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ABSTRACT

We extract aggregate supply and aggregate demand shocks for the US economy from macroeconomic data on inflation, real GDP growth, core inflation and the unemployment gap. We first use unconditional non-Gaussian features in the data to achieve identification of these structural shocks while imposing minimal economic assumptions. We find that recessions in the 1970s and 1980s are better characterized as driven by supply shocks while later recessions were driven primarily by demand shocks. The Great Recession exhibited large negative shocks to both demand and supply. We then use conditional (time-varying) non-Gaussian features of the structural shocks to estimate "macro risk factors" for supply and demand shocks that drive "bad" (negatively skewed) and "good" (positively skewed) variation for supply and demand shocks. The Great Moderation, a general decline in the volatility of many macroeconomic time series since the 1980s, is mostly accounted for by a reduction in the good demand variance risk factor. In contrast, the risk factors driving bad variance for both supply and demand shocks, which account for most recessions, show no secular decline. Finally, we find that macro risks significantly contribute to the variation in yields, bond risk premiums and the term premium. While overall bond risk premiums are counter-cyclical, an increase in bad demand variance is associated with lower risk premiums on bonds.

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1 Introduction

Distinguishing supply shocks from demands shocks has long been an empirical goal of macroeconomics (e.g., Shapiro and Watson, 1988, Blanchard and Quah, 1989, or Gali, 1992), in part because the appropriate monetary and fiscal policy responses may be quite different for adverse demand versus supply shocks. In the field of asset pricing, supply shocks may prompt quite different responses in nominal bond prices than do demand shocks. It follows that variation in the magnitude of supply versus demand shocks may have important effects on the risk profile of nominal bonds and other asset prices.

We extract aggregate supply and demand shocks for the US economy from data on inflation, real GDP growth, core inflation and the unemployment gap. We begin by defining aggregate supply shocks as shocks that move inflation and real activity in the opposite direction. Similarly, demand shocks are defined as innovations that move inflation and real activity in the same direction. This identification scheme is motivated by Blanchard (1989), who finds empirically that the joint behavior of output, unemployment, prices, wages and nominal money in the U.S. is consistent with this structure.

Defining supply and demand shocks as above presents an identification problem. We resolve this issue without further economic assumptions, but instead using a novel approach exploiting unconditional higher-order moments in the data, which we show to be highly statistically significant. Despite this economically agnostic approach, we show that the structural shocks that we identify exhibit some intuitive properties. For example, in a classic paper, Blanchard and Quah (1989) use a vector-autoregressive dynamic structure to identify "demand-like" shocks as shocks that affect output temporarily, whereas supply disturbances have a permanent effect on output, with neither having a long-run effect on the unemployment rate. The shocks that we estimate also exhibit these dynamic properties even though we do not impose them.

Next, we define *macro risks* as the state variables that govern the time-varying variance, skewness and higher-order moments of supply and demand shocks. To model the time variation in these risk factors, we use the Bad Environment-Good Environment model (Bekaert and Engstrom, 2016), which we motivate by showing that it fits the data well relative to extant models, and because it offers a straightforward economic interpretation. In the model, the macro risk factors drive "good-type" (positively skewed) and "bad-type" (negatively skewed) variance of the structural demand and supply shocks. As the good-type variance increases, the distribution for the shock becomes more positively skewed. Increases in bad-type variance may pull skewness into negative territory.

The time variation in the macro risk factors allows for the covariance between inflation and real activity to potentially change through time. Theoretically, the sign and magnitude of this covariance are important determinants of the risk premium for nominal bonds (see Fama, 1981; Piazzesi and Swanson, 2008; Campbell, Sunderam and Viceira, 2016). When supply (demand) shocks dominate, real activity and inflation are negatively (positively) correlated, and bonds are a poor (good) hedge against macroeconomic fluctuations, presumably leading to relatively higher (lower) nominal term and risk premiums.

Our key results for macroeconomic data are as follows. First, we find that the prevalence of supply shocks was high during the 1970s and again during the Great Recession. In contrast macroeconomic variation in the 1980s and 1990s, particularly during recessions, was more strongly dominated by demand shocks. Second, our analysis suggests that the Great Moderation - a reduction in the volatility of many macroeconomic variables since the mid-1980s - is attributed largely to a decrease in good-type demand variance. Meanwhile, the bad-type variance risk factors for both supply and demand shocks have not experienced any secular decline. As a result the frequency and severity of recessions, which are associated with elevated bad-type volatility, have not changed much over our sample. These results offer a refinement to the work of Jurado, Ludvigson and Ng (2015), who find a strong counter-cyclical component to aggregate volatility.[1] Third, we offer a characterization of the Great Recession of 2008-2009. Some researchers suggest that the Great Recession of 2008-2009 was accompanied by a rather large negative aggregate demand shock (see, e.g., Bils, Klenow, and Malin, 2012, or Mian and Sufi, 2014), but there is little consensus on this issue (see, e.g., Ireland, 2011, or Mulligan, 2012, arguing for the importance of supply shocks). We find that negative demand and supply shocks contributed approximately equally to the Great Recession.

We also make contributions to the empirical asset pricing literature. Although many asset pricing paradigms (e.g., habit of Buraschi and Jiltsov, 2007, long-run risk of Bansal and Schaliastovich, 2013, or rare disasters of Gabaix, 2012) predict that the bond risk premium

[1] In particular, our macro uncertainty measures have a structural "demand" versus "supply" interpretation and generate different higher order (> 2) moments depending on being primarily "good" or "bad".

should be a function of expected second and higher order moments of macroeconomic fundamentals, the vast majority of the empirical literature has surprisingly focused on explaining expected bond returns with the expectations of the level of macroeconomic variables or, even more simply, actual realized macroeconomic data (see, e.g., Ludvigson and Ng, 2009). Notable exceptions are Wright (2011) and Bansal and Shaliastovich (2013). Wright (2011) links term premiums to inflation uncertainty, whereas Bansal and Shaliastovich (2013) link bond risk premiums to consumption and inflation volatility. Compared to these papers, our contribution is twofold. First, we show the importance of decomposing macroeconomic variation into components due to the variance of supply and demand shocks, and into the good and bad types of variance. We find that the time-variation in the macro risk factors for supply and demand implies that the covariance between inflation and real activity changes through time and switches sign. Our analysis links this time-variation to bond risk premiums by showing that demand (supply) variance negatively (positively) predicts bond excess returns. In particular, we show that while overall the expected excess bond returns are counter-cyclical, an increase in demand (supply) variance is associated with lower (higher) expected returns. Second, we quantify the relative importance of first and higher order macroeconomic moments for key term structure variables.

The remainder of the paper is organized as follows. In section 2, we describe how we theoretically identify aggregate supply and aggregate demand shocks and how we model macro risk factors. Section 3 describes the econometric methodology that we use to extract the structural shocks and the macro risk factors. In Section 4, we provide empirical estimates for the US economy from 1959 to 2015 and a structural interpretation of the macro data using our identification scheme. In Section 5, we link the macro risk factors to term structure data. We also assess whether they have predictive power for excess bond returns and explain term premium behavior. A final section summarizes our key results and sets out an agenda for future research.

2 Modeling Macro-Risks

2.1 Aggregate supply and demand shocks in a simplified model

Consider a bivariate system in real GDP Growth (g_t) and inflation (π_t):

$$
\begin{aligned}
g_t &= E_{t-1}[g_t] + u_t^g, \\
\pi_t &= E_{t-1}[\pi_t] + u_t^\pi,
\end{aligned}
\tag{1}
$$

where E_{t-1} denotes the conditional expectation operator. In a first departure from standard macroeconomic modeling, the shocks to output growth and inflation are a function of two structural shocks, u_t^s and u_t^d:

$$
\begin{aligned}
&u_t^\pi = -\sigma_{\pi s} u_t^s + \sigma_{\pi d} u_t^d, \\
&u_t^g = \sigma_{gs} u_t^s + \sigma_{gd} u_t^d, \\
&\sigma_{\pi s} > 0, \sigma_{\pi d} > 0, \sigma_{gs} > 0, \sigma_{gd} > 0, \\
&Cov(u_t^d, u_t^s) = 0, Var(u_t^d) = Var(u_t^s) = 1.
\end{aligned}
\tag{2}
$$

The first fundamental economic shock, u_t^s, is an aggregate supply shock, defined so that it moves GDP growth and inflation in opposite directions, as happens, for instance, in episodes of stagflation. The second fundamental shock, u_t^d , is an aggregate demand shock, defined so that it moves GDP growth and inflation in the same direction as would be the case in a typical economic boom or recession. Supply and demand shocks are assumed to be uncorrelated.

Note that the sample covariance matrix of the shocks from the bivariate system in (1) only yields three unique moments, but we need to identify four coefficients in equation (2) to extract the supply and demand shocks. Hence, absent additional assumptions, a system with Gaussian shocks would be underidentified. Fortunately, it has been well established that macroeconomic data exhibit substantial non-Gaussian features (see, e.g., Evans and Wachtel (1993) for inflation, and Hamilton (1989) for GDP growth). Our second departure from standard macroeconomic modeling is to assume that the demand and supply shocks are potentially non-Gaussian in that they may have non-zero unconditional skewness and excess kurtosis. For example, there are four available unconditional skewness and co-skewness moments for GDP growth and inflation. These four moments, in conjunction with the three available second moments, could in principle be used to identify the four $\sigma_{\pi/g,s/d}$ parameters (and two requisite unconditional skewness coefficients for the supply and demand shocks).

If the variance of demand and supply shocks is time-varying, the model also implies that the conditional variance between inflation and GDP growth shocks is time-varying and can switch signs:

$$Cov_{t-1}[u_t^g, u_t^\pi] = -\sigma_{\pi s}\sigma_{gs}Var_{t-1}u_t^s + \sigma_{\pi d}\sigma_{gd}Var_{t-1}u_t^d, \tag{3}$$

where the subscripts on the Cov and Var operators denote that they may vary over time. Thus, when demand shocks dominate the covariance is positive but when supply shocks dominate it is negative.

The main advantage of the supply and demand shocks definition above is that it carries minimal theoretical restrictions (only a sign restriction)[2]. However, these supply and demand shocks definitions do not necessarily correspond to demand and supply shocks in, say, a New Keynesian framework (see e.g. Woodford, 2003) or identified VARs in the Sims tradition (Sims, 1980).[3] The classic Blanchard and Quah (1989) paper famously identifies "demand like" shocks as those that affect output only temporarily whereas supply disturbances have a permanent effect on output, with neither having a long run effect on unemployment rate. However, Blanchard (1989) notes that these short- and long-run effects of supply and demand shocks are consistent with responses to shocks in the context of standard Keynesian models. For instance, supply shocks include productivity shocks which tend to have a longer run effect on output. We reverse the identification strategy here, by first exploiting the sign restrictions to identify the shocks, and then verifying their long-run impact on inflation and real activity in subsequent analysis. Furthermore, in this paper we abstract from further economic interpretation of demand and supply shocks and their sources. Such analysis would be of great economic interest, but would require an advanced general equilibrium model which tends to be highly stylized and can not accommodate meaningful time variation in higher order moments (see, e.g., van Binsbergen et.al., 2012).

[2]The idea to impose a minimal set of sign restrictions to achieve identification is reminiscent of Uhlig's (2005) identification scheme for monetary policy shocks.

[3]Furthermore, in some models the "supply" shocks might move real activity and inflation in the same direction: see, for instance, news shocks in Cochrane (1994).

2.2 Modeling Macro Risks

We define macro risk factors as determinants of the second and higher-order moments of supply and demand shocks. We parameterize the distribution of supply and demand shocks using a model that accommodates conditionally non-Gaussian distributions, the Bad Environment-Good Environment (BEGE) model (Bekaert and Engstrom, 2016).

2.2.1 Bad Environment - Good Environment Model

Following a BEGE structure, demand and supply shocks are component models of two independent distributions:

$$\begin{aligned} u_t^s &= \sigma_p^s \omega_{p,t}^s - \sigma_n^s \omega_{n,t}^s, \\ u_t^d &= \sigma_p^d \omega_{p,t}^d - \sigma_n^d \omega_{n,t}^d, \end{aligned} \tag{4}$$

where t is a time index, and σ_p^s, σ_n^s, σ_p^d, and σ_n^d are positive constants. We use the notation:

$$\begin{aligned} \omega_{p,t}^d &\sim \tilde{\Gamma}(p_t^d, 1), \\ \omega_{n,t}^d &\sim \tilde{\Gamma}(n_t^d, 1), \\ \omega_{p,t}^s &\sim \tilde{\Gamma}(p_t^s, 1), \\ \omega_{n,t}^s &\sim \tilde{\Gamma}(n_t^s, 1), \end{aligned} \tag{5}$$

to denote that $\omega_{p,t}^d$ follows a centered gamma distribution with shape parameter p_t^d and a unit scale parameter. The corresponding probability density function, $\phi(\omega_{p,t}^d)$, is given by:

$$\phi(\omega_{p,t+1}^d) = \frac{1}{\Gamma(p_t^d)} (\omega_{p,t+1}^d + p_t^d)^{p_t^d - 1} exp(-\omega_{p,t+1}^d - p_t^d),$$

for $\omega_{p,t+1}^d > -p_t^d$; with $\Gamma(\cdot)$ representing the gamma function. Similar definitions apply to $\omega_{n,t+1}^d$, $\omega_{p,t+1}^s$, and $\omega_{n,t+1}^s$. Unlike the standard gamma distribution, the centered gamma distribution has mean zero. For such distribution, the shape parameter represents the volatility of the random variable.

The top panel of Figure 1 illustrates that the probability density function of $\sigma_p^d \omega_{p,t}^d$ (the "good" component of the demand shock) is bounded from the left and has a right tail. Similarly, the middle panel of Figure 1 shows that the probability density function of $-\sigma_n^d \omega_{n,t}^d$ (the "bad" component) is bounded from the right and has a left tail. Finally, the bottom panel of Figure 1 plots the component model of these two components which has both tails.

The components of u_t^s have the same distributional properties. Hence, we define a "good" ("bad") shape parameter as one associated with a ω_p (ω_n)-shock.

The good (p_t^d, p_t^s) and bad (n_t^d, n_t^s) shape parameters of our macro shocks are assumed to vary through time in an autoregressive fashion as in Gourieroux and Jasiak (2006):

$$\begin{aligned} p_t^d &= \bar{p}^d(1-\phi_p^d) + \phi_p^d p_{t-1}^d + \sigma_p^d \omega_{p,t}^d, \\ p_t^s &= \bar{p}^d(1-\phi_p^s) + \phi_p^s p_{t-1}^s + \sigma_p^s \omega_{p,t}^s, \\ n_t^d &= \bar{n}^d(1-\phi_n^d) + \phi_n^d n_{t-1}^d + \sigma_n^d \omega_{n,t}^d, \\ n_t^s &= \bar{s}^d(1-\phi_n^s) + \phi_n^s p_{t-1}^s + \sigma_n^s \omega_{n,t}^s. \end{aligned} \tag{6}$$

Note that positive $\omega_{p,t}^d$ shocks drive up GDP growth, as do the $\omega_{p,t}^s$ shocks, and those shocks are associated with an increase in both p_t^d and p_t^s. We call this "good volatility" because it induces more positive skewness in GDP growth. Conversely, positive realizations of $\omega_{n,t}^d$ and $\omega_{n,t}^s$ shocks drive down GDP growth and they are associated with an increase in "bad" volatility and more negative skewness. This explains the "BEGE" moniker.

Using the demand shock as an example, Figure 2 illustrates possible conditional distributions of demand shocks which could arise as a result of the time variation in shape parameters in equation (6). In particular, the probability density function in the top panel of Figure 2 characterizes the situation where good volatility is relatively large and the component distribution has a pronounced right tail, while the probability density function in the bottom panel of Figure 2 corresponds to the case where bad volatility is relatively large and the component distribution exhibits a pronounced left tail.

2.2.2 Conditional Moments under the Bad Environment-Good Environment Model

At this point, we have set out an economy with 4 shocks ($\omega_{p,t}^d$, $\omega_{n,t}^d$, $\omega_{p,t}^s$, and $\omega_{n,t}^s$) and 4 state variables, which we collect in $X_t^{mr} = [p_t^s, n_t^s, p_t^d, n_t^d]'$. These 4 state variables summarize the macroeconomic risks in the economy. Using the properties of the centered gamma distribution, we have, for example:

$$\begin{aligned}
&E_{t-1}[u_t^s] = 0, \\
&E_{t-1}[(u_t^s)^2] = (\sigma_p^s)^2 p_t^s + (\sigma_n^s)^2 n_t^s, \\
&E_{t-1}[(u_t^s)^3] = 2(\sigma_p^s)^3 p_t^s - 2(\sigma_n^s)^3 n_t^s, \\
&E_{t-1}[(u_t^s)^4] - 3(E_{t-1}[(u_t^s)^2])^2 = 6(\sigma_p^s)^4 p_t^s + 6(\sigma_n^s)^4 n_t^s.
\end{aligned} \tag{7}$$

And analogously for u_t^d.

Thus, the BEGE structure implies that the conditional variance of inflation and output varies through time, with the time-variation potentially coming from either demand or supply shocks, and either bad or good volatility. In addition, the distribution of inflation and output shocks is conditionally non-Gaussian, with time variation in the higher order moments driven by variation in X_t^{mr}.

2.3 The Full Model

A model with only two macroeconomic variables such as the one presented above would be too narrow for our purposes and our estimates of supply and demand shocks are based on a more extensive model of the macroeconomy. First, we consider a four variable macro model, rather than a two variable system, adding core inflation and the unemployment gap. Core inflation, which strips out components of overall inflation that are particularly volatile such as energy and food prices, is, of course, a variable that is closely followed by monetary policy makers. Core inflation has been shown to be useful in forecasting future inflation. Ajello, Benzoni and Chyhruk (2012) in fact claim that adding core inflation to a macro system results in inflation forecasts that are as accurate as forecasts based on survey data (see Ang, Bekaert and Wei, 2007, for more on the accuracy of survey based inflation forecasts). This is relevant, because we use quarterly data starting in 1959 and thus cannot easily use survey forecasts (for instance, the quarterly Survey of Professional Forecasters started in 1969). Analogously, for many practitioners, the unemployment rate gap is preferred to GDP growth as an indicator of economic activity. Moreover, as Bauer and Rudebusch (2016) demonstrate, this variable is in fact little correlated with GDP growth and contains useful alternative information about real economic activity.

We collect the 4 macro variables in the vector X_t. Because we want to identify shocks to these four variables, it is important that we specify their conditional means carefully. Bond yields have well-established predictive power for economic variables (see Harvey, 1988, and many others, for the predictive ability of the term spread for GDP growth, for example) prompting us to add yields to the information set. Therefore, we collect the one-quarter and 10-year Treasury yield data in the vector Z_t.

We use a VARMA model to extract AS/AD shocks from X_t:

$$\Phi(L)X_t = BZ_{t-1} + \theta(L)u_t, \tag{8}$$

Where $\Phi(L)$ and $\theta(L)$ are vector polynomials in the lag operator. Furthermore:

$$u_t = \Sigma u_t^m + \Omega e_t \tag{9}$$

where $u_t^m = [u_t^s, u_t^d]$, the structural shocks, and Σ is a 4x2 matrix containing the exposures of macroeconomic shocks to AS/AD shocks. The vector e_t represents shocks uncorrelated with u_t, with mean zero, unit variance and zero skewness and excess kurtosis and Ω is a diagonal matrix. It is necessary to add these uncorrelated innovations to the macro series to avoid having a singularity in their covariance matrix. We assume that these orthogonal shocks have zero skewness and excess kurtosis mostly for convenience, but this assumption also aids in the identification of the supply and demand shocks; we assume all the excess skewness and kurtosis among the macro variables arises solely from the structural shocks. Note that these shocks may represent important shocks, not modelled in our framework, such as monetary policy shocks, stressed, e.g., in Campbell, Pflueger and Viceira (2015).

3 Identifying Macro Risks in the US economy

While there are multiple ways to estimate the system in equations (2), (4), (6), (8), and (9), the presence of the gamma distributed shocks makes the exercise nontrivial. We therefore split the problem into three manageable steps. First, we use standard techniques to estimate the VARMA(p,q) model and determine its order. Second, we filter the demand and supply shocks from the system in equation (9) by estimating a GMM system that includes higher-order unconditional moments of the macroeconomic variables. The use of higher-order moments is essential to achieve identification in our framework. Third, once the demand and supply shocks are filtered, we can estimate univariate BEGE systems on supply and demand shocks (exploiting the identifying assumption that they are independent) using approximate maximum likelihood as in Bates (2006).[4] We begin by describing the data we use.

3.1 Data

The data are quarterly from 1959:Q2 to 2015:Q2 (225 quarters). Potentially, we could have included data back to 1947:Q1 (the starting date for GDP data). The later start date is chosen to exclude a period when there was higher measurement error in the GDP data (Bureau of Economic Analysis, 1993). Moreover, US long-term rates were pegged by the Federal Reserve prior to the Treasury Accord of 1951. For inflation (core inflation) we use 100 times log changes in the headline CPI index (CPI excluding food and energy) measured for the last month of each quarter, from the Bureau of Labor Statistics (BLS). Real GDP growth is 100 times the log difference in real GDP (in chained 2009 dollars) from the Bureau of Economic Analysis. The unemployment rate gap is the difference between the unemployment rate (in percent) from the last month of each quarter from the BLS, and the estimated level of the natural rate of unemployment published by the Congressional Budget Office.

Interest rate data consists of yields, prices and returns for nominal U.S. Treasury securities. For maturities of length 1 quarter and 1, 2, 3, 4 and 5 years, estimated yields for zero-coupon securities are taken from the Fama-Bliss (1987) data set (part of the CRSP). For yields of maturity 10 years, data from 1959:Q2 through 1971:Q1 are from the McCullough-Kwon (1993) data set. From 1971:Q1-2015:Q2, data for 10-year yields are from Gürkaynak, Sack, and Wright (2010). Yields at maturities other than those discussed above are estimated by linear interpolation. We use continuously compounded yields, expressed as annualized percentages.

[4] A disadvantage of using a multi-step estimation process is that statistical inference is complicated by the fact that all steps after the first one use pre-estimated coefficients or filtered variables that are subject to sampling error. To account for these errors, we also execute the entire multi-step estimation process using bootstrapped data. The bootstrap procedure is described in Appendix A.

3.2 Estimating the VARMA (p, q) model

To estimate the time series model for X_t, including inflation, real GDP growth, core inflation, and the unemployment rate gap, we first de-mean the variables. We choose among a variety of time series models, in particular VAR(1), VAR(2), VARMA(1,1), VARMA(1,2), and VARMA(2,1), using standard information criteria. All models were estimated two ways, excluding and including the instruments Z_{t-1} (including 1-quarter and 10-year nominal Treasury yields). Models were estimated by quasi-ML (using a Gaussian likelihood function).

Because some of these models are heavily parameterized (the highest-order ones have over 50 parameters), we employ a two-step procedure to help ensure that we identify a global maximum of the likelihood functions. In a first step, we obtain starting values using a recursive-OLS procedure. Following Hannan and Rissanen (1982), we first estimate by OLS a vector-autoregression with a large number of lags. We use 6 lags, but that choice does not appear material for the results. We then recover the estimated residuals from this step, $\hat{u}_t$. These residuals serve as a "plug-in" estimator of lagged shocks for the VARMA model, and then we estimate the VARMA by OLS. This step is repeated until all of the estimated parameters of the VARMA and all of the estimated residuals converge, which we define as changing by less than 1e-6. In a second step, we use the parameter estimates from Step 1 as starting values for estimation by QML.

Model selection criteria are reported in Table 1. We use the standard Bayesian information criterion (BIC), but the Akaike information criterion (AIC) is modified to correct for small sample biases (Sugiura, 1978; Burnham and Anderson, 2004). The AIC model identifies the VARMA (1,1) model, including the yield instruments as optimal. The BIC criterion identifies the VARMA (1,1) model without instruments as optimal, but the VARMA (1,1) model with instruments is identified by the BIC as having the second best score and we use this model.

3.3 Identifying supply and demand shocks

The VARMA model delivers time series observations on u_t. Theoretically, it is possible to estimate the system defined by equations (2), (4), (6), (8), and (9) in one step, but computationally this is a very tall order. There are 4 unobserved state variables (the X_t^{mr}

vector) which have non-Gaussian innovations. However, note that if we can identify the coefficients in Σ in equation (9), we can filter the supply and demand shocks from the original macro shocks u_t. With these structural shocks in hand, we can estimate univariate BEGE systems on each of demand and supply shocks separately.

We use information in 2^{nd}, 3^{rd} and 4^{th} order unconditional moments of the shocks to the macroeconomic variables to identify loadings on supply and demand shocks. Specifically, we calculate 48 statistics starting from the four macroeconomic shocks. These are the unconditional standard deviations (4), correlations (6), univariate (scaled) skewness and excess kurtosis (8), selected co-skewness (12), and selected co-excess kurtosis measures (18). To calculate the covariance matrix of the sampling error for these statistics, we use a block bootstrapping routine. Specifically, we sample, with replacement, blocks of length 20 quarters of the 4 variable - vector of macroeconomic shocks, to build up a synthetic sample of length equal to that of our data. We calculate the same set of 2^{nd}, 3^{rd}, and 4^{th} order statistics for each of 10,000 synthetic samples. We then calculate the covariance matrix of these statistics across bootstrap samples. Inspecting this sample covariance matrix, we found that the sampling errors for some statistics are highly correlated, leading to ill-conditioning of the covariance matrix. To estimate a better-conditioned covariance matrix, we calculated a "shrinkage estimator" (Ledoit and Wolff, 2003), using a linear combination of the full covariance matrix (weight 0.95) and a diagonal version which zeros out the off-diagonal elements (weight 0.05). Our results are not sensitive to perturbations in this weighting scheme. We acknowledge that this covariance matrix estimator does not reflect sampling error associated with the VARMA parameters that were used to identify the macroeconomic shocks, which may lead to inefficiency of our estimates. We then estimate the loadings of the macroeconomic shocks onto the supply and demand shocks using Classical Minimum Distance (CMD henceforth) optimization (see, e.g., Wooldridge, 2002, pp. 445-446). The CMD estimation uses the inverse of the bootstrapped covariance matrix described above as the weighting matrix.

Table 2 reports the higher-order moments we use in the estimation. Not surprisingly, all volatility statistics are statistically significantly different from zero, but so are the coefficients of excess kurtosis. However, among the skewness coefficients, only the positive skewness of shocks to the unemployment gap is statistically significant and only one of 12 co-skewness coefficients is significant. The symmetric co-kurtosis measures (those involving terms such as

$x_1^2 x_2^2$) are all significantly different from zero and 6 out of 12 “asymmetric” (those involving terms such as $x_1^3 x_2$) co-kurtosis measures are statistically significant as well. The p-value for the joint significance of all the 3^{rd} and 4^{th} order moments is < 0.0001.

We next use the information in these higher order moments to identify the loadings on our supply and demand shocks. We estimate a total of 13 parameters using our 48 estimated statistics. These can be grouped into three sets:

- The loadings of four macro shocks onto supply and demand shocks (8 parameters) in the matrix Σ in (9), imposing the sign restrictions described above.
- The share of variation of the macro shocks that comes from idiosyncratic variation or measurement error, that is the matrix Ω in (9)). We assume this share is constant across the four variables (1 parameter). We do this to impose a prior that all 4 series contribute (jointly) to demand and supply shocks. If we do not impose this restriction, the system tends to drive the variance of idiosyncratic factors to zero for the less noisy macro series, in which case the noisier macro series (such as real GDP growth) do not contribute much to the identification of supply and demand shocks.
- The skewness and kurtosis of the supply and demand shocks (4 parameters). Note that we do not assume a parametric model for the distribution of supply and demand shocks at this stage: we simply estimate their skewness/kurtosis coefficients as free parameters.

Table 2 shows that our CMD estimation does not miss any individual moment by more than 2 standard errors. The test of the overidentifying restrictions does reject at the 5 percent level (p-value of 4.81%), showing that higher order moments indeed have statistical “bite”.

In Table 3, Panel A, we report the supply and demand loadings for the various macro variables. These are generally quite precisely estimated. Our estimates suggest that supply and demand contribute roughly equally to the variance of inflation. GDP growth and the unemployment gap load a little more heavily onto demand shocks than on supply shocks, with is also true for core inflation. We estimate the share of idiosyncratic variation for the four series to be relatively high at 47 percent. These sources of variation may represent measurement error in the macroeconomic data (see, e.g., Wilcox, 1992), but they may also represent unmodeled structural variation.

Based on these loadings, we invert the supply and demand shocks from the macro shocks using a Kalman filter assuming that the shocks e_t in equation (9) are i.i.d. Gaussian. Even when shocks are not Gaussian, the Kalman filter is still best in terms of root-mean-square error among all linear filters. The Kalman gain formula is:

$$K = \Sigma'(\Sigma\Sigma' + \Omega\Omega')^{-1}, \tag{10}$$

where Σ is the 4x2 loading of the macro shocks onto the supply and demand factors, and Ω is a diagonal 4x4 matrix of loadings onto the idiosyncratic shocks as in equation (9). Table 3, Panel B, reports Kalman gain coefficients, which are all of the intuitive sign.

In Panel C of Table 3, we show a variance decomposition illustrating how much of the demand/supply shock variance is accounted for by the 4 macro variables. That is, we compute, for example, $\frac{Cov(u_t^d, K_{d,\pi}\pi_t)}{Var(u_t^d)}$, where $K_{d,\pi}$ is the Kalman gain coefficient on inflation for the demand shock. By construction, these variables add up to one. The results show that the 4 different series contribute about equally to the structural shocks, with the real activity variables contributing slightly more to demand shocks, and inflation shocks contributing a bit more to the identification of supply shocks.

Finally, in Panel D of Table 3, we report the skewness and kurtosis of the filtered supply and demand shocks. Both shocks are leptokurtic but the demand shock is negatively skewed whereas the supply shock has slight positive skewness. The departure from the Gaussian distribution of the demand shocks is clearly more pronounced than that of the supply shock. Yet, a standard Jarque-Bera test rejects the null of normality at the 1 percent level for both shocks.

3.4 Estimating Macro Risk Factors

Note that the identification scheme for structural shocks described above is completely model-free, making our methodology applicable with any statistical model which can accommodate non-Gaussian features of the data. Given the structural shocks, we are left to identify the BEGE model parameters. We use an estimation and filtering apparatus due to Bates (2006). The methodology is similar in spirit to that of the Kalman filter, but the Bates routine is able to accommodate non-Gaussian shocks. The details of the estimation are in Appendix C.

3.4.1 Parameter Estimates

Using standard information criteria, we found that our full model with two latent variables driving the time variation in second and higher order moments was too rich for our time series of filtered shocks. For the supply shock, the good volatility process does not show substantial time variation and the good environment shock is essentially Gaussian featuring a high shape parameter of the corresponding gamma distribution. We therefore imposed the good environment process for supply to be Gaussian with a constant unit variance. Note that the unconditional variances of the demand and supply shocks are restricted to be 1, which reduces the number of parameters to estimate by 1 and the supply shock BEGE process therefore requires only 4 free parameters: σ_n^s, ϕ_n^s, σ_{nn}^s, and the share of the good variance $\bar{p}^s$.

For the demand shock, we find evidence for time variation in both good and bad variance, but the unconditional mean of the good volatility process becomes very high, indicating that the good volatility shocks were often nearly Gaussian.[5] However, it is not always high, sometimes becoming low enough to indicate a nontrivial degree of conditional non-Gaussianity. Moreover, a Gaussian stochastic volatility model for the p_t^d process is rejected by the data. Nevertheless, this situation resulted in an identification problem for the BEGE model, as the unconditional mean of p_t^d, was poorly identified.[6] We therefore restricted it to be 100, a restriction which is not rejected by the data.

The parameter estimates for the BEGE model are reported in Table 4. The table reports the various parameter estimates including the unconditional values of the p_t and n_t variables, which determine the extent of non-Gaussianity in the shock distributions. For the demand shocks, unconditionally, the good demand variable is nearly Gaussian by construction, but the bad environment variable is very non-Gaussian. In particular, its unconditional skewness is $\frac{2}{\sqrt{\bar{n}^d}}$, or 3.21 and its kurtosis is $\frac{6}{\bar{n}^d}$ or 15.45. The bad environment shape parameter is also far less persistent than the good environment variable, therefore capturing rather short-lived

[5]Recall that the macro risk factors also have an interpretation as the time-varying shape parameters of a model with gamma-distributed shocks. As shape parameters grow large, gamma distributions approach a Gaussian distribution.

[6]This identification problem likely arises because when its shape parameter becomes over 10, the gamma distribution becomes very close to Gaussian. Further increases in the shape parameter do not substantially change the shape of the distribution.

recessionary bursts (0.79 versus 0.96 autocorrelation). For the supply shock, we imposed the distribution of the good environment shock to be Gaussian. The supply bad-environment distribution is relatively more Gaussian compared to the demand shock with the unconditional mean of the shape parameter equal to 1.07. This implies unconditional skewness of 1.94 and kurtosis of 5.63. The shock has similar persistence to the bad environment demand shock, suggesting that supply driven recessions may have similar duration to demand driven recessions.[7]

3.4.2 Model Comparision

We tested the performance of the BEGE model to examine whether it fits the estimated supply and demand shocks as well as more well-known models that also feature time-varying second- and higher-order moments. Specifically, we looked at the performance of the BEGE model relative to regime-switching models of the Hamilton (1989)-type, and a model of Gaussian stochastic volatility. To evaluate the relative performance of the models, we used standard BIC and AIC (with the usual small sample correction) criteria.[8] These results are presented in Table 5. As shown in the top panel, for the supply shock, the BEGE model performs better than the stochastic volatility model but worse than the regime switching models using either criterion. For demand shocks, as reported in the middle panel, the BEGE model outperforms both other models on both criteria. When examining the performance jointly across supply and demand shocks, the BEGE model outperforms the other two models. We conclude that the BEGE model generally performs well in this competition.

4 Macro Risks in the US Economy

Having estimated macroeconomic dynamics, we can now use our model as a lense to interpret the history of key U.S. macroeconomic data over the 1959-2015 period. We begin by

[7]The astute reader will notice that five parameters are reported for the supply process, but there are only four independent parameters required for the estimation. However, the parameters $\bar{p}^s$ and $\bar{n}^s$ can be expressed as functions of the four model parameters. Their standard errors are calculated using the delta method. A similar method was used for the demand BEGE model.

[8]Because the BEGE and the Gaussian stochastic volatility models are estimated using approximate maximum likelihood as in Bates (2006), the comparison of these models to the regime switching models, which is estimated using exact maximum likelihood, is only informal.

characterizing the long-run effects of supply and demand shocks; we subsequently analyze the nature of recessions within our framework, followed by examining the time series and cyclical behavior of the macro risk factors themselves.

4.1 Impulse responses to aggregate supply and demand shocks

Our identification of supply and demand shocks utilizes a set of minimal linear sign restrictions and information in higher order moments. These sign restrictions are present in other classic papers as well, such as Gali (1992) and Shapiro and Watson (1988) but are typically accompanied by a set of additional economic restrictions (e.g., that demand shocks have no long run effect on the level of GDP as in the classic Blanchard and Quah (1989) paper) which we do not need. In this section, we characterize the long run effects of the structural shocks using standard impulse response analysis.

For the purposes of calculating impulse response functions for the macro data, we must model the joint evolution of the yield instruments with the macro series (because we allow yields to forecast the macro variables, having found strong evidence for such dynamics). For our main estimation, we therefore estimate a VARMA (1,1) using all six variables (the four macro variables plus the 1-quarter and 10-year yields), which represents a slight generalization of our main model of the macroeconomic time series because it allows lagged shocks for yields to additionally affect the conditional mean of the macroeconomic series. To compute the response of the four macroeconomic series at various horizons to the supply and demand shocks, we need the contemporaneous response of all the variables to supply and demand shocks. For the four macroeconomic series, these responses are the elements of the Σ matrix in equation (9). For the two yield variables, we extract the time series for reduced-form shocks from the VARMA (1,1)-estimation and simply regress these shocks onto the filtered supply and demand shocks. We stack these loadings together with the Σ matrix into a 6x2 matrix, Σ_2. Then the responses of the six endogenous variables to the two structural shocks, supply and demand, of unit size at horizon h, are given by the expression:

$$IR(h) = A^{h-1}(A + B)\Sigma_2, \tag{11}$$

where A and B are the AR and MA matrices from the VARMA-model, respectively. Note that the standard error for the impulse response coefficients must account not only for the estimation of the VARMA(1,1) parameters but also for the error incurred in identifying supply and demand shocks, which involves the higher order moments of VARMA residuals. To this end, we use a bootstrap procedure, which is described in detail in Appendix A. As a robustness check, in Appendix B we also calculate "model-free" impulse responses following Jorda (2005).

Table 6 contains the results, with the effects of demand (supply) shocks on the left (right) (recall that these shocks have unit variance by construction). The effects are consistent with the standard Keynesian interpretation. Demand shocks have large short run effects on real GDP growth (with the initial shock being 0.40 percent) but their cumulative effect on output is small (0.17 percent) and insignificantly different from zero. Supply shocks generate smaller short run GDP growth effects but their cumulative effect is 0.65 percent which is significantly different from zero. Demand and supply shocks have similar but opposite effects on the price level, with the cumulative effects close to +1 percent (-0.80 percent) in the case of demand (supply) shocks, but these effects are imprecisely measured. In sum, our identification scheme yields shocks whose long-run effects are consistent with a well-established macroeconomic literature.

4.2 Characterizing recessions using aggregate supply and demand shocks

Our identification of supply and demand shocks allows us to characterize recessions as either supply or demand driven (or a combination of both). Figure 3 graphs the filtered demand and supply shocks with NBER recessions shaded: it is apparent that many recessions are accompanied by a negative supply shock, but this appears more prevalent in the seventies. A large negative demand shock is very apparent for the Great Recession, but the recessions in the early eighties were also accompanied by large negative demand shocks.

Table 7 quantifies the visual impression by simply adding up the (net) demand and supply shocks over the recession period (that is, positive and negative shocks can cancel each other out). The 1969-70 and 1973-75 recessions did not feature strongly negative demand shocks but the other recessions did, with the 1981-82 and Great Recession featuring the largest negative demand shocks. All recessions featured negative supply shocks, with the largest negative shocks occurring in the 1974-1975 recession and the Great Recession. For the 1981-82 recession, the cumulative supply effect is effectively zero however. On a relative basis, the first four recessions were predominantly supply driven whereas three of last four were more demand driven (the exception being the 1990-91 recession). For the first five recessions, these results are broadly consistent with Gali's (1992) results, who also characterizes the 1973-75 recession as mostly supply driven and the 1981-82 recession as mostly demand driven. Our results for the Great Recession assign a perhaps surprisingly large role to supply shocks, but this is not inconsistent with the results in Ireland (2011) or Mulligan (2012), for example. At the same time, recent work by Bils, Klenow and Malin (2012) and Mian and Sufi (2014) using micro data stresses lower aggregate demand as the main cause of the steep drop in employment during the Great Recession.

The Great Recession of 2008-2009 stimulated much research on the effects of macroeconomic uncertainty on the economy (see, e.g., Ludvigson, Ma, and Ng, 2016; Carriero, Clark and Marcellino, 2016). The BEGE structure implies that shocks to supply and demand are correlated with changes in the macroeconomic risk factors. For example, the bad volatility demand shock is perfectly conditionally correlated with the bad demand shock (see equations (4) and (6)), so that uncertainty shocks affect the levels of macroeconomic variables by assumption. We therefore also investigate the behavior of the macroeconomic risk factors during recessions. Our model implies that the total conditional variance of demand and supply shocks are the sum of the good and bad components. These are plotted in Figure 4. The good demand variance (see Panel A) was relatively high in the 70s and the early 80s, and then decreased to low levels consistent with the Great Moderation (a further discussion of the Great Moderation is below). The bad demand variance shows much less pronounced low frequency variation but peaks in the recessions of 1960, the early eighties, 2001 and the recent Great Recession. It also shows short-lived peaks in the late sixties and twice in the decade between 2000 and the beginning of the Great Recession.

Panel B of Figure 4 performs the same exercise for supply variances. The level of good variance is time-invariant at a relatively low level. The bad supply variance appears higher in the stagflationary episodes of the 1970s, but closer inspection reveals that it peaks in all recessions with the exception of the 2001 recession. Its increase in the Great Recession is extreme, starting towards the end of the period and exceeding its unconditional average level of 0.52 until 2012Q1.[9]

[9]Campbell, Pflueger, and Viceira (2015) suggest that supply shock volatility decreases after 1980 but its decrease may have been masked by changes in monetary policy, at least until 2000.

Panel C of Figure 4 plots together the conditional variances of demand and supply shocks. Given that both supply and demand shocks have unit variance, the graph immediately gives a sense of which variance dominates. Supply variance tends to spike higher in recessions than demand variance does. The only secular decline that one might associate with the Great Moderation appears to come from the demand side.

One novel feature of our model is that it accommodates and provides estimates of the non-Gaussian features of the shocks. In particular, in environments dominated by elevated levels of bad supply variance, we would expect high-inflation scares and positive inflation skewness, whereas in aggregate demand environments, we may witness negative inflation skewness (deflation scares). For the real activity variables, recessions, being riskier macro environments, should be naturally accompanied by negative skewness for real GDP growth and positive skewness for the unemployment gap. Figure 5 graphs the (scaled) conditional skewness for our 4 macro variables. For real GDP growth and the unemployment gap, it is indeed the case that in recessions, there generally is a local trough in the skewness of GDP growth and a local peak in the skewness of the unemployment rate gap. The movements are largest in the recent Great Recession. For the inflation variables, we see positive spikes in conditional skewness in the first 4 recessions and the 1990 recession. However, in the recessions of 1980 and 2001, we witnessed negative skewness and in the Great Recession, there are large movements in skewness from positive to negative and back to positive, consistent with this period witnessing both large supply and demand shocks.

4.3 Time variation in conditional macro variances and the Great Moderation

Because our model generates time variation in the conditional variance of the macro variables, it can potentially inform the debate on the Great Moderation. The literature has mostly focused on output volatility and puts a "break point" for output volatility in the first quarter of 1984 (see McConnell and Perez-Quiros, 2000; Stock, Watson, Gali and Hall, 2002). For inflation, Baele et. al. (2015) suggest a later date, the first quarter of 1990. Whereas most of the discussion in the literature has tried to attribute the decreased volatility to either good luck or improvements in monetary policy (see e.g. Cogley and Sargent, 2005; Benati and Surico, 2009; Sims and Zha, 2006, and Baele et. al., 2015, and the references therein), our model offers an alternative perspective. First, there is no visual evidence of a break in supply variances at all. However, supply variances peak in recessions and so the recession-intensive 70s and 80s naturally feature higher supply variances than the period thereafter. While it is possible that monetary policy lowered the incidence of recessions, it is not obvious how monetary policy would stave off the volatility associated with supply shocks, and indeed does not appear to have done so in the 1990 and recent Great Recession. Second, for the demand variance, it is obvious that the more benign "good" variance process shows a distinct break in the mid-eighties, but the more pernicious "bad" variance continues to peak in recessions as it did before. This result is reminiscent of a recent finding in Gadea, Gomez Loscos and Prez-Quiros (2014), who, after examining a very long historical period, also conclude that declines in output volatility are associated with expansionary not recessionary periods.

We next test more formally whether inflation and real GDP growth have seen declines in volatility such as that suggested by the Great Moderation, and if so, whether changes in good demand variance, bad demand variance, or bad supply variance explain the shift. Table 8 reports simple dummy regressions for inflation (Panel A) and GDP growth (Panel B). The first three columns report the constant and slope of a regression of the conditional variance of either inflation or GDP growth on a constant and a dummy. We use conservative standard errors correcting for heteroscedasticity and serial correlation using 40 Newey-West lags, but we do not account for sampling error in the filtered macro risk factors.

The rest of the table then splits up the conditional variance in their demand and supply components, and the demand variance into its good and bad demand components. To facilitate comparisons with the literature, we focus mainly on changes in volatility from and initial period spanning 1959 to 1990 compared to the later period spanning from 1990 to 2000. For inflation, there is strong evidence of a decrease in variance after 1990, with the variance decreasing by about 1/5 of its magnitude before the break and the break being statistically significant at the 5 percent level. The additional tests reveal that the break is entirely due to a decrease in good demand variance. In other words, the Great Moderation may not imply smaller inflation volatility in future recessions. In Panel B of Table 7, the same analysis is performed for real GDP growth volatility. Similarly, the break point indeed is associated with the GDP variance decreasing by about 20 percent of its pre-break value, but the change is only significant at the 10 percent level. Here the decomposition analysis produces less clear results. We find a significant contribution from a reduction in bad supply variance, likely associated with the reduced incidence of recessions since 1980, but the (insignificant) reduction in demand variance is economically larger. While both good and bad demand variances contributed to the decrease, only the decrease in the volatility of good demand is economically meaningful, and the variance reductions are not statistically significant.

Lengthening our sample period to the present could increase the power of our tests, and also enables us to address a more recent question: "Is the Great Moderation over?" Baele et. al. (2015) use a macro-regime switching model suggesting that the Great Moderation for both inflation and output has ended, even before (for inflation) or just with the onset (for output) of the Great Recession. However, Gadea, Gomez Loscos and Prez-Quiros (2015) argue, based on a pure statistical analysis of GDP growth volatility, that the Great Moderation is alive and well, despite the Great Recession experience. To test these claims using our estimates of the conditional variance of inflation and output, we examine ending the sample in the fourth quarter of 2006 (just before the Great Recession) or the final quarter in 2015 (using the full sample).

For inflation, when the data from the Great Recession are ignored, the Great Moderation result and its decomposition we documented before is maintained and becomes statistically stronger. However, when we extend the sample to the end of 2015, the decline in the inflation variance weakens and becomes statistically insignificant. It is still the case though that the (good) demand variances become significantly lower post 1990. This suggests that if more non-recession data accumulate, we may well find that the Great Moderation for inflation holds up.

For real GDP growth, extending the sample to 2006 strengthens the Great Moderation evidence statistically somewhat, with now the demand variance also decreasing significantly at the 10% level. Yet, the evidence against constant overall and demand variances remains rather weak. The significant supply variance decline result is robust however. When we extend the sample to the end of 2015, the GDP variance overall decreases but the result is weaker economically than in McConnell and Perez-Quiros (2000) and Stock, Watson, Gali and Hall (2002), and not statistically significant. We no longer find evidence that the supply variance has changed, but still find the (good) demand variance to be lower than before.

We conclude that there is some evidence that the "good" demand variance has decreased over time, but there is no strong evidence that either "bad" demand variances or supply variances have declined. Our analysis of the structural sources of recessions suggest that we therefore should not expect them to be less variable in the future than they were in the past.

4.4 Conditional Covariances between Macroeconomic Time Series

From the perspective of theoretical asset pricing, an important implication of our structural framework regards the covariance between inflation and real activity. From Equation 3, it is evident that in an environment where demand (supply) variances dominate, the conditional covariance between inflation and real activity is positive (negative). To the extent that variances are persistent, changes in this covariance may have important ramifications for term and bond return premiums, which we examine in Section V. Surprisingly, to our knowledge, sign-switching correlations have so far only been documented for consumption growth and aggregate inflation (Hasseltoft and Burkhardt, 2012, Song, 2014, and Ermolov, 2015).

Figure 6 graphs the conditional covariance between, respectively, inflation and real GDP growth and also between core inflation and the unemployment gap (where the aforementioned signs are reversed). Overall, the covariance is mostly positive (roughly 70 percent of the time), which is driven by the important contribution of (good) demand variances to all macro variables. Yet, there are frequent sign changes, mostly associated with large supply shocks during recessions, especially in the early part of the sample period. Early in the Great Recession, demand shocks generate a local peak in the covariance but subsequent large supply shocks then bring the covariance down. A covariance of near zero can in fact hide some strong structural sources of comovement. To see this more clearly, we also show the (bad) supply and (good and bad) demand covariance components of the total covariance. For example, the near-zero correlation between real GDP and inflation from 2000 up to the onset of the Great Recession is the sum of a sizable positive covariance driven by good and bad demand shocks and a sizable negative covariance riven by bad supply shocks. In the Great Recession, the conditional bad variance of both kinds of shocks shoots up, with the bad demand shock first ratcheting the covariance upwards, and bad supply variance later bringing it in negative territory.

5 Macro Risks and the Term Structure

In this section, we explore the interaction of macro factors with the term structure of interest rates. In the preceding sections, we have identified three novel macro-risk factors (p_t^d , n_t^d, and n_t^s). These variables can be interpreted as "good" or "bad" conditional volatilities of demand and supply shocks, but their time variation also changes the entire conditional distribution of these shocks. For comparison with the existing literature on explaining bond yields and returns using macro data, we also examine the performance of "level" macro factors, which include expected inflation, expected core inflation and expected real GDP growth (We use the previously described VARMA(1,1) system to compute these expectations). We also use the unemployment gap as a macro level factor. Thus there are a total of 7 macro-factors we consider.

We address three questions. First, we ask whether macroeconomic factors help explain the yield curve. Second, we investigate the predictive power of our new macro risk factors for bond excess returns. Finally, we also explore how the macro risk factors affect term premiums.

5.1 Macro Risks and the Yield Curve

We start by computing the classic yield curve financial factors. The "level" factor is the equally weighted average of all yields (from the one year to the 10 year maturity); the "slope" factor is the difference between the 10 year yield and one quarter yield; and finally, the "curvature" factor subtracts twice the two-year rate from the sum of the one quarter rate and the 10 year yield. Taken together, these three factors span the overwhelming majority of variation in yields at all maturities. Thus, to operationalize our test of whether macro factors explain yields, we test whether the macro factors explain variation in these three factors. To assess whether macro factors are important determinants of these three financial factors, Table 9 reports R^2 statistics from regressions of the financial factors onto macro factors. Panel A reports results regarding the macro level factors and the macro risk factors. First, the explanatory power of the macro level factors alone for the financial factors is substantial, with the adjusted R^2's exceeding 70, 55, and 30 percent respectively for the level, slope, and curvature factors. Second, the macro risks contribute in a statistically significant fashion to the level and curvature factors[10], boosting the R^2's by about 6 percentage points in both cases. As a robustness check, in Panel B we check whether the boost in explanatory power due to the macro risk factors survives the inclusion of a second set of level macro factors in the regression, those constructed by Ang and Piazzesi (2003). The increase in R^2's due to the macro risk factors is essentially unaffected.

5.2 Macro Risks and Bond Return Predictability

The literature on bond return predictability is voluminous, but mostly focuses on using information extracted from the yield curve to predict future holding period returns (e.g. Cochrane and Piazzesi, 2005). Ludvigson and Ng (2009) find that "real" and "inflation" factors, extracted from a large number of macroeconomic time series, have significant forecasting power for future excess returns on nominal bonds. Moreover, this forecastability is above and beyond the predictive power contained in forward rates and yield spreads. Also, the bond risk premia implied by these regressions have a marked countercyclical component. Bansal and Shaliastovich (2013) show that consumption growth and inflation volatility predict excess bond returns. Cieslak and Pavola (2015) uncover short-lived predictability in bond returns by controlling for a persistent component in inflation expectations. Barillas (2011) shows that the predictability due to macro factors for excess bond returns is economically significant.

In Table 10, we explore the link between future bond returns and our macro factors. We focus on excess one-quarter holding period returns relative to the one quarter yield. This avoids the use of overlapping data which can spuriously increase R^2's in predictability regressions (see, e.g., Fama and French, 1988). Nonetheless, all standard errors are computed using 40 Newey-West (1987) lags. R^2's produced by the financial factors alone are significantly boosted by including both macro level factors and macro risk factors. For maturities from 1 to 10 years, the R^2's from regressions including only financial factors are around 7 percent. The R^2's increase to between 16 and 22 percent when macro level factors are included, and

[10]We use the bootstrap test of Bauer and Hamilton (2016) to determine statistical significance.

increase by an additional 2 to 4 percentage points when macro risk factors are included. These increases in explanatory power are statistically significant.

To delve into the economic mechanism by which macro risks forecast future bond returns, Table 11 presents the coefficients from forecasting regressions that include both level macro and macro risk factors.[11] Individually, there are few significant coefficients. Of the macro level factors, expected core inflation enters with a negative sign and is highly statistically significant for all maturities, while expected aggregate inflation enters with a positive significant coefficient of similar magnitude. The significance of expected inflation in such regressions is consistent with the results of Cieslak and Pavola (2015) (but their regression also includes yields). Of the macro risk factors, the bad demand variance has a negative significant coefficient and the bad supply variance a positive (albeit insignificant) coefficient. Therefore, consistent with intuition, being in a risky (that is volatile) demand environment, where bonds are good hedges against general macroeconomic risks, reduces the risk premium on bonds, and the reverse is true in the case of a supply environment. The effect of bad demand variance is economically large: for example, for the 5 year maturity a one standard deviation increase in the bad demand factor decreases the expected annualized excess bond return by 3.03 percentage points. The corresponding coefficients increase with bond maturity. The coefficient on the "good" demand risk factor is positive but insignificantly different from zero.[12]

Given that previous studies have considered macroeconomic "level" and "risk" factors in isolation and that factors measuring macroeconomic risk have received scant attention in such investigations, the relative predictive power of risk factors is of interest. Table 11 indicates that the adjusted R^2 from macro level factors alone in excess return regressions drops from 18 percent at the two year horizon to 15 percent for the 10 year bond. However, the contribution of macro risks to the R^2 increases with bond maturity, both statistically and economically, such that the total adjusted R^2 stays around 20 percent for all maturities.

[11] Including financial factors (level, slope, and curvature) in the regressions does not materially change any of the results.

[12] To further elaborate on the risk premium intuition, we also added the contemporaneous demand and supply shocks (u^d_{t+1} and u^s_{t+1}) to the bond return regressions. In unreported results, we find that the supply shocks carry positive but non-significant coefficients and the demand shocks carry negative coefficients that are significant at the 1% level and become larger in magnitude with maturity. That is, realized bond excess returns are high if a negative demand shock occurred during the holding period.

Ludvigson and Ng (2009) found the bond risk premiums implied by their predictive regressions, which included both yield variables and macro-factors, to be counter-cyclical. It is not difficult to obtain counter-cyclical real bond risk premiums in economic models, e.g., in habit models with counter-cyclical prices of risk (see, e.g., Wachter, 2006). Our framework suggests that not all recessions are equal in this respect. Our predictive regressions indicate that risk premiums are, everything else equal, lower when the macro-environment is primarily demand driven. To check on the cyclicality of bond risk premiums that are implied by our regressions, we use the fitted values of the predictive regressions[13] as an estimate of the risk premium and regress it on a NBER dummy, the ratio of the aggregate demand variance, including the good and bad variances, to the corresponding aggregate supply variance, and the interaction of the two. We rescale the demand/supply ratio variable to have a standard deviation of one. Table 12 reports the results. First, coefficients on the NBER dummy are positive and increase with maturity. Economically, the effect is rather large: an NBER recession increases the annualized expected excess return on a 10-year bond on average by 5.64 percentage points. However, the coefficients are not statistically significantly different from zero, so we find only weak statistical evidence of counter-cyclical risk premiums. Second, the demand/supply ratio is indeed negatively associated with risk premiums, and especially so in recessions for the 5 and 10 year bonds. Again, these effects are economically large for the longer maturities, but not statistically significant. For example, for the 10 year bond, if the demand/supply ratio were to increase by 1 standard deviation, the annualized bond risk premium would not increase by 5.64 percentage points, but only by 2.82 (5.64-0.73-2.09) percentage points. Of course, it is important to recall that supply variances spike up as well in most recessions.

5.3 Macro Risks and Term Premiums

As we indicated before, most of the literature examining the link between the macroeconomy and bond risk premiums has focused on macro level factors.[14] One important exception is

[13]Including financial factors (level, slope, and curvature) to construct the expected excess bond returns does not materially change any of the results.

[14] An exception is Wachter (2006), where the risk premium depends on the surplus ratio, essentially a weighted average of past consumption shocks. However, the more recent theoretical literature (e.g., Buraschi and Jiltsov, 2007; Gabaix 2012; Bansal and Shaliastovich, 2013) suggests that focusing on second and higher order moments is more logical.

Wright (2011), who does not examine excess holding period returns, but an important and closely related component of bond yields, the term premium. Wright shows that term premiums are countercyclical and strongly affected by inflation uncertainty in a panel of countries.[15] We compute term premiums for the 5 year and 10 year maturity as the yield for each maturity minus the average of expected future short-term rates over the life of the bond. To measure the expected average short yield, we employ survey forecasts from the Blue Chip survey. Due to the limited availability of survey data, the sample we use for this exercise spans only 1983Q4-2015Q2 for the 5 year bond and 1986Q2-2015Q2 for the 10 year bond. We then regress the computed term premium on contemporaneous level macro factors and macro risk factors.

Results from this exercise are reported in Table 13. They are similar to the results in Table 11 on excess holding period returns. Expected core inflation, expected inflation and expected GDP growth significantly affect term premiums with the same signs as in the excess holding period return regressions. Moreover, the bad demand variance risk factor negatively and significantly affects the term premium, consistent with the idea that in such an environment bonds act as a good hedge. The adjusted R^2 is 69 percent for the 5 year and 67 percent for the 10 year bond. However, only for the 10-year term premium do the macro risk factors add significantly to the explanatory power of the macro level variables.

In Table 14, we examine the cyclicality of the term premiums. In line with Wright (2011) and Bauer, Rudebusch, and Wu (2014), we find that the term premium significantly increases in recessions, by 1.13 percent (0.77 percent) for the 5-year (10-year) bond. These numbers are economically significant and statistically significant at the 1 percent level. Surprisingly, we also find that the term premium is higher in demand environments, for the 5 year bond by about 0.5 percentage point (and significantly so), but the effect is not significant and smaller for the 10 year bond. However, the interaction effect with the NBER dummy has the expected negative sign and is significantly different from zero at the 1 percent significance level. The demand environment effects are large; a one standard deviation increase in the demand/supply variance ratio decreases the term premium by about 1 percentage point for the 5 year bond in a recession and about $\frac{2}{3}$ percentage point for the 10-year bond. Therefore, "demand effects" of this magnitude render the usual counter-cyclical term premium increase

[15] Bauer, Rudebusch, and Wu (2014) re-examine Wright's empirical evidence correcting for small sample bias in the VAR he runs to compute the term premium, but his main empirical conclusions remain robust.

in recessions economically (and statistically) insignificant.

6 Conclusion

In this article, we provide three main contributions. First, we develop a new identification methodology to decompose macroeconomic shocks into "demand" shocks which move inflation and GDP growth in the same direction and "supply shocks" which move inflation and GDP growth in opposite directions. The identification relies on non-Gaussianities in the macro data. We find aggregate demand shocks to be distinctly negatively skewed and leptokurtic, whereas supply shocks unconditionally show little skewness but are also leptokurtic. Despite this alternative identification, the long-run effects of the aggregate demand and supply shocks conform to standard intuition as in the seminal work of Blanchard and Quah (1989). Investigating the various recessions in our sample, we find the four recessions in the 1960s and 1970s to be predominantly supply driven, whereas of the last four, three were more demand driven (the exception being the 1990-91 recession). The Great Recession featured both large negative demand and supply shocks.

Second, we develop a new dynamic model for real economic activity and inflation, where the shocks are drawn from a Bad Environment - Good Environment model, which accommodates time-varying non-Gaussian features with "good" and "bad" volatility. We extract three macro-risk factors, bad and good volatilities for the aggregate demand shocks, and bad supply volatility (the good supply volatility is found to be time-invariant). Until about the mid-seventies conditional supply variances appear to dominate macroeconomic volatility, while afterwards demand variances are mostly relatively more important. However, supply shocks variances invariably peak in recessions. The "good" demand variance has decreased over time, but there is no strong evidence that either "bad" demand variances or supply variances have declined. Importantly, recessions continue to be accompanied by temporarily high bad demand and supply variances. We also provide new insights about the Great Moderation in that it appears to reflect primarily a decline in good demand variance. Finally, we find that the conditional correlation between inflation and real activity varies through time and regularly switches sign, as the relative importance of demand and supply risk factors varies over time.

Third, we link the macro factors extracted from the dynamic macro model, expected GDP growth, the unemployment gap, and expected (core) inflation and the macro risk variables represented by the conditional variances (shape parameters) of the demand and supply shocks, to the term structure. The macro variables explain 78 percent of the variation in the levels of yields. While the contribution of the macro risk factors to this R^2 is modest, it is nonetheless statistically significant. When we run predictive regressions of excess bond returns onto the macro variables, the R^2 is around 20 percent. Again, the contribution of the macro risk factors is statistically significant and increases with maturity. We find that increases in the bad aggregate demand variance significantly reduce bond risk premiums and also term premiums.

It would be useful to be elucidate how variation in risk premiums is accounted for by the various macro risk factors and decompose risk premiums into real and inflation components. To accomplish this, a term structure model is necessary. In future work, we plan to build a term structure model in which the macro variables (level and risk factors) feature as state variables. Despite the non-Gaussianities in their dynamics, the BEGE structure has the advantage that bond prices nonetheless remain affine in the state variables.

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Appendix A - Bootstrapping standard errors for the impulse responses

The VARMA parameters and the resulting reduced-form shocks are estimated with error, and so are the higher-order moments of the reduced-form shocks (and their covariance matrix). These sources of error affect the distribution of the sampling error of the loadings of the endogenous variables onto supply and demand shocks, the time series estimates of the supply and demand shocks, and the impulse response functions. To account for all of these sources of error, we use a bootstrapping routine.

We begin by sampling, with replacement, the reduced-form shocks from the estimated VARMA model. We assemble synthetic samples using 22 randomly chosen blocks of length 20 quarters. This results in synthetic samples of approximately the same length as our data (220 for bootstraps, 225 for the data). We use these shocks and the estimated VARMA parameters to build up synthetic samples of the endogenous variables. Note that we do not need any estimates of the covariance matrix of shocks to do this. Beginning from these synthetic samples, we follow the same procedures for each bootstrap sample that we do for the actual sample to calculate all the statistics of interest:

- Estimate VARMA(1,1) parameters on the synthetic sample. Here we deviate from the procedure used on the actual data by only estimating the VARMA by recursive-OLS and skipping the "second stage" quasi-maximum likelihood estimation, because the quasi-maximum likelihood estimation step is very time consuming.
- Estimate higher-order moments of the reduced form shocks and their covariance matrix
- Estimate loadings of the macro variables onto supply and demand using the GMM procedure on the higher order moments
- Invert supply and demand shocks suing the Kalman filter procedure
- Estimate the loadings of the yield variables onto the supply and demand shocks by OLS
- Estimate the impulse responses

Appendix B - Model-free Impulse Responses to Aggregate Demand and Supply Shocks

Following Jorda (2005), we calculate the model-free impulse responses using OLS regressions of the form:

$$Y_{t+h} = \beta_0 + \beta_1 Y_{t-1} + \beta_2 \hat{u}_{t-1}^{reduced} + \beta_3 \hat{u}_{t-1}^{supply} + \beta_4 \hat{u}_{t-1}^{demand} + \epsilon_{t+h},$$

where $\hat{u}^{reduced}$ are the residuals from the VARMA, and $\hat{u}^{supply}$ and $\hat{u}^{demand}$ are the inverted supply and demand shocks. Standard errors are computed as described in Appendix A.

The results are as follows:

Cumulative (20 Quarters) Responses		
	Demand shock	Supply shock
Real GDP level	0.56%	0.75%
	(0.35%)	(0.40%)
Price level	1.44%	-0.67%
	(0.53%)	(0.52%)

Appendix C - Maximum likelihood estimation of demand and supply shock dynamics

We restrict attention to the demand shock estimation, as the supply shock estimation is identical. The system to estimate is:

$$\begin{aligned}
&u^d_{t+1} = \sigma^d_p \omega^d_{p,t+1} - \sigma^d_n \omega^d_{n,t+1}, \\
&\omega^d_{p,t+1} \sim \Gamma(p^d_t, 1) - p^d_t, \\
&\omega^d_{n,t+1} \sim \Gamma(n^d_t, 1) - n^d_t, \\
&p^d_{t+1} = \bar{p}^d + \rho^d_p (p^d_t - \bar{p}^d) + \sigma^d_{pp} \omega^d_{p,t+1}, \\
&n^d_{t+1} = \bar{n}^d + \rho^d_n (n^d_t - \bar{n}^d) + \sigma^d_{nn} \omega^d_{n,t+1},
\end{aligned} \tag{12}$$

where only the time series of demand shock realizations, $\{u^d_t\}^T_{t=1}$ is observed.

The following notation is defined:

$U^d_t \equiv \{u^d_1, ..., u^d_t\}$ is the sequence of observations up to time t.

$F(i\phi, i\psi^1, i\psi^2 | U^d_t) \equiv E(e^{i\phi u^d_{t+1} + i\psi^1 p^d_{t+1} + i\psi^2 n^d_{t+1}} | U^d_t)$ is the next period's joint conditional characteristic function of the observation and the state variables.

$G_{t|s}(i\psi^1, i\psi^2) \equiv E(e^{i\psi^1 p^d_t + i\psi^2 n^d_t} | U^d_s)$ is the characteristic function of the time t state variables conditioned on observing data up to time s.

The estimation procedure is an application of Bates (2006)'s algorithm for the component model of two gamma distributed variables and consists of the time 0 initialization and 3 steps repeated for each observation in $\{u^d_t\}^T_{t=1}$. At time 0, the characteristic function of the state variables $G_{0|0}(i\psi^1, i\psi^2)$ is initialized. The distribution of p^d_0 and n^d_0 is approximated with gamma distributions. Note that the unconditional mean and variance of p^d_t are $E(p^d_t) = \bar{p}^d$ and $Var(p^d_t) = \frac{\sigma^2_{pp}}{1-\rho^{d2}_p} \bar{p}^d$, respectively. The approximation by the gamma distribution with the shape parameter k_0 and the scale parameter σ^p_0 is done by matching the first two unconditional moments. Using the properties of the gamma distribution, $k^p_0 = \frac{E^2 p^d_t}{Var(p^d_t)}$ and $\theta^p_0 = \frac{Var(p^d_t)}{E(p^d_t)}$. Thus, p^d_0 is assumed to follow $\Gamma(k^p_0, \theta^p_0)$ and n^d_0 is assumed to follow $\Gamma(k^n_0, \theta^n_0)$, where k^n_0 and θ^n_0 are computed in the same way. Using the properties of the expectations of the gamma variables, $G_{0|0}(i\psi^1, i\psi^2) = e^{-k^p_0 \ln(1-\theta^p_0 i\psi^1) - k^n_0 \ln(1-\theta^n_0 i\psi^2)}$. Given $G_{0|0}(i\psi^1, i\psi^2)$, computing the likelihood of U^d_T is performed by repeating the steps 1-3 below for all subsequent values of t.

Step 1. Computing the next period's joint conditional characteristic function of the observation and the state variables:

$$F(i\Phi, i\psi^1, i\psi^2|U_t^d) = E(E(e^{i\Phi(\sigma_p^d\omega_{p,t+1}^d - \sigma_n^d\omega_{n,t+1}^d) + i\psi^1(\bar{p}^d + \rho_p^d p_t^d + \sigma_{pp}^d\omega_{p,t+1}^d) + i\psi^2(\bar{n}^d(1-\rho_n^d) + \rho_n^d n_t^d + \sigma_{nn}^d\omega_{n,t+1}^d)}|U_t^d)$$
$$= E(e^{i\psi^1\bar{p}^d(1-\rho_p^d) + i\psi^2\bar{n}^d(1-\rho_n^d) + (i\psi^1\rho_p^d - \ln(1 - i\Phi\sigma_p^d - i\psi^1\sigma_{pp}^d) - i\Phi\sigma_p^d - i\psi^1\sigma_{pp}^d)p_t^d + (i\psi^2\rho_n^d - \ln(1 + i\Phi\sigma_n^d - i\psi^2\sigma_{nn}^d) + i\Phi\sigma_n^d - i\psi^2\sigma_{nn}^d)n_t^d}|U_t^d)$$
$$= e^{i\psi^1\bar{p}^d(1-\rho_p^d) + i\psi^2\bar{n}^d(1-\rho_n^d)}G_{t|t}(i\psi^1\rho_p^d - \ln(1 - i\Phi\sigma_p^d - i\psi^1\sigma_{pp}^d) - i\Phi\sigma_p^d - i\psi^1\sigma_{pp}^d, i\psi^2\rho_n^d - \ln(1 + i\Phi\sigma_n^d - i\psi^2\sigma_{nn}^d) + i\Phi\sigma_n^d - i\psi^2\sigma_{nn}^d).$$

Step 2. Evaluating the conditional likelihood of the time $t+1$ observation:

$$p(u_{t+1}^d|U_t^d) = \frac{1}{2\pi}\int_{-\infty}^{\infty} F(i\Phi, 0, 0|U_t^d)e^{-i\Phi u_{t+1}^d})d\Phi,$$

where the function F is defined in step 1 and the integral is evaluated numerically.

Step 3. Computing the conditional characteristic function for the next period, $G_{t+1|t+1}(i\psi^1, i\psi^2)$:

$$G_{t+1|t+1}(i\psi^1, i\psi^2) = \frac{\frac{1}{2\pi}\int_{-\infty}^{\infty} F(i\Phi, i\psi^1, i\psi^2|U_t^d)e^{-i\Phi u_{t+1}^d}d\Phi}{p(u_{t+1}^d|U_t^d)}.$$

As above, the function $G_{t+1|t+1}(i\psi^1, i\psi^2)$ is also approximated with the gamma distribution via matching the first two moments of the distribution. The moments are obtained by taking the first and second partial derivatives of the joint characteristic function:

$$E_{t+1}p_{t+1}^d = \frac{1}{2\pi p(u_{t+1}^d|U_t^d)}\int_{-\infty}^{\infty} F_{\psi^1}(i\Phi, 0, 0|U_t^d)e^{-i\Phi u_{t+1}^d}d\Phi,$$
$$Var_{t+1}p_{t+1}^d = \frac{1}{2\pi p(u_{t+1}^d|U_t^d)}\int_{-\infty}^{\infty} F_{\psi^1\psi^1}(i\Phi, 0, 0|U_t^d)e^{-i\Phi u_{t+1}^d}d\Phi - E_{t+1}^2 p_{t+1}^d,$$
$$E_{t+1}n_{t+1}^d = \frac{1}{2\pi p(u_{t+1}^d|U_t^d)}\int_{-\infty}^{\infty} F_{\psi^2}(i\Phi, 0, 0|U_t^d)e^{-i\Phi u_{t+1}^d}d\Phi,$$
$$Var_{t+1}n_{t+1}^d = \frac{1}{2\pi p(u_{t+1}^d|U_t^d)}\int_{-\infty}^{\infty} F_{\psi^2\psi^2}(i\Phi, 0, 0|U_t^d)e^{-i\Phi u_{t+1}^d}d\Phi - E_{t+1}^2 n_{t+1}^d,$$

where F_{ψ^i} denotes the derivative of F with respect to ψ^i. The expressions inside the integral are obtained in closed form by derivating the function $F(i\Phi, i\psi^1, i\psi^2|U_t^d)$ in step 1, and integrals are evaluated numerically. Using the properties of the gamma distribution, the values of the shape and the scale parameters are $k_{t+1}^p = \frac{E_{t+1}^2 p_{t+1}^d}{Var_{t+1}p_{t+1}^d}$ and $\theta_{t+1}^p = \frac{Var_{t+1}p_{t+1}^d}{E_{t+1}p_{t+1}^d}$, respectively. The expressions for k_{t+1}^n and θ_{t+1}^n are similar.

The total likelihood of the time series is the sum of individual likelihoods from step 2: $L(Y_T) = \ln p(u_1^d|k_0^p, \theta_0^p) + \sum_{t=2}^T \ln p(u_{t+1}^d|U_t^d)$.

Appendix D - Additional Results on Explanatory Power of Macro Risks

Explanatory Power (Adjusted R^2) of Macro Risk Factors for Yield Curve Factors over Realizations of Macroeconomic Time Series. The sample is quarterly from 1959Q2 to 2015Q2. Macro level factors are real GDP growth, aggregate and core inflation, and unemployment gap. Financial factors are level, slope, and curvature factors. Level factor is the average over 1-10 year yields. Slope factor is 10 year yield minus 1 quarter yields. The curvature factor is 10 year yield plus 1 quarter yield minus 2 times 2 year yield. The increase in adjusted R^2 significance, which is always tested over the specification in the previous row, is Bauer-Hamilton (2016) adjusted significance using 5000 bootstrap runs. The asterisks, *, **, and *** correspond to statistical significance at the 10, 5, and 1 percent levels, respectively.

Realizations of Macroeconomic Level Factors and Macro Risks			
	Level	Slope	Curvature
Realizations of macroeconomic level factors	0.4849	0.5148	0.2009
Realizations of macroeconomic time series+macro risks	0.6140***	0.5334*	0.2667**

Explanatory Power (Adjusted R^2) of Macro Risk Factors for Quarterly Excess Bond Returns over Other Macroeconomic Level and Financial Factors. The sample is quarterly from 1959Q2 to 2015Q2. Ang-Piazzesi factors are lag 1 Ang and Piazzesi (2003) real and nominal factors. Macro level factors are expected real GDP growth, expected aggregate and core inflation, and unemployment gap. Financial factors are level, slope, and curvature factors. Level factor is the average over 1-10 year yields. Slope factor is 10 year yield minus 1 quarter yields. The curvature factor is 10 year yield plus 1 quarter yield minus 2 times 2 year yield. The increase in adjusted R^2 significance, which is tested over the specification in the previous row, is Bauer-Hamilton (2016) adjusted significance using 5000 bootstrap runs. The asterisks, *, **, and *** correspond to statistical significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Ang-Piazzesi (2003) factors				
Predictors	1 year bond	2 year bond	5 year bond	10 year bond
Ang-Piazzesi factors	0.0320	0.0339	0.0166	0.0068
Ang-Piazzesi factors + macro level factors	0.1559***	0.1800***	0.1576***	0.1515***
Ang-Piazzesi factors + macro level factors + macro risks	0.1848**	0.2157**	0.1932**	0.1928**
Panel B: Ang-Piazzesi (2003) and yield curve factors				
	1 year bond	2 year bond	5 year bond	10 year bond
3 financial factors	0.0715	0.0681	0.0716	0.075
3 financial factors + Ang-Piazzesi	0.1066**	0.0995**	0.0754	0.0689
3 financial factors + Ang-Piazzesi+ macro level factors	0.2053***	0.2133***	0.1738***	0.1594***
3 financial factors+Ang-Piazzesi+macro level factors + macro risks	0.2355**	0.2482**	0.2037**	0.1916**

Figure 1 – Components of Bad Environment - Good Environment Distribution.

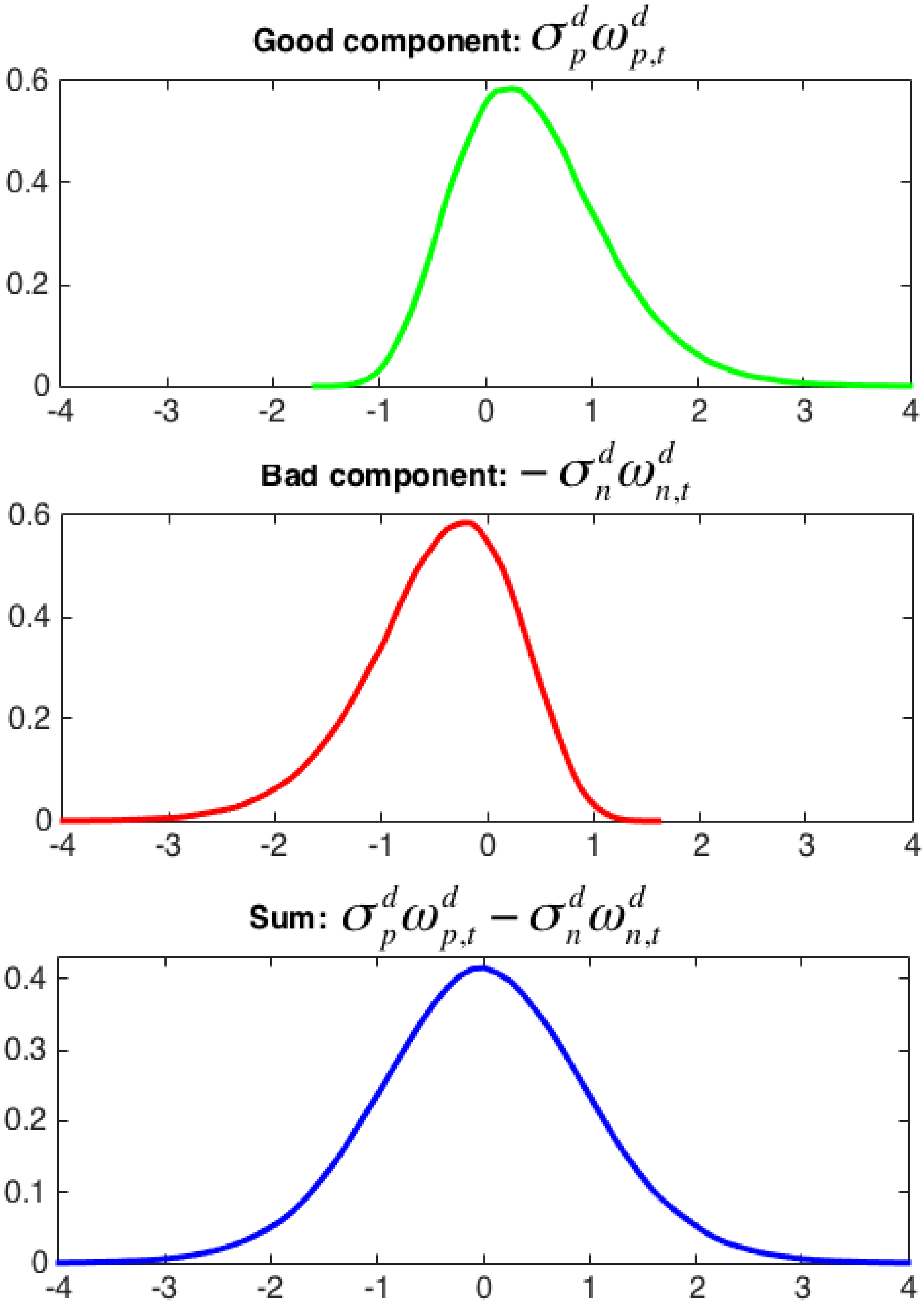


Figure 2 – Time-varying Shape Parameters of Bad Environment - Good Environment Distribution.

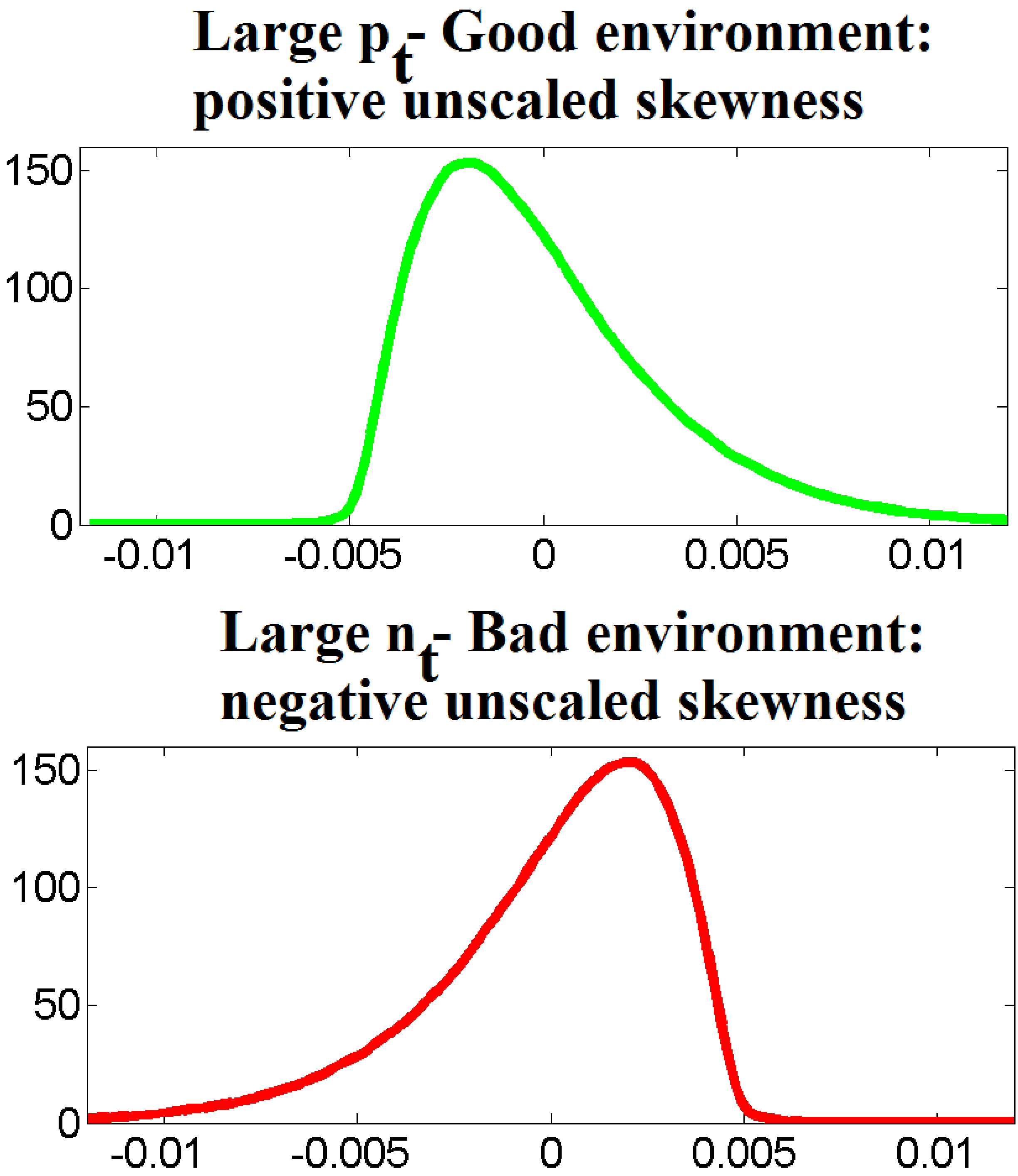


Figure 3 – Filtered Quarterly Demand and Supply Shocks. Shading corresponds to NBER Recessions.

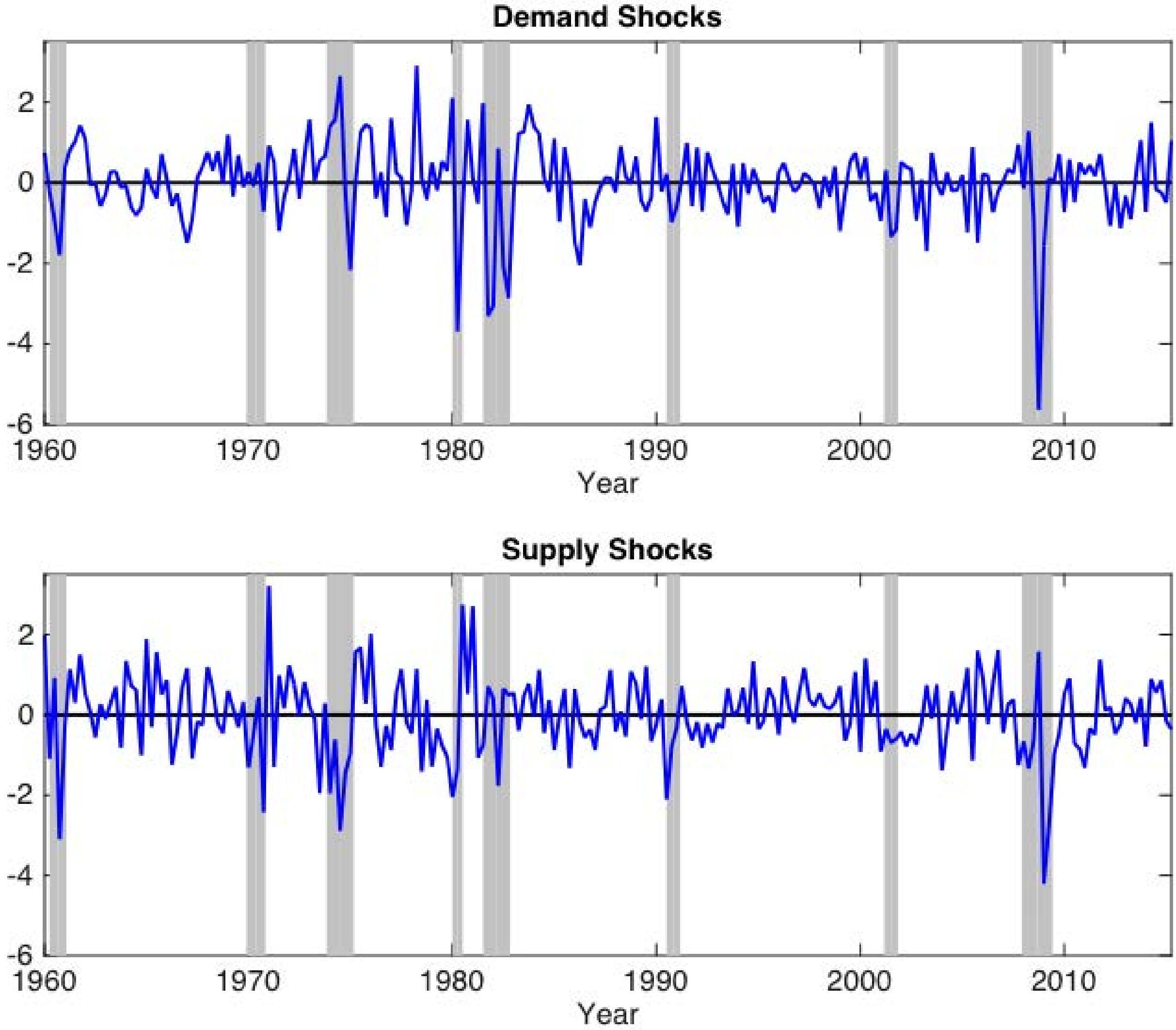


Figure 4 – Filtered Quarterly Demand and Supply Variances. Shading corresponds to NBER Recessions.

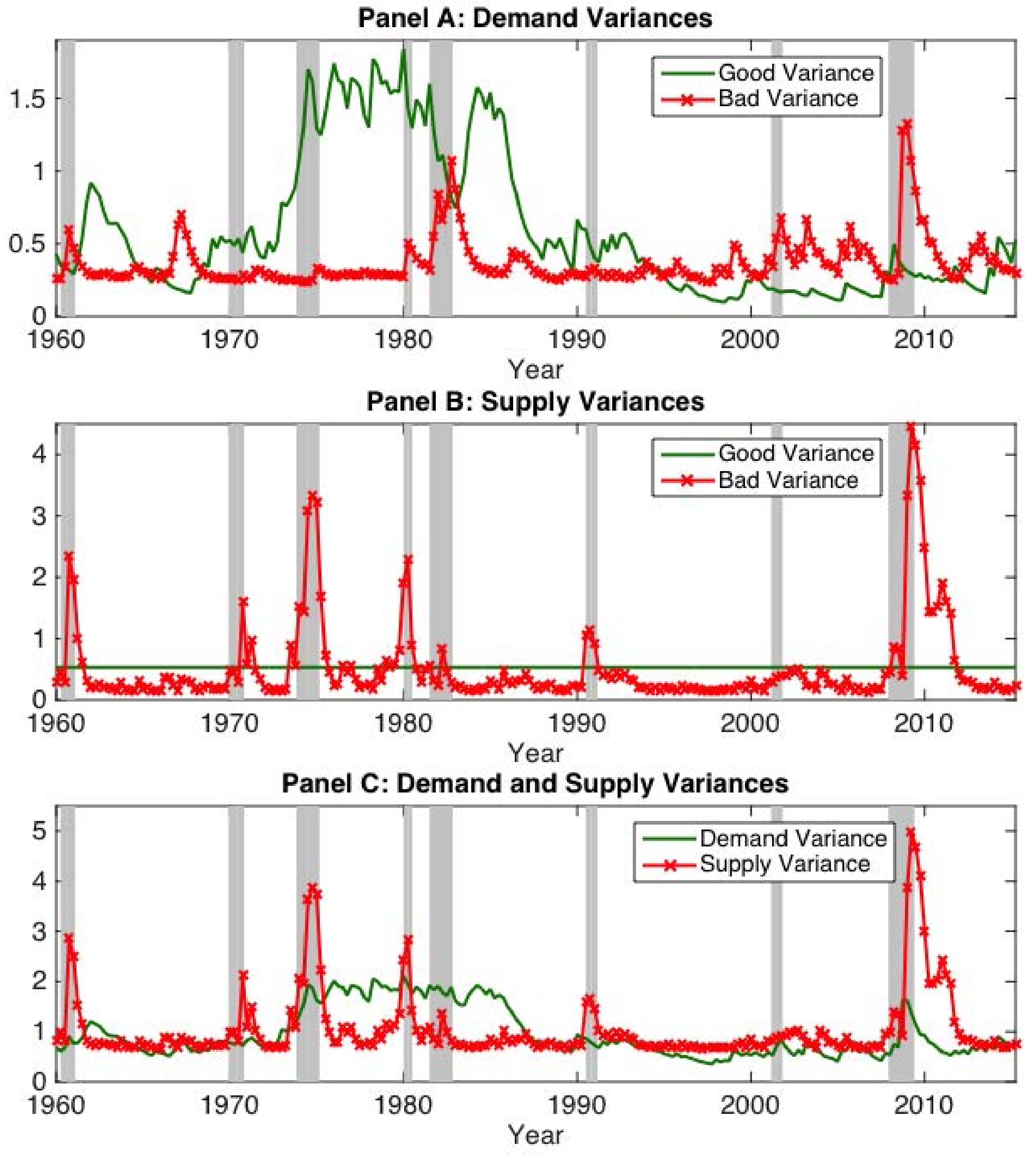


Figure 5 – Quarterly Conditional Skewness of Macroeconomic Variables. Shading corresponds to NBER Recessions.

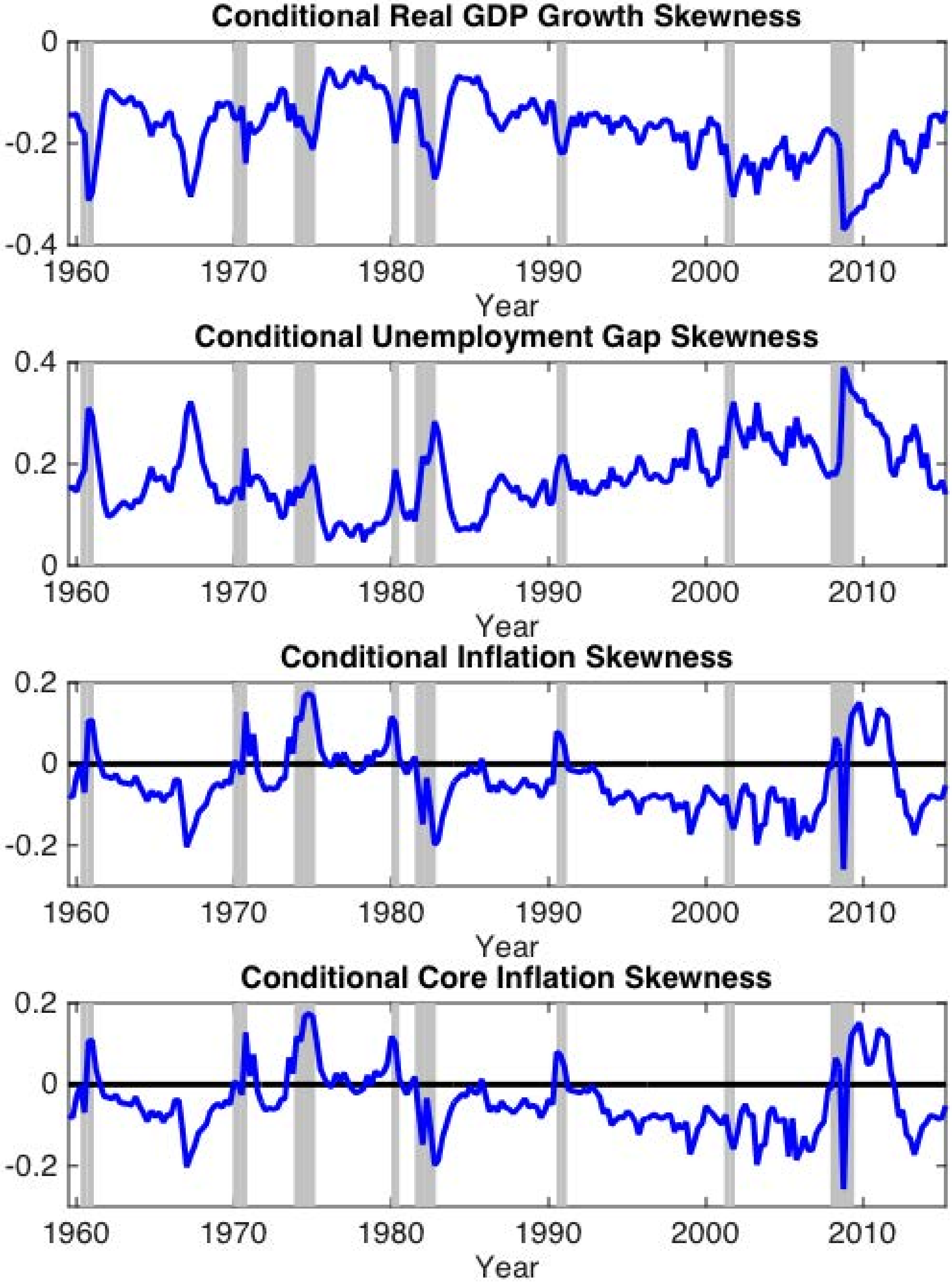
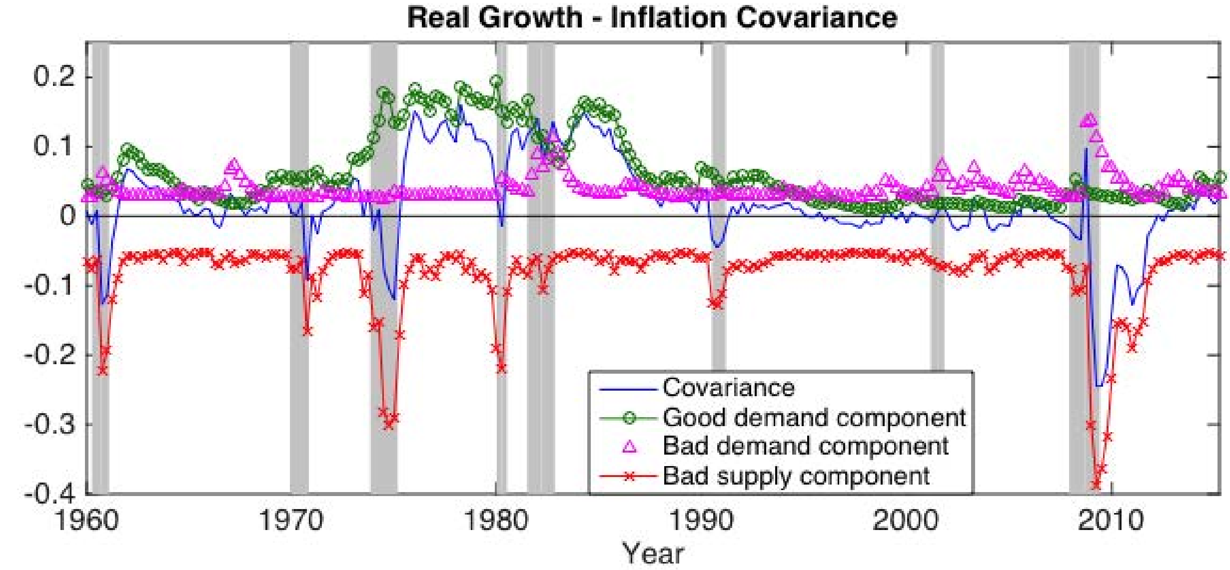


Figure 6 – Quarterly Conditional Covariance between Macroeconomic Variables. Shading corresponds to NBER Recessions.



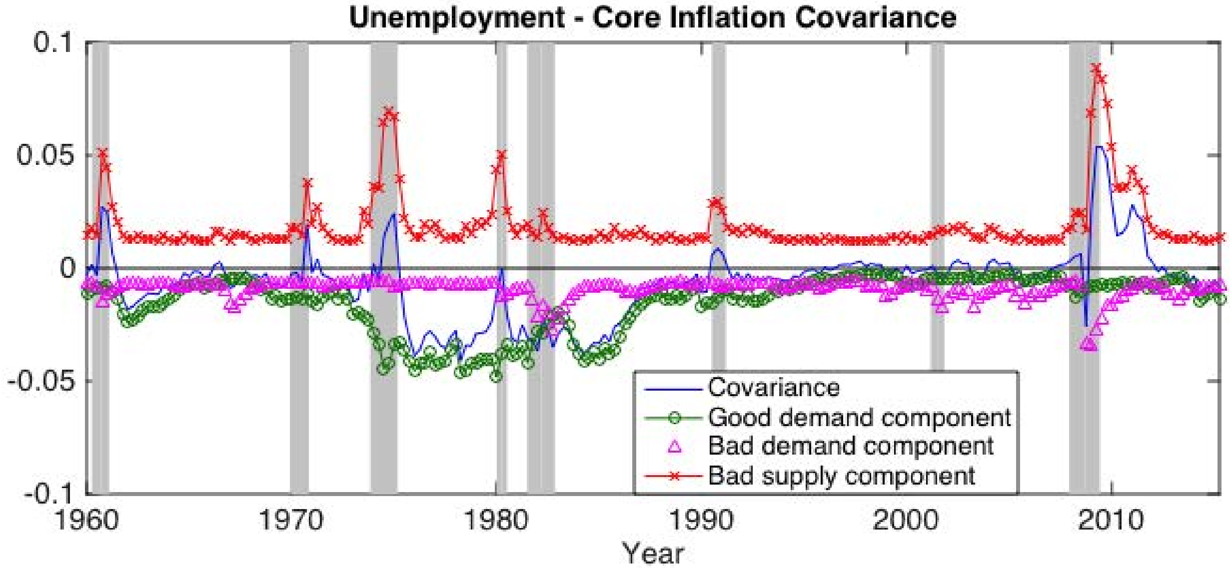


Table 1 – Model Selection for Expectations of Macro Variables. The sample is quarterly 1959Q2 to 2015Q2. Macro variables are real GDP growth, aggregate and core inflations, and unemployment gap. VAR and VARMA always include these 4 variables. Yields are 1 quarter and 10 year US Treasury yields. AIC and BIC are Akaike and Bayesian information criteria, respectively. The models are sorted by AIC.

Model	number of parameters	loglikelihood	AIC	BIC
VARMA(1,1)+yields	50	-433.7	979.5	1207.1
VARMA(1,2)+yields	66	-420.9	995.2	1290.1
VARMA(1,2)	58	-434.1	1000.6	1262.2
VARMA(2,1)+yields	66	-423.8	1001.1	1296.0
VARMA(1,1)	42	-457.2	1007.0	1199.8
VARMA(2,1)	58	-437.5	1007.4	1269.0
VAR(2)+yields	50	-458.2	1028.6	1256.1
VAR(2)	42	-473.6	1039.7	1232.5
VAR(1)+yields	34	-503.3	1080.2	1237.6
VAR(1)	26	-521.3	1097.8	1219.2

Table 2 – Higher Order Moments of Macroeconomic Shocks Used for Classical Minimum Distance Estimation. u_t^g, u_t^π, $u_t^{\pi^{core}}$, and u_t^u are the shocks to real GDP growth, aggregate inflation, core inflation and unemployment gap, respectively. The data is quarterly from 1959Q2 to 2015Q2. The covariance matrix for moments is calculated via a block-bootstrap with a block length of 20 quarters using a shrinkage technique that places 95 percent weight on the full bootstrapped covariance matrix, and a 5 percent weight on a matrix composed of only the diagonal elements of the covariance matrix. Asterisks, *, **, and **** correspond to statistical significance of individual moments at the 10, 5, and 1 percent levels, respectively.

			Volatility			
	u_t^π	u_t^g	$u_t^{\pi^{core}}$	u_t^u		
data	0.5430***	0.7503***	0.3103***	0.2560***		
standard error	(0.0834)	(0.0709)	(0.0457)	(0.0185)		
fitted	0.5008	0.7267	0.3395	0.2614		
			Skewness			
	u_t^π	u_t^g	$u_t^{\pi^{core}}$	u_t^u		
data	-1.2632	0.1275	0.1866	0.6860***		
standard error	(0.9124)	(0.3064)	(0.4598)	(0.2372)		
fitted	-0.2328	-0.3188	-0.2804	0.3576		
			Excess Kurtosis			
	u_t^π	u_t^g	$u_t^{\pi^{core}}$	u_t^u		
data	10.3646**	1.6505**	2.3854**	1.9179***		
standard error	(5.1438)	(0.7314)	(1.1802)	(0.6808)		
fitted	0.4552	0.8090	0.6070	0.9314		
			Correlations			
	$u_t^\pi u_t^g$	$u_t^\pi u_t^{\pi^{core}}$	$u_t^\pi u_t^u$	$u_t^g u_t^{\pi^{core}}$	$u_t^g u_t^u$	$u_t^{\pi^{core}} u_t^u$
data	0.0505	0.4879***	-0.0602	-0.0116	-0.5763***	-0.0097
standard error	(0.0983)	(0.0658)	(0.0584)	(0.1206)	(0.0478)	(0.1060)
fitted	0.0766	0.5487	-0.1040	0.1175	-0.5496	-0.1446
			Co-skewness			
	$(u_t^\pi)^2 u_t^g$	$(u_t^\pi)^2 u_t^{\pi^{core}}$	$(u_t^\pi)^2 u_t^u$	$(u_t^g)^2 u_t^\pi$	$(u_t^g)^2 u_t^{\pi^{core}}$	$(u_t^g)^2 u_t^u$
data	-0.7728	-0.2339	0.7322*	-0.2404	-0.1860	0.1877
standard error	(0.4328)	(0.3097)	(0.4016)	(0.1780)	(0.1912)	(0.3358)
fitted	-0.2316	-0.2474	0.2416	-0.2982	-0.3185	0.3314
	$(u_t^{\pi^{core}})^2 u_t^\pi$	$(u_t^{\pi^{core}})^2 u_t^g$	$(u_t^{\pi^{core}})^2 u_t^u$	$(u_t^u)^2 u_t^\pi$	$(u_t^u)^2 u_t^g$	$(u_t^u)^2 u_t^{\pi^{core}}$
data	0.0814	-0.1920	0.0847	-0.1989	-0.4535	-0.0265
standard error	(0.3184)	(0.1459)	(0.2143)	(0.1384)	(0.3097)	(0.2290)
fitted	-0.2632	-0.2721	0.2833	-0.3172	-0.3443	-0.3392
			Excess Co-kurtosis			
	$(u_t^\pi)^2(u_t^g)^2$	$(u_t^\pi)^2(u_t^{\pi^{core}})^2$	$(u_t^\pi)^2(u_t^u)^2$	$(u_t^g)^2 u_t^{\pi^{core}})^2$	$(u_t^g)^2(u_t^u)^2$	$(u_t^{\pi^{core}})^2(u_t^u)^2$
data	1.7346*	0.6331*	1.2858*	0.7458**	1.1438**	0.7440**
standard error	(1.0385)	(0.3624)	(0.7526)	(0.3166)	(0.5808)	(0.2958)
fitted	0.5978	0.5879	0.6107	0.5973	0.6246	0.6100
	$(u_t^\pi)^3 u_t^g$	$(u_t^\pi)^3 u_t^{\pi^{core}}$	$(u_t^\pi)^3 u_t^u$	$(u_t^g)^3 u_t^\pi$	$(u_t^g)^3 u_t^{\pi^{core}}$	$(u_t^g)^3 u_t^{\pi^{core}}$
data	4.1478	1.6103	-3.6442*	0.6476*	0.2348	-1.0978**
standard error	(2.6028)	(1.0459)	(2.0561)	(0.3878)	(0.4592)	(0.5212)
fitted	0.2481	0.5882	-0.2705	0.2811	0.2803	-0.6164
	$(u_t^{\pi^{core}})^3 u_t^\pi$	$(u_t^{\pi^{core}})^3 u_t^g$	$(u_t^{\pi^{core}})^3 u_t^u$	$(u_t^u)^3 u_t^\pi$	$(u_t^u)^3 u_t^g$	$(u_t^u)^3 u_t^{\pi^{core}}$
data	1.1992*	-0.1287	-0.6296*	0.1202	-1.3911**	0.1151
standard error	(0.6307)	(0.4176)	(0.3684)	(0.2634)	(0.6803)	(0.5523)
fitted	0.5877	0.2458	-0.2681	-0.3491	-0.6336	-0.3483
J-stat	49.99**					
pval	(0.0482)					

Table 3 – Loadings of Macroeconomic Shocks on Demand and Supply Shocks. The coefficients are from Classical Minimum Distance estimation matching unconditional higher order moments of 4 macroeconomic shocks time series: real GDP growth (u_t^g), aggregate (u_t^π) and core inflation ($u_t^{\pi core}$) and unemployment gap (u_t^u). Standard errors in parentheses account for sampling error in the higher-order moments and the VARMA(1,1) parameters.

Panel A: Loadings of Macro Shocks Onto Supply and Demand				
Shock	Supply loading	Demand Loading		
u_t^π	-0.2319	0.2618		
	(0.0625)	(0.0625)		
u_t^g	0.3352	0.4015		
	(0.0975)	(0.1585)		
$u_t^{\pi core}$	-0.1587	0.1787		
	(0.0434)	(0.0529)		
u_t^u	-0.1125	-0.1464		
	(0.0216)	(0.0464)		
idiosyncratic variance share	0.4702			
	(0.0752)			
Panel B: Kalman Gain of Macro Shocks for Supply and Demand				
Shock	u_t^π	u_t^g	$u_t^{\pi core}$	u_t^u
Supply	-0.7389	0.4837	-1.083	-1.3036
	(0.1934)	(0.1054)	(0.2070)	(0.2489)
Demand	0.6597	0.4578	0.9642	-1.3393
	(0.2143)	(0.1021)	(0.2991)	(0.2170)
Panel C: Variance Decomposition of Demand and Supply Shocks				
Shock	u_t^π	u_t^g	$u_t^{\pi core}$	u_t^u
Supply	26.28%	24.87%	26.36%	22.49%
Demand	23.83%	25.36%	23.77%	27.05%
Panel D: Unconditional moments of supply and demand				
	Skewness	Excess kurtosis		
Supply	0.4210	3.2861		
	(0.6769)	(1.7520)		
Demand	-1.5941	4.6540		
	(0.7807)	(2.2930)		

Table 4 – Model Comparision for Aggregate Demand and Aggregate Supply Shocks. AIC refers to Akaike information criterion and BIC refers to Bayesian information criterion. The models are sorted by AIC. Regime-switching model refers to the 2 state regime-switching model. For both supply and demand shocks, it is the best regime-switching model in terms of AIC and BIC among 1 state, 2 state, 3 state, and 4 state models. BEGE is the n-tail only BEGE for supply and full BEGE with n- and p-tails for demand. These are the best BEGE models in terms of AIC and BIC.

Panel A: Supply Shock				
Model	Log-likelihood	Number of parameters	AIC	BIC
Regime-switching	-296.70	5	603.36	620.35
BEGE	-300.37	4	608.74	622.33
Gaussian stochastic volatility	-303.87	3	613.74	623.93
Panel B: Demand Shock				
Model	Log-likelihood	Number of parameters	AIC	BIC
BEGE	-282.19	6	572.38	585.97
Regime-switching	-286.58	5	583.16	600.15
Gaussian stochastic volatility	-306.70	3	619.40	629.59
Panel C: Supply and Demand Shocks				
	Log-likelihood	Number of parameters	AIC	BIC
BEGE	-582.56	10	1185.12	1226.03
Regime-switching	-583.28	10	1186.56	1227.47
Gaussian stochastic volatility	-610.57	6	1233.14	1257.69

Table 5 – Bad Environment - Good Environment Parameter Estimates for Demand and Supply Processes. Parameter estimates are obtained using Bates (2006) approximate maximum likelihood methodology. Standard errors in parentheses are approximate maximum likelihood asymptotic standard errors. As demand and supply shocks are assumed to have variances exactly equal to 1, parameters $\bar{p}^s$ and $\bar{n}^s$ can be solved as functions of other model parameters, and their standard errors are calculated using the delta method.

	Supply shock	Demand shock
$\bar{p}$	0.5289	100
	(0.1127)	–
$\bar{n}$	1.0663	0.3883
	(1.4523)	(0.2085)
σ_p	–	0.0803
	–	(0.0051)
σ_n	0.6647	0.9565
	(0.4081)	(0.2593)
ρ_p	–	0.9636
		(0.0193)
ρ_n	0.7895	0.7880
	(0.0830)	(0.2608)
σ_{pp}	–	2.0129
		(0.6282)
σ_{nn}	1.0296	0.1889
	(0.5154)	(0.2593)

Table 6 – VARMA(1,1) Impulse Responses of Real GDP and Aggregate Price Level to One Standard Deviation Demand and Supply Shocks. The cumulative impulse responses include the quarter 0 (where the shocks happened) responses. Standard errors in parentheses are bootstrap standard errors.

Panel A: Contemporaneous (Quarter 0) Responses		
	Demand shock	Supply shock
Real GDP level	0.40%	0.34%
	(0.16%)	(0.10%)
Price level	0.26%	-0.23%
	(0.06%)	(0.06%)
Panel B: Cumulative (20 Quarters) Responses		
	Demand shock	Supply shock
Real GDP level	0.17%	0.65%
	(0.28%)	(0.25%)
Price level	0.97%	-0.80%
	(0.53%)	(0.43%)

Table 7 – Decomposition of Real GDP Growth during NBER Recessions into Demand and Supply Components. Aggregate demand component of the GDP growth is computed as σ_{gd} multiplied by the sum of aggregate demand shocks over the period of the recession. Aggregate supply component of the GDP growth is computed as σ_{gs} multiplied by the sum of aggregate supply shocks over the period of the recession.

NBER Recession	GDP growth: Demand component	GDP growth: Supply Component
1960Q2-1961Q1	-1.04%	-1.20%
1969Q4-1970Q4	-0.06%	-1.16%
1973Q4-1975Q1	1.55%	-2.54%
1980Q1-1980Q2	-0.64%	-1.14%
1981Q3-1982Q4	-3.41%	-0.09%
1990Q3-1991Q1	-0.55%	-1.07%
2001Q1-2001Q4	-1.26%	-0.86%
2008Q1-2009Q2	-2.77%	-2.69%

Table 8 – Decomposing Great Moderation into Changes in Demand and Supply Volatility. Coefficients in Panel A are OLS regression coefficients from regressing the dependent variable on a constant equal to 1 and a dummy variable which is 0 before 1990Q4 and 1 between 1991Q1 and 2000Q4 for the sample of 1959Q2-2000Q4 (specification Dummy-2000), 0 before 1990Q4 and 1 between 1991Q1 and 2006Q4 for the sample of 1959Q2-2006Q4 (specification Dummy-2006) , and 0 before 1990Q4 and 1 between 1991Q1 and 2015Q2 for the sample of 1959Q2-2015Q2 (specification Dummy-2015). Coefficients in Panel B are OLS regression coefficients from regressing the dependent variable on a constant equal to 1 and a dummy variable which is 0 before 1983Q4 and 1 between 1984Q1 and 2000Q4 for the sample of 1959Q2-2000Q4 (specification Dummy-2000), 0 before 1983Q4 and 1 between 1984Q1 and 2006Q4 for the sample of 1959Q2-2006Q4 (specification Dummy-2006), and 0 before 1983Q4 and 1 between 1984Q1 and 2015Q2 for the sample of 1959Q2-2015Q2 (specification Dummy-2015). Standard errors in parentheses are Newey-West (1987) standard errors computed with 40 lags. The standard errors for the constant are from the regression using only data up to 2000Q4. The standard errors for the constant for samples spanning until 2006Q4 and 2015Q2 are slightly different, but these differences are economically and statistically negligible. The asterisks, *, **, and *** correspond to statistical significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Aggregate Inflation				
Dependent variable	Constant	Dummy-2000	Dummy-2006	Dummy-2015
Aggregate Volatility	0.2460***	-0.0514**	-0.0510***	-0.0345
	(0.0183)	(0.0206)	(0.0193)	(0.0223)
Supply volatility	0.0551***	-0.0111	-0.0109*	0.0023
	(0.0056)	(0.0074)	(0.0065)	(0.0114)
Demand volatility	0.0823***	-0.0403**	-0.0401***	-0.0368**
	(0.0150)	(0.0157)	(0.0153)	(0.0153)
Good demand volatility	0.0587***	-0.0374***	-0.0410***	-0.0401***
	(0.0140)	(0.0149)	(0.0149)	(0.0144)
Bad demand volatility	0.0237***	-0.0028	0.0008	0.0033
	(0.0019)	(0.0020)	(0.0031)	(0.0035)
Panel B: Real GDP Growth				
Dependent variable	Constant	Dummy-2000	Dummy-2006	Dummy-2015
Aggregate volatility	0.5585***	-0.0932*	-0.1009*	-0.0786
	(0.0512)	(0.0536)	(0.0516)	(0.0542)
Supply volatility	0.1221***	-0.0320**	-0.0312**	-0.0085
	(0.0126)	(0.0134)	(0.0130)	(0.0219)
Demand volatility	0.1936***	-0.0612	-0.0698*	-0.0700*
	(0.0413)	(0.0424)	(0.0407)	(0.0395)
Good demand volatility	0.1371***	-0.0549	-0.0695*	-0.0749*
	(0.0388)	(0.0418)	(0.0410)	(0.0390)
Bad demand volatility	0.0565***	-0.0063	-0.0003	0.0049
	(0.0059)	(0.0056)	(0.0082)	(0.0094)

Table 9 – Explanatory Power (Adjusted R^2) of Macro Risk Factors for Yield Curve Factors. The sample is quarterly from 1959Q2 to 2015Q2. Ang-Piazzesi factors are lag 1 Ang and Piazzesi (2003) real and nominal factors. Macro level factors are expected real GDP growth, expected aggregate and core inflation, and unemployment gap. Financial factors are level, slope, and curvature factors. Level factor is the average over 1-10 year yields. Slope factor is 10 year yield minus 1 quarter yields. The curvature factor is 10 year yield plus 1 quarter yield minus 2 times 2 year yield. The increase in adjusted R^2 significance, which is always tested over the specification in the previous row, is Bauer-Hamilton (2016) adjusted significance using 5000 bootstrap runs. The asterisks, *, **, and *** correspond to statistical significance at the 10, 5, and 1 percent levels, respectively.

Panel A: Macro Level Factors and Macro Risks			
	Level	Slope	Curvature
Macro level factors	0.7155	0.5818	0.2795
Macro level factors + macro risks	0.7755***	0.5892	0.3343**
Panel B: Ang-Piazzesi Factors, Macro Level Factors, and Macro Risks			
	Level	Slope	Curvature
Ang-Piazzesi (2003) factors	0.1784	0.2432	0.0928
Ang-Piazzesi (2003) factors + macro level factors	0.7296***	0.5843***	0.3085***
Ang-Piazzesi (2003) factors + macro level factors + macro risks	0.7775***	0.6027	0.3429**

Table 10 – Explanatory Power (Adjusted R^2) of Macro Risk Factors for Quarterly Excess Bond Returns over Macro Level and Financial Factors. The sample is quarterly from 1959Q2 to 2015Q2. Ang-Piazzesi factors are lag 1 Ang and Piazzesi (2003) real and nominal factors. Macro level factors are expected real GDP growth, expected aggregate and core inflation, and unemployment gap. Financial factors are level, slope, and curvature factors. Level factor is the average over 1-10 year yields. Slope factor is 10 year yield minus 1 quarter yields. The curvature factor is 10 year yield plus 1 quarter yield minus 2 times 2 year yield. The increase in adjusted R^2 significance, which is tested over the specification in the previous row, is Bauer-Hamilton (2016) adjusted significance using 5000 bootstrap runs. The asterisks, *, **, and *** correspond to statistical significance at the 10, 5, and 1 percent levels, respectively.

	1 year bond	2 year bond	5 year bond	10 year bond
3 financial factors	0.0715	0.0681	0.0716	0.0750
3 financial factors + macro level factors	0.2109***	0.2178***	0.1788***	0.1591***
3 financial factors + macro level factors + macro risks	0.2301*	0.2424**	0.2085**	0.1988**

Table 11 – Explanatory Power (Adjusted R^2) of Macro Factors for Quarterly Excess Bond Returns. The sample is quarterly from 1959Q2 to 2015Q2. The excess returns are annualized 1 quarter holding period returns on zero coupon US Treasuries. Macro risks (p_t^d, n_t^d, and n_t^s) are scaled to have unit variance. Standard errors in parentheses are Newey-West standard errors with 40 lags. The increase in adjusted R^2 significance is Bauer-Hamilton (2016) adjusted significance using 5000 bootstrap runs. The asterisks, * , **, and *** correspond to statistical significance at the 10, 5, and 1 percent levels, respectively.

	1 year bond	2 year bond	5 year bond	10 year bond
constant	0.9624***	2.6468***	6.7833**	14.2700**
	(0.2943)	(0.8466)	(3.0182)	(6.0308)
$E_t\pi_{t+1}^{core}$	6.8551***	15.4054***	30.2019***	49.9707***
	(1.5998)	(2.7506)	(3.7516)	(6.2916)
$E_t\pi_{t+1}$	-7.8497***	-17.2407***	-34.9451***	-57.7668***
	(1.5207)	(2.6357)	(4.0636)	(7.6564)
$E_t g_{t+1}$	0.4143	0.9182	1.9110	3.8141
	(0.8104)	(1.4089)	(2.0339)	(2.8579)
$ugap_t$	0.0392	0.2961	0.7349	1.5665
	(0.0751)	(0.1795)	(0.6481)	(1.3377)
p_t^d	0.2943	0.5264	1.0352	1.1977
	(0.1946)	(0.4577)	(1.3542)	(2.7203)
n_t^d	-0.5017***	-1.1972***	-3.0267***	-6.1206***
	(0.1363)	(0.2394)	(0.6591)	(1.2606)
n_t^s	0.1002	0.1912	0.4010	0.7555
	(0.2041)	(0.4058)	(0.7319)	(1.0865)
Adjusted R^2 without macro risks	0.1577	0.1814	0.1604	0.1479
Adjusted R^2 with macro risks	0.1793*	0.2097**	0.1990**	0.2001***

Table 12 – Cyclicality of Expected Excess Bond Returns. The sample is quarterly 1959Q2-2015Q2. The dependent variable is the expected annualized quarterly excess return computed from the OLS regressions of realized annualized quarterly excess returns on 4 macro level factors (expected aggregate and core inflations, expected real GDP growth, and unemployment gap) and 3 macro risks (good and bad demand variance and bad supply variance). NBER recession is a dummy equal to 1 if there is a recession in that quarter. Demand/supply-ratio is the ratio of aggregate demand variance (good+bad) to aggregate supply variance (good+bad). Demand/supply-ratio is scaled to have the standard deviation of 1. Standard errors are Newey-West standard errors computed with 40 lags.

	1 year bond	5 year bond	10 year bond
constant	0.1914	1.5795	3.3505
	(0.4076)	(1.9782)	(3.3727)
NBER-dummy	0.8691	3.6316	5.6361
	(0.6250)	(2.8888)	(4.9554)
demand/supply-ratio	-0.0172	-0.2478	-0.7336
	(0.2463)	(1.1384)	(1.9008)
NBER-dummy×demand/supply-ratio	-0.1979	-1.0040	-2.0924
	(0.3114)	(1.4453)	(2.4745)
Adjusted R^2	0.0297	0.0239	0.0236

Table 13 – Explanatory Power (Adjusted R^2) of Macro Factors for Term Premiums. The dependent variable is annualized term premium computed as the observed US Treasury long yield minus the expected 1 quarter US Treasury yield over the life of the long yield. Expected average short yield is from Blue Chip survey and are available semi-annually. The sample is 1983Q4-2015Q2 for 5 year bond and 1986Q2-2015Q2 for 10 year bond. The standard deviation of each macro risk factor (p_t^d, n_t^d, and n_t^s) is scaled to 1. Standard errors in parentheses are Newey-West standard errors with 40 lags. The increase in adjusted R^2 significance is Bauer-Hamilton (2016) significance using 5000 bootstrap runs. The asterisks, * , **, and *** correspond to statistical significance at the 10, 5, and 1 percent levels, respectively.

	5 year bond	10 year bond
constant	0.9548***	1.5578***
	(0.2741)	(0.2195)
$E_t\pi_{t+1}^{core}$	7.2809***	8.6933***
	(0.8006)	(0.8701)
$E_t\pi_{t+1}$	-5.3035***	-6.3997***
	(0.8144)	(0.8616)
$E_t g_{t+1}$	2.2232***	2.7737***
	(0.2239)	(0.2196)
$ugap_t$	-0.0079	0.1799
	(0.0863)	(0.1502)
p_t^d	-0.1211	0.0115
	(0.1041)	(0.1353)
n_t^d	-0.1847***	-0.2247***
	(0.0641)	(0.0502)
n_t^s	0.0657	0.0237
	(0.0769)	(0.1343)
Adjusted R^2 without macro risks	0.6823	0.6437
Adjusted R^2 with macro risks	0.6933	0.6717**

Table 14 – Cyclicality of Term Premium. The dependent variable is annualized term premium computed as the observed US Treasury long yield minus the expected 1 quarter US Treasury yield over the life of the long yield. Expected average short yield is from Blue Chip survey and are available semi-annually. The sample is 1983Q4-2015Q2 for 5 year bond and 1986Q2-2015Q2 for 10 year bond. NBER recession is a dummy equal to 1 if there is a recession in that quarter. Demand/supply-ratio is the ratio of aggregate demand variance (good+bad) to aggregate supply variance (good+bad). Demand/supply- ratio is scaled to have the standard deviation of 1. Standard errors are Newey-West standard errors computed with 40 lags. The asterisks, *, **, and *** correspond to statistical significance at the 10, 5, and 1 percent levels, respectively.

	5 year bond	10 year bond
const	-0.5706	0.4615**
	(0.3579)	(0.2020)
NBER-dummy	1.1325***	0.7727***
	(0.2943)	(0.1533)
demand/supply-ratio	0.5209***	0.1744
	(0.0674)	(0.1936)
NBER-dummy*demand/supply-ratio	-0.9655***	-0.6470***
	(0.0916)	(0.1934)
Adjusted R^2	0.2269	0.0272