here, d_t^* indicates the potential level of dividends in the economy. There are two shocks in this economy. One is real dividends shock, $u_{d,t}$, and the other is trend shock, $u_{\tau,t}$. Both can be described with

$$u_t = \Phi u_{t-1} + \Sigma \varepsilon_t, \quad \varepsilon \sim N(0, I_2). \tag{A.8}$$

Here, we assume the level of dividends $\bar{d}(S_t)$ depends on the state. The strength with which the Federal Reserve tries to pursue its goal—a stabilization policy—also changes over time. The stabilization policy is "aggressive" or "loose" depending on its responsiveness. We capture this time variation with a regime-switching policy coefficient, $\phi(S_t)$. We impose that $\xi \geq 0$ governs the extent to which the real rate affects dividends dynamics. We define the Markov transition probability p_{ij}, i.e., the probability of changing from regime i to regime j, $\forall i, j \in \{1, ..., K\}$.

Because of the random-walk with drift assumption, we can re-express (A.7) in terms of deviation from potential level, i.e., $\hat{r}_t = r_t - \bar{r}(S_t)$ and $\hat{d}_t = d_t - d_t^*$,

$$\begin{aligned} \hat{d}_t &= c(S_t) + \gamma \hat{d}_{t-1} + (1-\gamma)E_t \hat{d}_{t+1} - \xi \hat{r}_t - \gamma u_{\tau,t} + u_{d,t} \\ \hat{r}_t &= \phi(S_t)\hat{d}_t \end{aligned} \tag{A.9}$$

where we conveniently re-express $c(S_t) = \bar{d}(S_t) - \xi \bar{r}(S_t) + (1-2\gamma)\mu$. By plugging the second equation to the first equation in (A.9), the system reduces to a single regime-dependent equation

$$\chi(S_t)\hat{d}_t = c(S_t) + \gamma\hat{d}_{t-1} + (1-\gamma)E_t\hat{d}_{t+1} + \omega' u_t \tag{A.10}$$

where

$$\chi(S_t) = 1 + \xi\phi(S_t), \quad \omega = \begin{bmatrix} 1, & -\gamma \end{bmatrix}'.$$

Solution. There exists a unique bounded regime-dependent linear solutions of the form (see Davig and Leeper (2007) and Song (2017) for discussion)

$$\hat{d}_t = \psi_0(S_t) + \psi_1(S_t)\hat{d}_{t-1} + \psi_2(S_t)' u_t \tag{A.11}$$

for $p_{ji} \in [0, 1)$. Then, (A.10) can be expressed as

$$\begin{aligned} \Big\{\chi(S_t) - (1-\gamma)E_t\psi_1(S_{t+1})\Big\}\hat{d}_t &= c(S_t) + (1-\gamma)E_t\psi_0(S_{t+1}) + \gamma d_{t-1} \\ &+ \Big\{(1-\gamma)E_t\psi_2(S_{t+1})'\Phi + \omega'\Big\}u_t. \end{aligned} \tag{A.12}$$

Here, we assumed independence between S_{t+1} and ε_{t+1} and set $E_t[\psi_2(S_{t+1})'\Sigma\varepsilon_{t+1}] = 0$. We match the coefficients

1. $\psi_0(S_t) = \frac{c(S_t)+(1-\gamma)E_t\psi_0(S_{t+1})}{\chi(S_t)-(1-\gamma)E_t\psi_1(S_{t+1})}$,
2. $\psi_1(S_t) = \frac{\gamma}{\chi(S_t)-(1-\gamma)E_t\psi_1(S_{t+1})}$,
3. $\psi_2(S_t)' = \frac{(1-\gamma)E_t\psi_2(S_{t+1})'\Phi+\omega'}{\chi(S_t)-(1-\gamma)E_t\psi_1(S_{t+1})}$.

To build intuition into the solution coefficients, consider the case of fixed regime. We can express

$$\begin{aligned} \psi_0 &= \frac{c}{\chi - (1-\gamma)(\psi_1 + 1)} \\ \psi_1 &= \frac{\chi \pm \sqrt{\chi^2 - 4(1-\gamma)\gamma}}{2(1-\gamma)} \\ \psi_2 &= w'\big(\chi I - (1-\gamma)(\psi_1 I + \Phi)\big)^{-1}. \end{aligned} \tag{A.13}$$

Among the two roots, we select

$$\psi_1 = \frac{\chi - \sqrt{\chi^2 - 4(1-\gamma)\gamma}}{2(1-\gamma)} \leq 1$$

to preserve stationarity of $\hat{d}_t$ dynamics. This is true for $\chi \geq 1$. Note that

$$\begin{array}{ll} \lim_{\gamma\to 0}\psi_0(\gamma) = \frac{c}{\chi-1} & \lim_{\gamma\to 1}\psi_0(\gamma) = \frac{c}{\chi} \\ \lim_{\gamma\to 0}\psi_1(\gamma) = 0 & \lim_{\gamma\to 1}\psi_1(\gamma) = \frac{1}{\chi} \\ \lim_{\gamma\to 0}\psi_2(\gamma) = w'(\chi I - \Phi)^{-1} & \lim_{\gamma\to 1}\psi_2(\gamma) = \frac{1}{\chi}w'. \end{array} \tag{A.14}$$

Dividend growth. Note that

$$\begin{aligned} \Delta d_{t+1} &= \Delta\hat{d}_{t+1} + \Delta d^*_{t+1} \\ &= \mu + \psi_0(S_{t+1}) + (\psi_1(S_{t+1}) - 1)\psi_0(S_t) + (\psi_1(S_{t+1}) - 1)\psi_1(S_t)\hat{d}_{t-1} \\ &+ \left\{(\psi_1(S_{t+1}) - 1)\psi_2(S_t)' + \psi_2(S_{t+1})'\Phi\right\}u_t + (\psi_2(S_{t+1})' + e_2')\Sigma\varepsilon_{t+1}. \end{aligned} \tag{A.15}$$

We can express the expected n-period-ahead dividend growth rate as

$$E_t\Delta d_{t+n}|_{S_t=j} \;=\; \psi^e_{n,0}(j) + \psi^e_{n,1}(j)\hat{d}_{t-1} + \psi^e_{n,2}(j)'u_t. \tag{A.16}$$

For ease of exposition, define

$$\begin{aligned} \Psi_{n+1,1} &= \Pi\Psi_{n,1} \odot \Psi_1, \quad n \geq 1, \quad \Psi_{1,1} = \Psi_1 \\ f(\Psi_{n,1}, \Psi_x) &= \Pi\Psi_{n,1} \odot \Psi_x. \end{aligned} \tag{A.17}$$

We can obtain

$$
\begin{aligned}
\psi^e_{n,0} &= \Pi(j,:)\bigg((\Pi^{n-1}-\Pi^{n-2})\Psi_0+\sum_{j=1}^{n-2}(\Pi^{n-1-j}-\Pi^{n-2-j})f(\Psi_{j,1},\Psi_0) \\
&\qquad +f(\Psi_{n-1,1},\Psi_0)+\Psi_{n,1}\odot\Psi_0-\Psi_{n-1,1}\odot\Psi_0\bigg)+\mu \\
\psi^e_{n,1} &= \Pi(j,:)\bigg(\Psi_{n,1}\odot\Psi_1-\Psi_{n-1,1}\odot\Psi_1\bigg) \\
\psi^e_{n,2} &= \Pi(j,:)\bigg(\Psi_{n,1}\odot\Psi_2-\Psi_{n-1,1}\odot\Psi_2+\sum_{j=1}^{n-2}\Pi^{j-1}\big\{f(\Psi_{n-j,1},\Psi_2)-f(\Psi_{n-1-j,1},\Psi_2)\big\}\Phi^j \\
&\qquad +\Pi^{n-2}\big\{f(\Psi_{1,1},\Psi_2)-\Psi_2\big\}\Phi^{n-1}+\Pi^{n-1}\Psi_2\Phi^n\bigg).
\end{aligned}
\tag{A.18}
$$

These expressions are valid for $n \geq 3$.

We can deduce from (A.14) that there exists $1 \leq n$ such that

$\lim_{\gamma\to 0}\psi^e_{n,0}(\gamma) > 0$	$\lim_{\gamma\to 1}\psi^e_{n,0}(\gamma) > 0$
$\lim_{\gamma\to 0}\psi^e_{n,1}(\gamma) = 0$	$\lim_{\gamma\to 1}\psi^e_{n,1}(\gamma) < 0$
$\lim_{\gamma\to 0}\psi^e_{n,2}(\gamma) < 0$	$\lim_{\gamma\to 1}\psi^e_{n,2}(\gamma) > 0$

It is possible that $\lim_{\gamma\to 1}\psi^e_{n,2}(\gamma) \leq 0$ for large n. The key takeaway is that the expected dividend growth dynamics critically depends on the value of γ. For $u_{d,t}$ to increase both the level and growth rate of dividends, we need γ to be sufficiently close to one.

Expected risk-free rates. Using the solution expression for dividends (A.11), we can re-express the risk-free rate as

$$
\begin{aligned}
r_t &= \bar{r}(S_t)+\phi(S_t)\psi_0(S_t)+\phi(S_t)\psi_1(S_t)\hat{d}_{t-1}+\phi(S_t)\psi_2(S_t)'u_t \\
&= r_0(S_t)+r_1(S_t)\hat{d}_{t-1}+r_2(S_t)'u_t.
\end{aligned}
\tag{A.19}
$$

The goal is to compute

$$
E_t r_{t+n}|_{S_t=j} = r^e_{n,0}(j)+r^e_{n,1}(j)\hat{d}_{t-1}+r^e_{n,2}(j)'u_t.
$$

For ease of exposition, define

$$R_{n+1,1} = \Pi R_{n,1} \odot \Psi_1, \quad n \geq 1, \quad R_{1,1} = R_1 \tag{A.20}$$
$$f(R_{n,1}, \Psi_x) = \Pi R_{n,1} \odot \Psi_x.$$

We can express

$$r^e_{n,0}(j) = \Pi(j,:)\left(\Pi^{n-1}R_0 + R_{n,1} \odot \Psi_0 + \Pi^{n-2} f(R_{1,1}, \Psi_0) + \sum_{j=1}^{n-2} \Pi^{n-2-j} f(R_{j+1,1}, \Psi_0)\right) \tag{A.21}$$

$$r^e_{n,1}(j) = \Pi(j,:)R_{n,1} \odot \Psi_1$$
$$r^e_{n,2}(j) = \Pi(j,:)\left(\Pi^{n-1}R_2\Phi^n + R_{n,1} \odot \Psi_2 + \sum_{j=0}^{n-2} \Pi^{n-2-j} f(R_{j+1,1}, \Psi_2)\Phi^{n-1-j}\right).$$

These expressions are valid for $n \geq 3$.

Stochastic discount factor. The log pricing kernel is assumed as

$$m_{t+1} = -r_t - \frac{1}{2}\lambda(S_t)'\Sigma\Sigma'\lambda(S_t) - \lambda(S_t)'\Sigma\varepsilon_{t+1} \tag{A.22}$$

where the market price of risk $\lambda(S_t)$ follows a Markov process. The real risk-free rate is assumed in (A.7).

Price to dividend ratio. We conjecture that the log price to dividend ratio has the following expression

$$z_t = z_0(S_t) + z_1(S_t)\hat{d}_{t-1} + z_2(S_t)'u_t. \tag{A.23}$$

Market return. We rely on Campbell-Shiller log-linear approximation to preserve (conditionally) linear log market return dynamics $r_{d,t+1} = \kappa_0 + \kappa_1 z_{t+1} - z_t + \Delta d_{t+1}$. We can express the dividend growth rate as

$$
\begin{aligned}
r_{d,t+1} &= \mu + \kappa_0 + \kappa_1 z_0(S_{t+1}) - z_0(S_t) + \psi_0(S_{t+1}) + \kappa_1 z_1(S_{t+1})\psi_0(S_t) + (\psi_1(S_{t+1}) - 1)\psi_0(S_t) \\
&\quad + \Big(\kappa_1 z_1(S_{t+1})\psi_1(S_t) - z_1(S_t) + (\psi_1(S_{t+1}) - 1)\psi_1(S_t)\Big)\hat{d}_{t-1} \\
&\quad + \Big(\kappa_1 z_1(S_{t+1})\psi_2(S_t)' + \kappa_1 z_2(S_{t+1})'\Phi - z_2(S_t)' + (\psi_1(S_{t+1}) - 1)\psi_2(S_t)' + \psi_2(S_{t+1})'\Phi\Big)u_t \\
&\quad + \Big(\kappa_1 z_2(S_{t+1})' + \psi_2(S_{t+1})' + e_2'\Big)\Sigma\varepsilon_{t+1}.
\end{aligned}
$$

Define

$$
r_{d\Delta,t+1} = r_{d,t+1} - \Delta d_{t+1}. \tag{A.24}
$$

We can express $E_t r_{d\Delta,t+n}$ as

$$
E_t r_{d\Delta,t+n}|_{S_t=j} \;=\; r^e_{d\Delta n,0}(j) + r^e_{d\Delta,n,1}(j)\hat{d}_{t-1} + r^e_{d\Delta,n,2}(j)'u_t. \tag{A.25}
$$

For ease of exposition, define

$$
\begin{aligned}
Z_{n+1,1} &= \Pi Z_{n,1} \odot \Psi_1, \quad n \geq 1, \quad Z_{1,1} = Z_1 \qquad \text{(A.26)} \\
f(Z_{n,1}, \Psi_x) &= \Pi Z_{n,1} \odot \Psi_x.
\end{aligned}
$$

We can obtain

$$
\begin{aligned}
r^e_{d\Delta,n,0} &= \Pi(j,:)\Big(\kappa_0 + \kappa_1 \Pi^{(n-1)} Z_0 - \Pi^{(n-2)} Z_0 + \kappa_1 \Pi^{(n-2)} f(\Psi_{1,1}, \Psi_0) \qquad \text{(A.27)} \\
&\quad + \sum_{j=1}^{n-2} \Pi^{n-2-j}\big\{\kappa_1 f(\Psi_{j+1,1}, \Psi_0) - f(\Psi_{j,1}, \Psi_0)\big\} + \kappa_1 Z_{n,1} \odot \Psi_0 - Z_{n-1,1} \odot \Psi_0\Big) \\
r^e_{d\Delta,n,1} &= \Pi(j,:)\Big(\kappa_1 Z_{n,1} \odot \Psi_1 - Z_{n-1,1} \odot \Psi_1\Big) \\
r^e_{d\Delta,n,2} &= \Pi(j,:)\Big(\kappa_1 Z_{n,1} \odot \Psi_2 - Z_{n-1,1} \odot \Psi_2 + \kappa_1 \Pi^{n-1} Z_2 \Phi^n - \Pi^{n-2} Z_2 \Phi^{(n-1)} \\
&\quad + \sum_{j=1}^{n-1} \Pi^{j-1} \kappa_1 f(Z_{n-j,1}, \Psi_2)\Phi^j - \sum_{j=1}^{n-2} \Pi^{j-1} f(Z_{n-1-j,1}, \Psi_2)\Phi^j\Big).
\end{aligned}
$$

These expressions are valid for $n \geq 3$.

Note that

$$E_t r_{d,t+n} = E_t r_{d\Delta,t+n} + E_t \Delta d_{t+n}. \tag{A.28}$$

Thus, the expected n-period-ahead return can be expressed as

$$E_t r_{d,t+n}|_{S_t=j} \;=\; r^e_{d,n,0}(j) + r^e_{d,n,1}(j)\hat{d}_{t-1} + r^e_{d,n,2}(j)' u_t \tag{A.29}$$

where

$$\begin{aligned} r^e_{d,n,0} &= r^e_{d\Delta,n,0} + \psi^e_{n,0} \\ r^e_{d,n,1} &= r^e_{d\Delta,n,1} + \psi^e_{n,1} \\ r^e_{d,n,2} &= r^e_{d\Delta,n,2} + \psi^e_{n,2}. \end{aligned} \tag{A.30}$$

Solving the Euler equation. We log-linearization the equation to solve for $z_0(S_t)$, $z_1(S_t)$, and $z_2(S_t)$,

$$0 \;\approx\; E\Big[E(m_{t+1} + r_{d,t+1}|S_{t+1}) + \frac{1}{2}Var(m_{t+1} + r_{d,t+1}|S_{t+1})|S_t\Big]. \tag{A.31}$$

Note that

$$\begin{aligned} m_{t+1} + r_{d,t+1} = {} & \mu + \kappa_0 + \kappa_1 z_0(S_{t+1}) - z_0(S_t) + \psi_0(S_{t+1}) \\ & + \kappa_1 z_1(S_{t+1})\psi_0(S_t) + (\psi_1(S_{t+1}) - 1)\psi_0(S_t) - r_0(S_t) \\ & + \Big(\kappa_1 z_1(S_{t+1})\psi_1(S_t) - z_1(S_t) + (\psi_1(S_{t+1}) - 1)\psi_1(S_t) - r_1(S_t)\Big)\hat{d}_{t-1} \\ & + \Big(\kappa_1 z_1(S_{t+1})\psi_2(S_t)' + \kappa_1 z_2(S_{t+1})'\Phi - z_2(S_t)' + (\psi_1(S_{t+1}) - 1)\psi_2(S_t)' \\ & \quad + \psi_2(S_{t+1})'\Phi - r_2(S_t)'\Big)u_t - \frac{1}{2}\lambda(S_t)'\Sigma\Sigma\lambda(S_t) \\ & + \Big(\kappa_1 z_2(S_{t+1})' + \psi_2(S_{t+1})' + e_2' - \lambda(S_t)'\Big)\Sigma\varepsilon_{t+1}. \end{aligned}$$

We first calculate

$$
\begin{aligned}
&E(m_{t+1}+r_{d,t+1}|S_{t+1})+\frac{1}{2}Var(m_{t+1}+r_{d,t+1}|S_{t+1}) \qquad \text{(A.32)}\\
=\;& \mu+\kappa_0+\kappa_1 z_0(S_{t+1})-z_0(S_t)+\psi_0(S_{t+1})+\kappa_1 z_1(S_{t+1})\psi_0(S_t)+(\psi_1(S_{t+1})-1)\psi_0(S_t)-r_0(S_t)\\
&+\Big(\kappa_1 z_1(S_{t+1})\psi_1(S_t)-z_1(S_t)+(\psi_1(S_{t+1})-1)\psi_1(S_t)-r_1(S_t)\Big)\hat{d}_{t-1}\\
&+\Big(\kappa_1 z_1(S_{t+1})\psi_2(S_t)'+\kappa_1 z_2(S_{t+1})'\Phi-z_2(S_t)'+(\psi_1(S_{t+1})-1)\psi_2(S_t)'+\psi_2(S_{t+1})'\Phi-r_2(S_t)'\Big)u_t\\
&-\Big(\kappa_1 z_2(S_{t+1})'+\psi_2(S_{t+1})'+e_2'\Big)\Sigma\Sigma'\lambda(S_t)\\
&+\frac{1}{2}\Big(\kappa_1 z_2(S_{t+1})'+\psi_2(S_{t+1})'+e_2'\Big)\Sigma\Sigma'\Big(\kappa_1 z_2(S_{t+1})+\psi_2(S_{t+1})+e_2\Big).
\end{aligned}
$$

Market price of risk. We assume that

$$\lambda(S_t)=\lambda_0(S_t)+\lambda_1(S_t)\hat{d}_{t-1}+\lambda_2(S_t)u_t. \qquad \text{(A.33)}$$

Plugging (A.33) into (A.32), we get

$$
\begin{aligned}
&E(m_{t+1}+r_{d,t+1}|S_{t+1})+\frac{1}{2}Var(m_{t+1}+r_{d,t+1}|S_{t+1}) \qquad \text{(A.34)}\\
=\;& \mu+\kappa_0+\kappa_1 z_0(S_{t+1})-z_0(S_t)+\psi_0(S_{t+1})+\kappa_1 z_1(S_{t+1})\psi_0(S_t)+(\psi_1(S_{t+1})-1)\psi_0(S_t)\\
&-r_0(S_t)-\big(\kappa_1 z_2(S_{t+1})'+\psi_2(S_{t+1})'+e_2'\big)\Sigma\Sigma'\lambda_0(S_t)\\
&+\Big(\kappa_1 z_1(S_{t+1})\psi_1(S_t)-z_1(S_t)+(\psi_1(S_{t+1})-1)\psi_1(S_t)-r_1(S_t)\\
&\quad-\big(\kappa_1 z_2(S_{t+1})'+\psi_2(S_{t+1})'+e_2'\big)\Sigma\Sigma'\lambda_1\Big)\hat{d}_{t-1}\\
&+\Big(\kappa_1 z_1(S_{t+1})\psi_2(S_t)'+\kappa_1 z_2(S_{t+1})'\Phi-z_2(S_t)'+(\psi_1(S_{t+1})-1)\psi_2(S_t)'+\psi_2(S_{t+1})'\Phi\\
&\quad-r_2(S_t)'-\big(\kappa_1 z_2(S_{t+1})'+\psi_2(S_{t+1})'+e_2'\big)\Sigma\Sigma'\lambda_2\Big)u_t\\
&+\frac{1}{2}\Big(\kappa_1 z_2(S_{t+1})'+\psi_2(S_{t+1})'+e_2'\Big)\Sigma\Sigma'\Big(\kappa_1 z_2(S_{t+1})+\psi_2(S_{t+1})+e_2\Big).
\end{aligned}
$$

We can solve for by combining (A.31) with (A.34)

$$\begin{aligned} Z_1 &= (I - \kappa_1 D(\Psi_1)\Pi)^{-1}\Big(\Pi(\Psi_1 - 1)\odot\Psi_1 - R_1 - k_1\Pi^B(I_K\otimes(Z_2\Sigma\Sigma'))\Lambda_1 \\ &\quad -\Pi^B\big(I_K\otimes((\Psi_2+\mathbf{e}_2)\Sigma\Sigma')\big)\Lambda_1\Big) \\ Z_2 &= \kappa_1\Pi Z_2\Phi - k_1\Pi^B(I_K\otimes(Z_2\Sigma\Sigma'))\Lambda_2 + \kappa_1\Pi Z_1\odot\Psi_2 + (\Pi\Psi_1 - 1)\odot\Psi_2 + \Pi\Psi_2\Phi - R_2 \\ &\quad -\Pi^B\big(I_K\otimes((\Psi_2+\mathbf{e}_2)\Sigma\Sigma')\big)\Lambda_2. \end{aligned}$$

In case $\lambda_2(S_t) = \lambda_2$, we can simplify it further below. Using $vec(ABC) = (C'\otimes A)vec(B)$, we express

$$\begin{aligned} vec(Z_2) = \Big(I - \big((\Phi - \Sigma\Sigma'\lambda_2)'\otimes(\kappa_1\Pi)\big)\Big)^{-1} vec\Big(\kappa_1\Pi Z_1\odot\Psi_2 + (\Pi\Psi_1 - 1)\odot\Psi_2 \\ +\Pi\Psi_2\Phi - R_2 - (\Pi\Psi_2 + \mathbf{e}_2)\Sigma\Sigma'\lambda_2\Big). \end{aligned} \tag{A.35}$$

The constant term is

$$Z_0 = (I - \kappa_1\Pi)^{-1}\Big(\mu + \kappa_0 + \Pi\Psi_0 + \kappa_1\Pi Z_1\odot\Psi_0 + (\Pi\Psi_1 - 1)\odot\Psi_0 - R_0 - \Pi\Xi\Sigma\Sigma'\odot\Lambda_0 + \Pi\Upsilon\Big) \tag{A.36}$$

where

$$\Xi(i) = \kappa_1 z_2(i)' + \psi_2(i)' + e_2', \quad \Upsilon(i) = \frac{1}{2}\Xi(i)\Sigma\Sigma'\Xi(i)'.$$

Risk premium. The risk premium for the dividend claim is

$$\begin{aligned} E[r_{d,t+1} - r_t|S_t] + \frac{1}{2}Var[r_{d,t+1}|S_t] &= -Cov[r_{d,t+1}, m_{t+1}|S_t] \\ &= (\Pi(j,:)\Xi)'\Sigma\Sigma'\lambda_0(S_t) \\ &\quad +(\Pi(j,:)\Xi)'\Sigma\Sigma'\lambda_1\hat{d}_{t-1} + (\Pi(j,:)\Xi)'\Sigma\Sigma'\lambda_2 u_t. \end{aligned} \tag{A.37}$$

The following definition links dividends and prices

$$R_{d,t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} = \frac{\left(1 + \frac{P_{t+1}}{D_{t+1}}\right)\frac{D_{t+1}}{D_t}}{\frac{P_t}{D_t}}$$

where $R_{d,t+1}$ denotes the rate of return of the asset from period t to period $t+1$, P_t the price of this asset in period t and D_{t+1} the dividend paid at the beginning of period $t+1$. Campbell and Shiller take a first-order Taylor approximation of the equation relating the log stock return to log stock prices and dividends

$$\begin{aligned} r_{d,t+1} &= \log\big(1+\exp(pd_{t+1})\big) + \Delta d_{t+1} - pd_t \qquad (A.38) \\ &\approx \log\big(1+\exp(pd)\big) + \frac{\exp(pd)}{1+\exp(pd)}(pd_{t+1}-pd) + \Delta d_{t+1} - pd_t \\ &= \underbrace{\log\big(1+\exp(pd)\big) - \frac{\exp(pd)}{1+\exp(pd)}pd}_{\kappa_0} + \underbrace{\frac{\exp(pd)}{1+\exp(pd)}}_{\kappa_1} pd_{t+1} - pd_t + \Delta d_{t+1}. \end{aligned}$$

The approximate equation is solved forward, imposing a terminal condition that the log price-dividend ratio does not follow an explosive process

$$pd_t \approx \text{constant} + \sum_{j=1}^{\infty} \kappa_1^{j-1}\Delta d_{t+j} - \sum_{j=1}^{\infty} \kappa_1^{j-1} r_{d,t+j}. \qquad (A.39)$$

Rearrange equation (A.38) by using equation (A.39)

$$\begin{aligned} r_{d,t+1} - E_t r_{d,t+1} &= \kappa_1\big(pd_{t+1} - E_t pd_{t+1}\big) + \big(\Delta d_{t+1} - E_t \Delta d_{t+1}\big), \qquad (A.40) \\ &= (E_{t+1} - E_t)\kappa_1 pd_{t+1} + (E_{t+1} - E_t)\Delta d_{t+1}, \\ &= (E_{t+1} - E_t)\left(\sum_{j=0}^{\infty} \kappa_1^j \Delta d_{t+1+j}\right) - (E_{t+1} - E_t)\left(\sum_{j=1}^{\infty} \kappa_1^j r_{d,t+1+j}\right). \end{aligned}$$

We relate the unexpected stock return in period $t+1$ to news about cash flows (dividends) and news about future returns

$$r_{d,t+1} - E_t r_{d,t+1} \approx (E_{t+1} - E_t)\left(\sum_{j=0}^{\infty} \kappa_1^j \Delta d_{t+1+j}\right) - (E_{t+1} - E_t)\left(\sum_{j=1}^{\infty} \kappa_1^j r_{d,t+1+j}\right) \qquad (A.41)$$

where κ_1 is a discount coefficient. (A.41) is an accounting identity. An increase in expected future dividend growth (returns) is associated with a capital gain (loss) today.

We assume that news about future returns can be further decomposed into news about risk-free rate and news about risk premium. Denote news about cash flows by N_{CF}, news about risk-free rate by N_{RF}, and news about risk premium by N_{RP}. Put together,

$$\begin{aligned} N_{CF,t+1} &= (E_{t+1} - E_t)\left(\sum_{j=0}^{\infty} \kappa_1^j \Delta d_{t+1+j}\right) \\ N_{RF,t+1} &= (E_{t+1} - E_t)\left(\sum_{j=1}^{\infty} \kappa_1^j r_{t+1+j}\right). \\ N_{RP,t+1} &= (E_{t+1} - E_t)\left(\sum_{j=1}^{\infty} \kappa_1^j (r_{d,t+1+j} - r_{t+1+j})\right). \end{aligned} \tag{A.42}$$

Plugging (A.42) into (A.41), we express the unexpected stock return by sum of news about cash flows, risk-free rate, and risk premium:

$$r_{d,t+1} - E_t r_{d,t+1} = N_{CF,t+1} - N_{RF,t+1} - N_{RP,t+1}. \tag{A.43}$$

We provided the return response to the MNAs. We now attempt to examine the informational content of MNAs. To facilitate the decomposition of (A.43), we look for proxies for N_{CF}, N_{RF}, and N_{RP}.

Suppose that

$$\begin{aligned} E_t \Delta d_{t+j+1}|_{S_t=k} &= \psi^e_{j+1,0}(k) + \psi^e_{j+1,1}(k)\hat{d}_{t-1} + \psi^e_{j+1,2}(k)' u_t, \\ E_t r_{t+j+1}|_{S_t=k} &= r^e_{j+1,0}(k) + r^e_{j+1,1}(k)\hat{d}_{t-1} + r^e_{j+1,2}(k)' u_t. \end{aligned} \tag{A.44}$$

then

$$\begin{aligned} E_{t+1}\Delta d_{t+j+1}|_{S_{t+1}=i,S_t=k} &= \psi^e_{j,0}(i) + \psi^e_{j,1}(i)\hat{d}_t + \psi^e_{j,2}(i)' u_{t+1}, \\ &= \psi^e_{j,0}(i) + \psi^e_{j,1}(i)\psi_0(k) + \psi^e_{j,1}(i)\psi_1(k)\hat{d}_{t-1} + \\ &\quad +(\psi^e_{j,1}(i)\psi_2(k)' + \psi^e_{j,2}(i)'\Phi)u_t + \psi^e_{j,2}(i)'\Sigma\varepsilon_{t+1}, \\ E_{t+1} r_{t+j+1}|_{S_{t+1}=i,S_t=k} &= r^e_{j,0}(i) + r^e_{j,1}(i)\hat{d}_t + r^e_{j,2}(i)' u_{t+1}, \\ &= r^e_{j,0}(i) + r^e_{j,1}(i)\psi_0(k) + r^e_{j,1}(i)\psi_1(k)\hat{d}_{t-1} + \\ &\quad +(r^e_{j,1}(i)\psi_2(k)' + r^e_{j,2}(i)'\Phi)u_t + r^e_{j,2}(i)'\Sigma\varepsilon_{t+1}. \end{aligned} \tag{A.45}$$

We can deduce that

$$
\begin{aligned}
& E_{t+1}\Delta d_{t+j+1}|_{(S_{t+1}=i,S_t=k)} - E_t\Delta d_{t+j+1}|_{(S_t=k)} \\
= & \left(\psi^e_{j,0}(i) + \psi^e_{j,1}(i)\psi_0(k) - \psi^e_{j+1,0}(k)\right) + \left(\psi^e_{j,1}(i)\psi_1(k) - \psi^e_{j+1,1}(k)\right)\hat{d}_{t-1} \\
& +\left(\psi^e_{j,1}(i)\psi_2(k)' + \psi^e_{j,2}(i)'\Phi - \psi^e_{j+1,2}(k)'\right)u_t + \psi^e_{j,2}(i)'\Sigma\varepsilon_{t+1}, \\
& E_{t+1}r_{t+j+1}|_{(S_{t+1}=i,S_t=k)} - E_t r_{t+j+1}|_{(S_t=k)} \\
= & \left(r^e_{j,0}(i) + r^e_{j,1}(i)\psi_0(k) - r^e_{j+1,0}(k)\right) + \left(r^e_{j,1}(i)\psi_1(k) - r^e_{j+1,1}(k)\right)\hat{d}_{t-1} \\
& +\left(r^e_{j,1}(i)\psi_2(k)' + r^e_{j,2}(i)'\Phi - r^e_{j+1,2}(k)'\right)u_t + r^e_{j,2}(i)'\Sigma\varepsilon_{t+1}.
\end{aligned} \tag{A.46}
$$

For $j \geq 1$, define

$$
\begin{aligned}
N^{CF}_{j,0} &= \kappa_1^j\left(\psi^e_{j,0}(i) + \psi^e_{j,1}(i)\psi_0(k) - \psi^e_{j+1,0}(k)\right) \\
N^{CF}_{j,1} &= \kappa_1^j\left(\psi^e_{j,1}(i)\psi_1(k) - \psi^e_{j+1,1}(k)\right) \\
N^{CF}_{j,2} &= \kappa_1^j\left(\psi^e_{j,1}(i)\psi_2(k)' + \psi^e_{j,2}(i)'\Phi - \psi^e_{j+1,2}(k)'\right) \\
N^{CF}_{j,3} &= \kappa_1^j\psi^e_{j,2}(i)'.
\end{aligned} \tag{A.47}
$$

When $j = 0$,

$$
\begin{aligned}
N^{CF}_{0,0} &= (\psi_0(i) - \Pi(k,:)\Psi_0) + (\psi_1(i) - \Pi(k,:)\Psi_1)\psi_0(k) \\
N^{CF}_{0,1} &= (\psi_1(i) - \Pi(k,:)\Psi_1)\psi_1(k) \\
N^{CF}_{0,2} &= (\psi_1(i) - \Pi(k,:)\Psi_1)\psi_2(k)' + (\psi_2(i)' - \Pi(k,:)\Psi_2)\Phi \\
N^{CF}_{0,3} &= \psi_2(i)' + e_2'.
\end{aligned} \tag{A.48}
$$

Similarly, for $j \geq 1$,

$$
\begin{aligned}
N^{RF}_{j,0} &= \kappa_1^j \Big(r^e_{j,0}(i) + r^e_{j,1}(i)\psi_0(k) - r^e_{j+1,0}(k) \Big) \\
N^{RF}_{j,1} &= \kappa_1^j \Big(r^e_{j,1}(i)\psi_1(k) - r^e_{j+1,1}(k) \Big) \\
N^{RF}_{j,2} &= \kappa_1^j \Big(r^e_{j,1}(i)\psi_2(k)' + r^e_{j,2}(i)'\Phi - r^e_{j+1,2}(k)' \Big) \\
N^{RF}_{j,3} &= \kappa_1^j r^e_{j,2}(i)'.
\end{aligned}
\tag{A.49}
$$

We can express

$$
\begin{aligned}
N_{CF,t+1} &= \sum_{j=0}^{\infty} \Big(N^{CF}_{j,0} + N^{CF}_{j,1}\hat{d}_{t-1} + N^{CF}_{j,2} u_t + N^{CF}_{j,3}\Sigma\varepsilon_{t+1} \Big) \\
N_{RF,t+1} &= \sum_{j=1}^{\infty} \Big(N^{RF}_{j,0} + N^{RF}_{j,1}\hat{d}_{t-1} + N^{RF}_{j,2} u_t + N^{RF}_{j,3}\Sigma\varepsilon_{t+1} \Big) \\
N_{RP,t+1} &= N_{CF,t+1} - N_{RF,t+1} - (r_{d,t+1} - E_t r_{d,t+1}).
\end{aligned}
\tag{A.50}
$$