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Short- and Long-Run Business Conditions and Expected Returns

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Abstract. Numerous studies argue that the market risk premium is associated with expected economic conditions and show that proxies for expected business conditions indeed predict aggregate market returns. By directly estimating short- and long-run expected economic growth, we show that short-run expected economic growth is *negatively* related to future returns, whereas long-run expected economic growth is *positively* related to aggregate market returns. In addition, our findings indicate that the risk premium has both high- and low-frequency fluctuations and highlight the importance of distinguishing short- and long-run economic growth in macro-asset pricing models.

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Keywords: business condition • expected stock return • business cycle • long run • short run

1. Introduction

The relation between the market risk premium and expected business conditions has been a question of long-standing interest to financial economists. Numerous studies (e.g., Chen et al. 1986, Fama and French 1989, Fama 1990) argue that expected business conditions should be linked to expected stock returns. However, early studies rarely used direct measures of expected business conditions. Instead, researchers typically used financial variables as proxies for expected business conditions. Fama and French (1989), for example, argued that the dividend yield and the term premium capture the long- and short-term aspects of business conditions, respectively. As a result, these financial variables have predictive power for future market returns through their link to business conditions. More recently, several studies have attempted to use more direct proxies for expected business conditions. In particular, using direct measures on expected business conditions based on survey data, Campbell and Diebold (2009) found that expected real gross domestic product (GDP) growth is negatively correlated with expected future returns.

In this study, using a standard vector autoregression (VAR) system, we directly estimate expected economic growth rates (such as industrial production and GDP growth) in both the short and long run based on actual economic growth. We then explore the predictive ability of expected short- and long-run business conditions. We find that by measuring expected growth directly, expected short- and long-run business conditions have distinctive predictive ability for future returns. Short-run expected economic growth is significantly *negatively* related to future excess returns, but long-run expected economic growth is significantly *positively* related to aggregate market returns. Thus, our findings highlight the important difference between the short- and long-run aspects of business conditions in predicting the aggregate risk premium.

In addition, we show that our expected growth variables can also predict excess bond returns. Our findings are also robust to different measures of expected economic growth rates. Although short-run and long-run business conditions are positively correlated in the data, our regression, which includes two positively correlated explanatory variables, does not suffer from a standard multicollinearity problem, in which coefficient estimates of individual independent variables typically have large standard errors. By contrast, our coefficient estimates have small standard errors and are statistically significant. A Monte Carlo simulation also confirms that our evidence is real and not driven by spurious regressions. In terms of economic magnitude, a one-standard-deviation increase in short-run economic growth forecasts a 5.07% lower expected return per annum, whereas a one-standard-deviation increase in long-run economic growth forecasts a 9.36% higher expected return per annum.

The issues of whether and how economic conditions are linked to the risk premium are particularly important for macro-finance literature. Our empirical evidence on the relation between expected returns and expected economic growth has implications for leading asset pricing models. In existing leading models (e.g., Campbell and Cochrane 1999, Bansal and Yaron 2004), the key driver of the risk premium is typically a highly persistent state variable, leading to persistent first-order autoregressive (AR(1)) risk premia. However, our findings suggest that the expected risk premium has two components with different frequencies. One has a relative high frequency and the other is more persistent. The distinctive predictive power of short- and long-run growth highlights the necessity of modeling richer cash flow dynamics or richer shock transmission mechanisms. Thus, our findings suggest that one possible future research avenue is to modify existing successful asset pricing models to account for this important link between business conditions and expected returns in the data. Indeed, among others, Drechsler and Yaron (2011) and Colacito (2014) have used richer cash flow dynamics in their models. It would be interesting to see whether models with richer cash flow dynamics can produce our empirical findings.

Apart from the analysis using actual growth data, we also extend the survey-based analysis in Campbell and Diebold (2009) by examining several alternative survey data. Indeed, when using alternative survey data on expected business conditions to forecast stock returns, we find that the survey-based expected short-run business condition is a strong contrarian predictor for future stock returns. However, the survey-based expected long-horizon business condition has little to no power in predicting returns. Given that survey expectations of future business conditions might be contaminated by investor misperception, the weaker predictive power of long-horizon business conditions is consistent with our main finding based on actual data. A high expectation of long-run economic growth rates, for example, could reflect either investor optimism or a genuinely high future long-run growth rate. According to our findings based on actual growth data, these two forces have opposite implications for future market returns, thus weakening the predictive power of long-run growth forecasts based on survey data. However, for expectations of short-run business conditions, these two forces reinforce each other, increasing the predictive power of the short-run business condition forecasts in a countercyclical fashion.

This study is related to an extensive literature on return predictability, which is too vast to cite here (for a survey, see Lettau and Ludvigson 2009). Specifically, this paper contributes to a broader agenda of using economically motivated macro-fundamental variables to predict asset returns. Studies in this vein include Lettau and Ludvigson (2001), Li (2001), Cooper and Priestley (2009), and Ludvigson and Ng (2009), among others. We complement previous studies by investigating the predictive power of both short-run and long-run growth simultaneously and highlighting the distinct power of these two positively correlated variables. By estimating expected growth directly, our method also complements the survey-based approach in Campbell and Diebold (2009), since survey data are subject to investor optimism/pessimism.

Our findings indicate that the risk premium has significant high-frequency and low-frequency movements. Earlier studies (e.g., Fama and French 1989) tended to find highly persistent risk premia. More recently, using a latent variable approach within a present value model, van Binsbergen and Koijen (2010) also found that the expected risk premium is very persistent. On the other hand, a few recent studies highlight the high-frequency (i.e., low-persistence) movements in the risk premium. In particular, using option data, Martin (2013) found large high-frequency fluctuations in the risk premium. Using a statistical method based on a dynamic latent factor system, Kelly and Pruitt (2013) also found that expected market returns are more volatile and less persistent than earlier studies suggested. Using a fundamental macroeconomic variable (i.e., short-run economic growth), we also identify high-frequency movements in the risk premium, and thus our approach is complementary to the methods in the existing studies that use cross-sectional stock returns or options prices. Moreover, our evidence reconciles the above studies by identifying both high- and low-frequency movements simultaneously. The two frequencies in the expected return are also reminiscent of studies by Adrian and Rosenberg (2008), who emphasize that volatility has two important components with different frequencies. If expected returns are related to volatility, then expected returns naturally have two components with different levels of persistence.

The remainder of this paper is organized as follows. Section 2 describes our measure of short- and long-run economic growth. Section 3 discusses the results of our main predictive regressions and robustness checks. Section 4 compares our results with existing literature on the relation between risk premia and economic conditions. Section 5 reviews our study's main conclusions.

2. Short- and Long-Run Economic Growth

In this section, we first use a standard VAR approach to estimate both short- and long-run economic conditions. We subsequently investigate how these estimated short- and long-run expected growth rates predict the aggregate stock market risk premium.

2.1. Econometric Design

Fama and French (1989) show that expected returns feature both a clear business cycle pattern and a longer-term aspect of business conditions. We thus estimate expected economic growth in both the short and long run, and we examine how they are related to the risk premium. To proceed, let us assume that Y_t is a vector of variables with industrial production (IP) growth as its first element. The rest of the variables in the vector Y_t are predictive variables that have been shown to have power in forecasting IP growth. To estimate expected IP growth, we model Y_t by using the following VAR system:

$$Y_t = A + B_1 Y_{t-1} + B_2 Y_{t-2} + \epsilon_t. \tag{1}$$

The choice of the predictive variables is guided by both parsimony and previous studies. First, the term premium is probably the most well-known leading predictor for business conditions (see, e.g., Estrella and Hardouvelis 1991, Plosser and Rouwenhorst 1994). Indeed, an inverted yield curve has been a reliable signal of an imminent recession. Second, it is also well known that the stock market leads the real economy. Thus, we include both the term premium and the dividend price ratio in our VAR system. In addition, Fama and French (1989) show that the term premium captures the business cycle component, and the dividend price ratio captures longer aspects of the business conditions. This evidence also makes the term premium and the dividend price ratio natural choices for our VAR system to predict both short- and long-run economic growth.

Since our purpose is to use the VAR system to predict future economic growth, it is especially important to keep the model parsimonious. With too many predictive variables, the in-sample fit can be good, but the out-of-sample (OOS) forecast ability for stock returns can be weak. As a result, we choose only the dividend price ratio and the term premium as our predictive variables for parsimony. Once the parameters in Equation (1) are estimated, one can obtain the short- and long-run expected economic growth rates:

$$\mu_{s,t} \equiv E_t \sum_{j=1}^{T_s} g_{t+j} \quad \text{and} \quad \mu_{l,t} \equiv E_t \sum_{j=1}^{T_l} g_{t+j}, \tag{2}$$

where $1 \le T_s < T_l$, and g_t is the growth rate in period t. Thus, $\mu_{s,t}$ and $\mu_{l,t}$ measure short- and long-run economic growth, respectively. In our empirical analysis, we choose T_s = 6 months and T_l = 5 years.[1] Then, we study how economic growth is related to the aggregate risk premium by standard long-horizon overlapping regressions (see, e.g., Fama and French 1989),

$$\sum_{j=1}^{h} r_{t+j} = \alpha + \beta_{s,h}\mu_{s,t} + \beta_{l,h}\mu_{l,t} + \epsilon_{t+h}, \tag{3}$$

where r_t is the (log) excess market return and h is the forecast horizon.

We first use the full sample to estimate the VAR coefficients and then calculate short- and long-run expected economic growth at time t using the data available until time t. This approach is consistent with the in-sample predictability analysis in Lettau and Ludvigson (2001, 2005), Cochrane and Piazzesi (2005), Lustig and Van Nieuwerburgh (2005), Baker and Wurgler (2006, 2007), and Ludvigson and Ng (2009), among others.[2] Nonetheless, we later still estimate the VAR coefficients recursively using real-time data only and repeat the long-horizon return predictability regressions as our robustness checks. The recursive estimation also reveals predictive power of economic growth for excess returns.

In the VAR regression (1), we choose the lag to be two. This is the most parsimonious specification that can yield a meaningful difference between short-run and long-run growth estimations. In addition, we find that the second lag indeed contains information regarding future economic growth. In particular, when predicting future one-quarter IP growth, the value of R^2 using the one-lagged dividend–price (DP) ratio is about 0%, and the coefficient is statistically insignificant (t-statistic = −0.84). On the other hand, the value of R^2 is increased to 6% when both one-lagged and two-lagged DP ratios are included in the predictive regression. Moreover, panel A of Table 1 shows that the one-lagged DP ratio, two-lagged DP ratio, one-lagged term premium, and two-lagged term premium are all significant predictors of the IP growth rate. This evidence highlights the importance of using at least two-lagged DP ratios and term premia in predicting future economic growth.

2.2. Correction for Generated Regressors

According to the econometric design in Section 2.1, the estimated short- and long-run growth rates are generated regressors, and thus the coefficient estimation in the predictive regressions needs to take this into account and their standard errors should be corrected for it. As a result, we use generalized method of moments (GMM) estimation to adjust the standard errors for all the regressions in the paper, as long as the GMM estimation is applicable.[3]

Specifically, for the VAR system, $Y_t = A + B_1 Y_{t-1} + B_2 Y_{t-2} + \epsilon_t$, we construct the following 21 moment equations:

$$E[x(Y_t - A - B_1 Y_{t-1} - B_2 Y_{t-2})] = 0, \tag{4}$$

where $x = 1$, Y_{t-1}, and Y_{t-2}. From the VAR system, we can estimate the short- and long-run expected growth rates, $\mu_{s,t}$ and $\mu_{l,t}$ (they both can be considered as functions of unknown parameters in the VAR system). Then, for the predictive regressions,

Table 1. VAR Estimation and Summary Statistics

A: VAR estimation

	g_{t-1}	g_{t-2}	DP_{t-1}	DP_{t-2}	$term_{t-1}$	$term_{t-2}$	R^2
g_t	0.32	−0.01	−1.83	1.90	−0.01	0.01	0.25
	(5.97)	(−0.25)	(−5.76)	(5.98)	(−1.91)	(2.80)	
DP_t	0.009	0.01	0.84	0.10	−0.00	0.00	0.86
	(0.89)	(1.30)	(14.67)	(1.80)	(−1.23)	(0.62)	
$term_t$	−1.27	−1.86	4.89	−3.08	0.81	0.10	0.80
	(−1.30)	(−1.94)	(0.85)	(−0.54)	(14.74)	(1.88)	

B: Summary statistics

	$\mu_{s,t}$	$\mu_{l,t}$	DP_t	$term_t$	int_t	$infl_t$	$default_t$	s_t
Mean	1.38	14.27	0.03	1.13	4.32	3.70	0.96	0.16
Std. dev.	1.51	6.28	0.01	1.34	3.11	4.74	0.45	0.03
AC(1)	0.62	0.94	0.98	0.88	0.94	0.21	0.88	0.99
Skewness	−0.28	−0.13	0.53	0.08	1.29	0.57	1.86	−0.74
Kurtosis	3.28	1.88	2.78	3.05	5.79	5.20	8.04	4.15

C: Correlation matrix

	$\mu_{s,t}$	$\mu_{l,t}$	DP_t	$term_t$	int_t	$infl_t$	$default_t$	s_t
$\mu_{s,t}$	1.00	0.64	−0.07	0.53	−0.38	−0.21	−0.13	−0.27
$\mu_{l,t}$	0.64	1.00	0.37	0.75	−0.45	−0.16	0.16	−0.41
DP_t	−0.07	0.37	1.00	−0.29	0.13	0.18	0.07	0.14
$term_t$	0.53	0.75	−0.29	1.00	−0.54	−0.27	0.18	−0.52
int_t	−0.38	−0.45	0.13	−0.54	1.00	0.37	0.38	0.51
$infl_t$	−0.21	−0.16	0.18	−0.27	0.37	1.00	0.05	0.29
$default_t$	−0.13	0.16	0.07	0.18	0.38	0.05	1.00	−0.13
s_t	−0.27	−0.41	0.14	−0.52	0.51	0.29	−0.13	1.00

Notes. Panel A reports the results of VAR estimation for IP growth rates with two predictive variables, the DP ratio and the term premium. The lag for the VAR system is chosen to be 2. The ordinary least squares t-statistics are reported in parentheses. Panel B reports the mean, standard deviation, first-order autocorrelation (AC(1)), skewness, and kurtosis of predictive variables. The predictive variables are the estimated short- and long-run expected IP growth ($\mu_{s,t}$ and $\mu_{l,t}$), the dividend–price ratio (DP_t), the term premium ($term_t$), the interest rate (int_t, annualized), the inflation rate ($infl_t$, annualized), the default premium ($default_t$), and the surplus ratio (s_t). Expected IP growth rates are estimated based on Equations (1) and (2) with IP growth, the DP ratio, and the term premium in the VAR system. The mean and standard deviation are in terms of percentage points. Panel C reports the correlation matrix of the predictive variables. The sample is quarterly from 1947 to 2012.

$\sum_{j=1}^{h} r_{t+j} = \alpha + \beta_{s,h}\mu_{s,t} + \beta_{l,h}\mu_{l,t} + e_{t+h}$, we obtain the following three moment equations:

$$E\left[z\left(\sum_{j=1}^{h} r_{t+j} - \alpha - \beta_{s,h}\mu_{s,t} - \beta_{l,h}\mu_{l,t}\right)\right] = 0, \tag{5}$$

where $z = 1$, $\mu_{s,t}$, and $\mu_{l,t}$.

Then we combine Equations (4) and (5) to conduct standard GMM estimation with 24 moment equations for 24 unknown parameters to address the concern that $\mu_{s,t}$ and $\mu_{l,t}$ are generated regressors in the predictive regressions. In the GMM estimation, we use the Newey and West (1987) t-statistics with lag $h+6$, where h is the forecast horizon. Later on, to better evaluate the significance of our GMM t-statistics (with Newey–West correction) and address the issue of small-sample bias, we also perform a Monte Carlo experiment.

2.3. Data

Following the studies on the link between macro variables and the risk premium (e.g., Fama and French 1990, Lettau and Ludvigson 2001, Cooper and Priestley 2009), we focus our return predictability analysis on the post–World War II (WWII) period from 1947 to 2012. In fact, the quarterly GDP data, obtained from the Federal Reserve Bank of St. Louis, also start from 1947. Our main estimations of expected growth rates are based on the quarterly growth of industrial production, which spans from 1927 to 2012, obtained from the St. Louis Fed. The stock returns on the Center for Research in Security Prices (CRSP) value-weighted index are obtained from CRSP. Excess returns are computed as the difference between the gross return and the 30-day T-bill rate. For bond returns, we use the Fama and Bliss (1987) data from CRSP to calculate the annual excess bond returns at a monthly frequency over the sample period of June 1952 (1952m6) to December 2012 (2012m12).

The default premium is defined as the yield spread between BAA and AAA bonds obtained from the Federal Reserve Bank of St. Louis. The term premium is defined as the difference between the 20-year

Treasury bond yield and the 1-year yield, obtained from the St. Louis Fed. The inflation rate is calculated from the monthly consumer price index, obtained from CRSP. The real interest rate is defined as the difference between the 30-day T-bill rate and inflation. The consumption–wealth ratio (CAY) is defined as in Lettau and Ludvigson (2001), obtained from the authors' website. Campbell and Cochrane's (1999) surplus ratio is approximated by a smoothed average of the past 40-quarter consumption growth as in Wachter (2006). Finally, the monthly dividend yield is calculated as the difference between the log of the last 12-month dividend and the log of the current level of the CRSP valued-weighted index. The quarterly observation is taken as the one in the last month of the corresponding quarter.

2.4. Summary Statistics

We provide summary statistics for the expected short- and long-run economic growth rates and their relation to business cycles. Panel B of Table 1 also provides summary statistics for the predictive variables in our paper. We present the data at a quarterly frequency, since our main analysis uses quarterly observations. Short-run expected growth has an AR(1) coefficient of 0.62, and long-run expected growth has a persistence coefficient of 0.94 at a quarterly frequency. As expected, our long-run expected growth is quite persistent but less persistent than some traditional predictors, such as the consumption–surplus ratio and the dividend–price ratio. Thus, our predictive results are less subject to the spurious regression criticism as a result of highly persistent predictors.

Panel C of Table 1 presents the correlation matrix of those predictive variables. Short-run expected growth is negatively correlated with the DP ratio and the default premium, but positively correlated with the term premium. Long-run expected growth is positively correlated with the DP ratio, the default premium, and the term premium. Among all the macro variables, the term premium is most closely correlated with short- and long-run growth rates, with correlations of 0.53 and 0.75, respectively. Since we use the term premium as one predictive variable in our VAR system, the high correlation between the term premium and $\mu_{l,t}$ and $\mu_{s,t}$ is not surprising. The correlation between expected growth and the DP ratio is not particularly high: −0.07 for short-run growth and 0.37 for long-run growth. Finally, the correlation between short- and long-run growth rates is positive and 0.64.

Although long-run and short-run growth rates tend to comove together on average, the correlation is far from perfect. Basu et al. (2006) also document that short-run and long-run growth rates can be different as a result of new technology shocks. According to their findings, when technology improves, there are sharp decreases, rather than increases, in input and investment. Output rarely changes. With a lag of several years, input and investment return to normal and output rises strongly. Thus, technology shocks could weaken the correlation between short-run and long-run growth, and potentially lead to a negative correlation during some specific periods. Garleanu et al. (2012) also argue that it could be optimal for firms to wait for a period of time before adopting general-purpose technology, leading to decoupling between short-run and long-run growth.

2.5. Predicting Short- and Long-Run Economic Growth

By construction, short- and long-run expected economic growth, $\mu_{s,t}$ and $\mu_{l,t}$, should have predictive power for future growth. In this subsection, we check whether short- and long-run expected economic growth can indeed predict short- and long-run economic growth, respectively. In Table 2, we use the estimated $\mu_{s,t}$ and $\mu_{l,t}$ to predict future economic growth, including IP growth, GDP growth, dividend growth, and earnings growth. In panels A–D of Table 2, we regress those economic growth measures on the short-run business condition $\mu_{s,t}$. The results show that $\mu_{s,t}$ can significantly predict future economic growth. As the prediction horizon increases, the R^2 value tends to decrease. This indicates that $\mu_{s,t}$ contains more information about future short-run business conditions than long-run business conditions. By contrast, in panels E–H, we use long-run expected growth to predict future economic growth. As the forecast horizon increases, the R^2 value tends to increase, indicating that $\mu_{l,t}$ contains more information about future long-run business conditions.

Specifically, using short-run growth to predict IP growth, R^2 decreases from 25% to 4% from a quarterly horizon to a five-year horizon. On the other hand, using long-run growth to predict IP growth, R^2 increases from 1% to 11% from a quarterly horizon to a five-year horizon. These results provide assuring evidence that our expected growth variables are reasonable proxies for future business conditions.

3. Predictive Regressions

In their pathbreaking work, Fama and French (1989) present convincing evidence on the link between business conditions and expected returns. As suggested by Fama and French (1989), fleshing out the details for the apparent rich variation in expected returns in response to business conditions is an exciting challenge. In this paper, we take an initial step to tackle this challenge.

3.1. Predicting Excess Market Returns

We use the VAR system discussed in Section 2.1 to obtain short- and long-run expected economic

Table 2. Predicting Economic Growth

Horizon	1 quarter	2 quarters	1 year	2 years	3 years	4 years	5 years
			I: Using short-run expected economic growth				
			A: Predicting future IP growth				
Short run	0.67	1.17	1.64	1.60	1.75	1.38	1.50
t-GMM	4.09	4.61	4.01	2.38	2.25	1.76	2.04
R^2	0.25	0.25	0.19	0.10	0.09	0.04	0.04
			B: Predicting future GDP growth				
Short run	0.30	0.51	0.69	0.66	0.70	0.49	0.46
t-GMM	4.35	4.54	3.48	2.12	1.74	1.12	1.06
R^2	0.21	0.22	0.16	0.07	0.05	0.02	0.01
			C: Predicting future dividend growth				
Short run	0.30	0.66	1.47	2.43	2.83	2.87	2.96
t-GMM	1.98	2.40	3.06	2.66	2.33	2.13	2.36
R^2	0.04	0.06	0.11	0.11	0.10	0.10	0.09
			D: Predicting future earnings growth				
Short run	3.05	5.14	7.02	8.40	7.93	4.60	3.03
t-GMM	1.91	2.37	2.73	1.77	1.64	1.19	1.00
R^2	0.11	0.10	0.08	0.08	0.06	0.03	0.01
			II: Using long-run expected economic growth				
			E: Predicting future IP growth				
Long run	0.04	0.11	0.27	0.51	0.61	0.59	0.57
t-GMM	1.29	1.68	2.17	2.68	2.61	2.38	2.21
R^2	0.01	0.03	0.08	0.18	0.20	0.14	0.11
			F: Predicting future GDP growth				
Long run	0.03	0.06	0.13	0.23	0.27	0.26	0.23
t-GMM	1.67	1.97	2.27	2.57	2.28	1.82	1.45
R^2	0.03	0.06	0.10	0.15	0.13	0.09	0.06
			G: Predicting future dividend growth				
Long run	0.04	0.09	0.26	0.67	0.99	1.16	1.20
t-GMM	0.84	1.04	1.53	2.17	2.28	2.15	2.06
R^2	0.01	0.02	0.06	0.15	0.23	0.28	0.28
			H: Predicting future earnings growth				
Long run	0.37	0.83	1.76	3.43	3.66	2.33	1.21
t-GMM	1.36	1.54	1.80	1.79	1.75	1.75	1.37
R^2	0.03	0.04	0.09	0.22	0.23	0.13	0.04

Notes. This table reports the long-horizon regression of future economic growth (including IP growth, GDP growth, dividend growth, and earnings growth) on the short- and long-run economic conditions. We use expected IP growth rates as measures of expected economic conditions. Expected IP growth rates are estimated based on Equations (1) and (2) with IP growth, the DP ratio, and the term premium in the VAR system. We use the full sample to estimate parameters in the VAR system and then obtain the expected growth rate at time t using the data available until time t. The data on aggregate dividend growth and earnings growth are from the web page of Robert Shiller (http://www.econ.yale.edu/~shiller/data.htm, accessed 2013). In panels A–D, we use short-run expected IP growth to forecast future economic growth. In panels E–H, we use long-run expected IP growth to forecast future economic growth. The GMM t-statistics with Newey–West correction (with lag $h+6$) are reported.

growth. Short-run growth is measured as the six-month expected growth rate, whereas long-run growth is measured as the five-year expected growth rate. Table 3 reports our main results of regressing excess market returns on the short- and long-run expected growth rates.

In panels A and B of Table 3, we regress excess market returns (from one-quarter up to five-year horizons) on short- and long-run expected growth rates, respectively. We find that while long-run expected growth always predicts future market returns positively and significantly, short-run expected growth cannot predict future market returns significantly. However, as we argued in the introduction, short- and long-run expected growth could have distinct predictive power. Recall that short- and long-run expected growth rates are positively correlated (the correlation is 0.64); that is, the short-run expected growth could also contain information about long-run expected growth. Thus, it is important to include both variables in our predictive regressions to alleviate the omitted variable concern. In panel C, we regress future excess market returns on both short- and long-run expected growth. In this case, short-run economic growth has negative predictive power at a 5% significance level at one-year and two-year horizons and with less significance at longer horizons. Long-run economic growth has positive predictive power at a 5% significance level at all horizons.[4] In addition, our 9% R^2 at a six-month horizon is comparable with the 4.91% R^2 in Campbell and

Table 3. Long-Horizon Stock Return Predictability

Horizon	1 quarter	2 quarters	1 year	2 years	3 years	4 years	5 years
A: Predicting excess returns with short-run growth							
Short run	0.58	0.67	0.58	1.56	2.97	3.99	4.92
t-GMM	1.26	0.79	0.37	0.62	1.00	1.23	1.30
B: Predicting excess returns with long-run growth							
Long run	0.30	0.55	0.97	1.72	2.43	2.87	3.38
t-GMM	2.49	2.52	2.60	2.64	2.92	2.86	2.64
C: Predicting excess returns with short- and long-run growth							
Short run	−0.34	−1.32	−3.36	−4.96	−5.47	−5.67	−6.93
t-GMM	−0.67	−1.44	−2.07	−2.03	−1.94	−1.85	−1.75
Long run	0.35	0.75	1.49	2.48	3.25	3.72	4.42
t-GMM	2.44	2.67	2.77	2.82	3.04	3.18	3.06
R^2	0.04	0.09	0.17	0.28	0.37	0.41	0.45
D: Testing the null hypothesis H_0: $\beta_{s,h}\beta_{l,h} \geq 0$							
p-value	0.21	0.00	0.00	0.00	0.00	0.00	0.00
E: Simulation for r_t, g_t, DP_t, and $term_t$							
t-GMM(short run, 0.025)	−1.70	−1.90	−2.20	−2.44	−2.59	−2.74	−2.79
t-GMM(short run, 0.05)	−1.45	−1.62	−1.83	−2.04	−2.16	−2.27	−2.34
t-GMM(short run, rank)	0.23	0.07	0.03	0.05	0.07	0.09	0.12
t-GMM(long run, 0.975)	2.03	2.19	2.43	2.72	2.93	3.09	3.24
t-GMM(long run, 0.95)	1.79	1.94	2.12	2.37	2.50	2.64	2.75
t-GMM(long run, rank)	0.99	0.99	0.99	0.98	0.98	0.98	0.97
R^2 (lower bound)	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
R^2 (upper bound)	0.02	0.04	0.08	0.14	0.18	0.22	0.26
F: Simulation for g_t, DP_t, and $term_t$							
t-GMM(short run, 0.025)	−1.88	−1.94	−1.98	−1.97	−2.00	−1.97	−2.08
t-GMM(short run, 0.05)	−1.60	−1.65	−1.67	−1.65	−1.68	−1.67	−1.72
t-GMM(short run, rank)	0.25	0.08	0.02	0.02	0.03	0.04	0.05
t-GMM(long run, 0.975)	1.67	1.72	1.83	2.05	2.25	2.38	2.48
t-GMM(long run, 0.95)	1.40	1.47	1.59	1.74	1.89	2.01	2.07
t-GMM(long run, rank)	1.00	1.00	1.00	1.00	0.99	0.99	0.99
R^2 (lower bound)	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
R^2 (upper bound)	0.02	0.03	0.06	0.11	0.16	0.22	0.24

Notes. This table reports long-horizon regressions of excess market returns on short- and long-run expected economic growth. We use expected IP growth rates as measures of expected economic conditions. Expected IP growth rates are estimated based on Equations (1) and (2) with IP growth, the DP ratio, and the term premium in the VAR system. We use the full sample to estimate parameters in the VAR system and then obtain the expected growth rate at time t using the data available until time t. All the predictive regressions are based on quarterly observations from 1947 to 2012. The short-run business condition is measured as the six-month expected growth rate, and the long-run business condition is measured as the five-year expected growth rate. The GMM t-statistics with Newey–West correction (with lag $h+6$) are reported. In panel D, we use the bootstrap method to test the null hypothesis that the coefficients on the short- and long-run expected economic growth have the same sign. The p-value refers to the probability that the null hypothesis is true. The results of Monte Carlo experiments are reported in panels E and F. In panel E, we simulate for excess market return (r_t), IP growth (g_t), DP ratio (DP_t), and term premium ($term_t$). The terms t-GMM(short run, 0.025) and t-GMM(short run, 0.05) are the 2.5% and 5% quantiles of GMM t-statistics with Newey–West correction for short-run growth in Monte Carlo experiments. The term t-GMM(short run, rank) is the percentage of 10,000 simulated t-statistics that is smaller than the corresponding GMM t-statistics from panel C for short-run growth. The terms t-GMM(long run, 0.975) and t-GMM(long run, 0.95) are the 97.5% and 95% quantiles of GMM t-statistics with Newey–West correction for long-run growth in Monte Carlo experiments. The term t-GMM(long run, rank) is the percentage of 10,000 simulated t-statistics that is smaller than the corresponding GMM t-statistics from panel C for long-run growth. And R^2 (lower bound) is the 2.5% quantile of the Monte Carlo-generated R^2, and R^2 (upper bound) is the 97.5% quantile of the Monte Carlo-generated R^2. In panel F, we repeat the Monte Carlo experiments in panel E by simulating only for IP growth, DP ratio, and term premium, but using the real data for excess market return r_t.

Diebold (2009), which relies on survey data on economic growth. Moreover, Campbell and Diebold (2009) show that the future return is high when expected business conditions are depressed, and the future return is low when expected business conditions are strong, consistent with the predictive power of our short-run growth. However, our results indicate that when the long-run business condition is good, the expected return is high rather than low.

In panel D, we use the bootstrap method to test the null hypothesis that the coefficients on the short- and long-run expected economic growth have the same sign. The procedure is as follows: (1) we obtain the short- and long-run expected growth rates from the VAR estimation; (2) we regress the market excess returns on the short- and long-run growth and store the coefficient estimates and residuals; (3) we bootstrap a sample of residuals with the same number of observations in the original sample and calculate the bootstrapped excess returns, $r_{\text{bootstrap},t} = \hat{\alpha} + \hat{\beta}_{s,h}\mu_{s,t} + \hat{\beta}_{l,h}\mu_{l,t} + \epsilon_{\text{bootstrap},t}$; (4) we regress the bootstrapped excess returns on the short- and long-run growth and store the new coefficient estimates; and (5) we repeat steps (3) and (4) for 10,000 times. We count the percentage of the cases in which the two beta estimates have the same sign as the p-value. The results show that p-values are close to zero except for the case of one-quarter-ahead predictive regression. This suggests that the coefficients on short- and long-run economic growth indeed have different signs, a key result of our paper.

In panels E and F, we use Monte Carlo experiments to derive the thresholds to evaluate the statistical significance of the GMM t-statistics in panel C. The purpose of this exercise is to address potential small-sample biases. A large literature has shown that the standard t-statistics based on asymptotic theory can have poor finite sample properties. In particular, when predictor variables are persistent and the innovations in the predictors are highly correlated with the variable being predicted, the small-sample biases can be severe (see, for example, Stambaugh 1986, 1999; Valkanov 2003; Campbell and Yogo 2006). More recently, based on simulation, Ang and Bekaert (2007) showed that the Newey–West t-statistics have substantial size distortions when forecasting stock returns using persistent variables, especially in long-horizon regressions.

To address the issue of small-sample bias, we follow Ang and Bekaert (2007) and perform a Monte Carlo experiment to investigate whether the statistical inference based on GMM t-statistics with Newey–West correction is affected by size distortions. Specifically, we simulate the three instrumental variables (IP growth, DP ratio, and term premium) and return data for the Monte Carlo experiment under the null hypothesis of no predictability:

$$r_t = a_0 + \epsilon_{0,t},$$
$$Y_t = \hat{A} + \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + \epsilon_t, \tag{6}$$

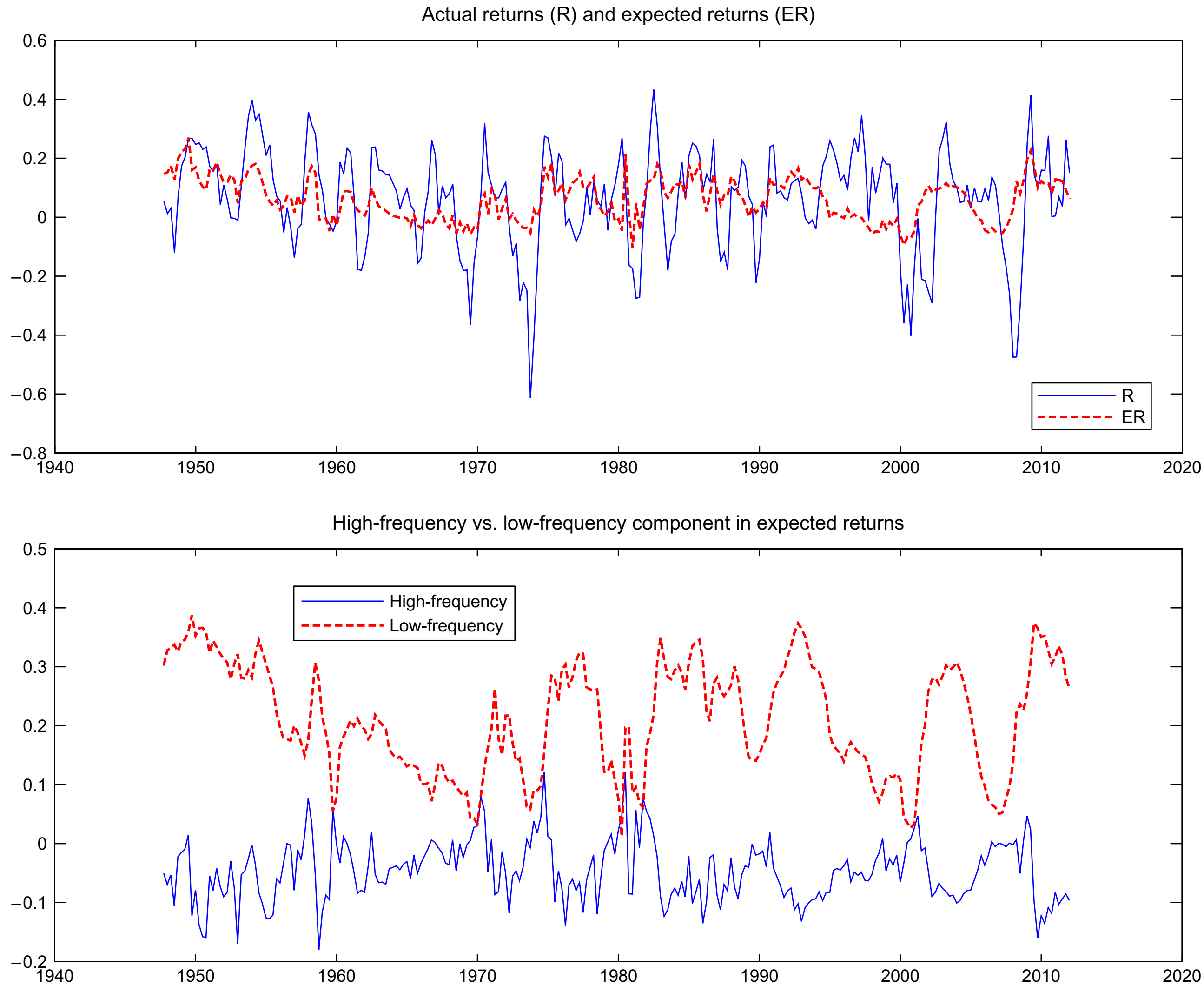
where $Y_t = (g_t, DP_t, term_t)'$; the error terms are jointly normal. The parameter values we use for our Monte Carlo experiments are estimated from actual data for g_t, DP_t, $term_t$, and r_t; that is, a_0 is the mean of actual stock returns in our sample, and $\hat{A}, \hat{B}_1, \hat{B}_2$ are the estimated coefficients from the VAR system using actual data of g_t, DP_t, and $term_t$. Finally, we estimate the sample covariance matrix for the joint residual vector $\bar{\epsilon}_t = (\epsilon_{0,t}, \epsilon_t')'$ from the actual data, and then we use the estimated sample covariance as the covariance matrix for the innovation vector $\bar{\epsilon}_t$. In this way, we explicitly take account of the small-sample bias in Strambaugh (1986, 1999).

For each experiment, we simulate $100 + T$ observations, where T is the sample size for the actual data. We then use the last T observations to perform the VAR estimation and the predictive regressions, using the GMM method described in Section 2.2. We repeat this procedure 10,000 times. This method gives us the distribution of the GMM t-statistics testing the null hypothesis that $\gamma_1 = 0$ and $\gamma_2 = 0$, along with the distribution of the regression R^2. The results are reported in panel E of Table 3.

To evaluate the statistical significance of our main results in panel C of Table 3, we provide the 2.5% and 5% quantiles of the simulated t-statistics for $\mu_{s,t}$ and the 95% and 97.5% quantiles of the simulated t-statistics for $\mu_{l,t}$. Overall, short-run economic growth has negative predictive power at a 10% significance level at one-year and two-year horizons; long-run economic growth has positive predictive power at a 5% significance level at all horizons except the five-year horizon, at which the significance level is 10%. To further evaluate our main results, we also provide the percentage rank of our GMM t-statistics from panel C in the 10,000 simulated t-statistics; that is, we count the portion of 10,000 simulated t-statistics that is smaller than the corresponding GMM t-statistics from panel C. Taking one-year-ahead predictive regression, for example, the percentage rank for the short run is 0.03, which means that only 3% of 10,000 simulated t-statistics are smaller than −2.07 (the GMM t-statistics for short-run growth). This is similar in spirit to the one-sided p-value. Similarly, the percentage rank for the long run is 0.99, which means that almost 99% of 10,000 simulated t-statistics are smaller than 2.77 (the GMM t-statistics for long-run growth). Comparing the last row of panel C with the last row of panel E suggests that our high R^2 value is not purely by chance. On the other hand, we could not completely rule out potential overfitting issues of our model, and thus, it is not necessary for theory models to match our high R^2. In sum, the results in panel E suggest that our main results in panel C are still mostly statistically significant after accounting for potential small-sample issues.

In addition, because investor long-run economic growth is quite persistent, our predictive regressions are also subject to the spurious regression critique of Ferson et al. (2003). Even though stock returns are not highly autocorrelated, the expected returns can be persistent. Ferson et al. (2003) argue that predictive regressions for stock returns have a potential spurious regression bias related to the classic studies of Yule (1926) and Granger and Newbold (1974). To address this concern, we perform another simple Monte Carlo simulation analysis, reported in panel F of Table 3. Basically, panel F shows the results of repeating the Monte Carlo experiments in panel E by only simulating for IP growth, DP ratio, and term premium, but using the actual data for excess market return r_t. As in panel E, panel F also reports the 2.5% and 97.5% quantiles of the t-statistics from the simulation. It can be seen that the 2.5% quantiles are usually very close to −1.96. Thus, the spurious regression critique of

Figure 1. (Color online) (Top) Actual and Expected Returns; (Bottom) High- vs. Low-Frequency Component in Expected Returns



Notes. The top panel plots the realized annual aggregate excess market returns and the annual expected returns. The expected returns are calculated based on a predictive regression of returns on short- and long-run economic growth. The expected returns are also decomposed into a constant, a high-frequency component and a low-frequency component according to the predictive regression. The bottom panel plots the high-frequency and low-frequency components in the expected returns. The high- and low-frequency components are not demeaned, and the level has no economic meaning. One should instead focus on the variation of these two components.

Ferson et al. (2003) does not pose an issue for our analysis.

The top panel of Figure 1 plots the expected return from the predictive regression in panel C along with the actual excess return at an annual frequency. The expected return series is much less variable than actual returns, but they do align with each other. The predictive power of our variables is not only statistically significant but also economically important. All else equal, a one-standard-deviation increase in short-run IP growth leads to about a $1.51\% \times 3.36 = 5.07\%$ decrease in the next year's expected return; a one-standard-deviation increase in long-run IP growth leads to about a $6.28\% \times 1.49 = 9.36\%$ increase in the next year's expected return. These numbers are also comparable with other prominent predictors. For example, one-standard-deviation increases in the DP ratio, CAY, and the net payout ratio tend to increase the risk premium by 3.60%, 7.39%, and 10.2% per annum, respectively.[5] The bottom panel plots the short-run and long-run components of the expected returns.

Since short-run and long-run growth rates have a positive correlation of 0.64, one might worry that our significant results in panel C are driven by multicollinearity and hence are spurious. However, this critique cannot explain our results, since multicollinearity usually leads to small t-statistics, whereas our t-statistics are quite large. Furthermore, the variance inflation factor (VIF) for our predictors is only 1.69, much less than the critical cutoff of 10 suggested by Kutner et al. (2004). This confirms that multicollinearity is unlikely to plague our results. Thus, the improvement from panels A and B to panel C might reflect a classic omitted variables problem rather than multicollinearity.[6]

One might argue that our results could be mechanically driven by the countercyclical property of the risk premium over business cycles. For example, during a recession, expected short-run growth is low and expected long-run growth might be high. Since the risk premium tends to be high at this time, it implies that long-run expected growth is positively related to future returns and short-run expected growth is negatively related to future returns. However, this argument implies that short-run growth and long-run growth are negatively correlated, at least during recessions, whereas their correlation is 64% during the whole sample in the data and the correlation is still 60% during recessions. In addition, long-run (five-year) growth during recessions is actually slightly lower than average long-run growth (14.02% versus 14.27%). Thus, our results are not mechanically driven by the countercyclical property of the risk premium. We shall explore more on the underlying sources in Section 3.4.

In addition, our findings have important implications for leading existing asset pricing models. For parsimony, most existing models, such as those of Campbell and Cochrane (1999) and Bansal and Yaron (2004), tend to feature a highly persistent state variable that drives the variation in the risk premium. The high persistence is needed to produce large amplification effects and hence high stock return volatility. As a result, in these models, the risk premium is typically an AR(1) process with persistence around 0.97 at a quarterly frequency. Therefore, these models cannot account for the findings in our study that there are both higher- and lower-frequency movements in the risk premium. Moreover, several other recent studies (e.g., Kelly and Pruitt 2013, Martin 2013) also found that there are significant higher-frequency variations in expected stock returns. Thus, it would be interesting to extend the existing models to study the underlying mechanism in these high-frequency movements in the risk premium. One potential way to reconcile our findings is to allow the model to feature two state variables with different persistence levels. Indeed, Drechsler and Yaron (2011) and Colacito (2014) feature richer cash flow dynamics in their models, and it would be interesting to see whether models with richer cash flow dynamics can produce our empirical findings.

Finally, several existing studies (see, e.g., Daniel and Marshall 1997, Parker and Julliard 2005, Backus et al. 2010, Yu 2012) document that the comovement between the real sector economy and the stock market return is much stronger over the long run than over the short run. This evidence suggests that the correlation between long-run expected growth and returns is higher than that between short-run expected growth and returns, consistent with our findings.

3.2. Robustness Checks

Table 4 shows the results of our robustness tests. In panel A, we use quarterly GDP growth (from 1947 to 2012) instead of IP growth to measure short- and long-run expected economic growth. The predictive results are quantitatively similar. In addition, the results with GDP growth tend to be slightly stronger. In particular, the predictive power of the short-run growth is statistically more significant.

In Table 3, to obtain a precise estimation on expected growth, we have used industrial production growth data in the full sample from 1927 to 2012. The longer sample can potentially yield more precise coefficient estimations in the VAR system and thus more precise estimations on true expected growth. On the other hand, these coefficient estimations could potentially be contaminated by the less accurately measured pre-WWII macro data. Thus, we repeat the VAR estimation on expected growth rates using data after WWII from 1947 to 2012. The results are reported in panel B of Table 4. As we can see, the predictive power (i.e., the R^2) is quantitatively similar to but slightly weaker than that in panel C of Table 3. Thus, it appears that using pre-WWII data may help improve the estimation of coefficients in the VAR system and hence enhance the predictive ability of the estimated expected growth rates. As a result, in the subsequent analysis, we still calculate expected growth rates based on the VAR coefficient estimates from the long sample. Nonetheless, the results are quantitatively similar if the VAR coefficients are estimated using post-WWII data only, as illustrated by the similarity between panel B of Table 4 and panel C of Table 3.

In panel C of Table 4, estimations for expected IP growth rates are based on recursively estimated parameters in a real-time fashion. Thus, these estimations have no look-ahead bias. To take into account that the growth rate in any given quarter or month cannot be observed at the end of that quarter or month, we take one more lag in regressions—that is, we regress excess returns from time t to time $t+h$ on $\mu_{s,t-1}$ and $\mu_{l,t-1}$, which are the short- and long-run expected growth rates estimated at time $t-1$. The overall predictive power of economic growth is smaller in this real-time case. Nonetheless, both short-run and long-run growth can still predict the aggregate risk premium, again with opposite signs.[7]

Thus far, we have not used monthly IP growth data to estimate expected long-run growth. Since we use Equation (2) to estimate long-run growth, small measurement errors in coefficient estimations could

Table 4. Robustness Check for Long-Horizon Stock Return Predictability

Horizon	1 quarter	2 quarters	1 year	2 years	3 years	4 years	5 years
			A: One-shot estimation with GDP data				
Short run	−0.42	−2.87	−6.84	−10.54	−12.39	−12.59	−15.24
t-GMM	−0.49	−1.89	−3.05	−3.07	−3.35	−3.37	−3.03
Long run	0.97	2.14	4.11	7.07	9.38	10.78	12.81
t-GMM	2.25	2.59	2.72	2.73	3.02	3.09	3.03
R^2	0.05	0.10	0.19	0.31	0.42	0.46	0.51
			B: One-shot estimation with IP data from 1947 to 2012				
Short run	−0.37	−1.24	−3.20	−4.82	−5.78	−6.28	−7.33
t-GMM	−1.26	−2.52	−3.77	−3.03	−3.01	−2.93	−2.70
Long run	0.63	1.28	2.42	4.05	5.52	6.42	7.61
t-GMM	2.12	2.17	2.23	1.78	1.81	1.69	1.57
R^2	0.04	0.08	0.16	0.24	0.33	0.35	0.38
			C: Rolling window estimation for IP				
Short run	−0.86	−1.73	−2.61	−3.65	−4.84	−4.23	−6.22
t-NW	−2.97	−3.58	−3.18	−2.50	−3.01	−2.52	−3.01
Long run	0.24	0.47	0.72	1.08	1.50	1.58	2.06
t-NW	3.39	3.81	3.60	2.74	3.52	2.86	2.80
R^2	0.03	0.06	0.07	0.09	0.13	0.12	0.16
			D: One-shot estimation for IP (monthly frequency)				
Short run	−0.68	−1.55	−4.25	−7.14	−8.79	−9.98	−11.74
t-GMM	−0.88	−1.15	−1.74	−1.94	−1.77	−1.86	−1.97
Long run	0.59	1.17	2.46	4.16	5.60	6.53	7.63
t-GMM	2.07	2.20	2.36	2.33	2.32	2.40	2.44
R^2	0.05	0.09	0.17	0.26	0.37	0.40	0.42
			E: Rolling window estimation for IP (monthly frequency)				
Short run	−0.84	−1.93	−4.24	−7.16	−8.99	−10.45	−12.90
t-NW	−2.10	−3.06	−3.99	−3.66	−3.69	−4.05	−4.40
Long run	0.38	0.78	1.60	2.57	3.42	3.96	4.82
t-NW	3.23	3.75	4.10	3.57	4.13	4.13	3.87
R^2	0.03	0.05	0.10	0.14	0.19	0.21	0.23
			F: Using vintage data (monthly frequency)				
Short run	−0.88	−1.80	−3.81	−5.78	−6.98	−7.92	−10.32
t-NW	−2.22	−2.88	−3.82	−3.40	−3.49	−3.81	−3.90
Long run	0.31	0.61	1.22	1.82	2.36	2.69	3.43
t-NW	2.93	3.42	3.91	3.31	3.92	3.68	3.22
R^2	0.02	0.04	0.07	0.09	0.11	0.12	0.15
			G: Using vintage data (quarterly frequency)				
Short run	−0.65	−1.12	−1.91	−2.32	−3.25	−2.95	−4.64
t-NW	−2.28	−2.48	−2.21	−1.61	−2.01	−1.66	−2.00
Long run	0.17	0.30	0.49	0.63	0.90	0.93	1.31
t-NW	2.68	2.93	2.63	1.94	2.71	2.11	2.14
R^2	0.01	0.02	0.03	0.03	0.05	0.05	0.07
			H: Control for default, term, interest, inflation, surplus ratio				
Short run	−0.33	−1.29	−3.70	−6.03	−6.69	−6.29	−6.62
t-GMM	−0.65	−1.38	−2.16	−2.26	−2.17	−1.98	−1.72
Long run	0.45	0.96	1.90	3.43	4.42	5.00	5.92
t-GMM	1.37	1.47	1.56	1.54	1.54	1.55	1.54
R^2	0.04	0.10	0.24	0.43	0.56	0.64	0.71
			I: Subsample 1947–1979				
Short run	−0.50	−1.52	−3.84	−6.05	−6.27	−5.26	−5.40
t-GMM	−0.90	−1.45	−1.99	−2.09	−2.29	−2.03	−1.71
Long run	0.38	0.80	1.51	3.26	4.40	4.35	5.29
t-GMM	1.27	1.37	1.50	1.53	1.46	1.55	1.51
R^2	0.11	0.19	0.38	0.60	0.75	0.85	0.90
			J: Subsample 1980–2012				
Short run	−1.20	−2.77	−6.30	−6.23	−8.31	−9.24	−12.88
t-GMM	−0.86	−1.09	−1.51	−1.65	−1.45	−1.36	−1.88
Long run	1.42	2.78	4.59	5.13	7.12	8.29	9.54
t-GMM	1.49	1.49	1.57	1.47	1.42	1.29	1.39
R^2	0.03	0.10	0.20	0.33	0.47	0.52	0.53

Table 4. (Continued)

Horizon	1 quarter	2 quarters	1 year	2 years	3 years	4 years	5 years
			K: Using lag 4 for the VAR system				
Short run	−0.40	−0.88	−1.84	−2.74	−3.31	−2.63	−3.49
t-GMM	−1.37	−1.80	−2.15	−2.94	−3.07	−2.50	−2.84
Long run	0.34	0.67	1.23	2.06	2.74	3.05	3.71
t-GMM	2.51	2.64	2.74	2.90	3.22	3.33	3.28
R^2	0.05	0.10	0.18	0.29	0.40	0.43	0.49
			L: Using the method of principal component analysis				
Short run	0.17	−0.78	−2.75	−4.49	−4.41	−4.51	−5.87
t-GMM	0.18	−0.55	−1.37	−1.51	−1.22	−1.23	−1.03
Long run	0.39	0.87	1.64	2.79	3.53	4.16	5.20
t-GMM	1.05	1.29	1.45	1.49	1.49	1.46	1.37
R^2	0.04	0.07	0.14	0.22	0.27	0.30	0.35
			M: Using data from 1927 to 2012				
Short run	−0.36	−0.44	−1.16	−2.68	−3.82	−4.87	−6.06
t-GMM	−0.79	−0.65	−0.97	−1.19	−1.13	−1.20	−1.32
Long run	0.38	0.64	1.41	2.94	4.40	5.41	6.10
t-GMM	1.72	1.63	1.70	1.71	1.56	1.58	1.67
R^2	0.02	0.03	0.07	0.15	0.25	0.31	0.35
			N: Out-of-sample tests				
OOS R^2	−0.03	−0.03	−0.02	0.07	0.22	0.19	0.08
ENC-T	−0.37	0.34	1.09	0.76	0.74	1.30	1.61
ENC-REG	−0.37	0.34	1.10	0.76	0.74	1.31	1.62
ENC-NEW	−1.96	1.96	6.88	4.69	4.41	7.91	10.11
OOS R^2 (with restrictions)	−0.01	0.01	0.02	0.07	0.22	0.21	0.17

Notes. This table reports various robustness checks of long-horizon regressions of excess market returns on short- and long-run expected economic growth. We use both expected IP growth rates (for all the panels except panel A) and expected GDP growth (for panel A only) as measures of expected economic conditions. The quarterly data for IP span from 1927 to 2012, and data for GDP span from 1947 to 2012. Expected IP growth rates are estimated based on Equations (1) and (2) with IP growth (or GDP growth), the DP ratio, and the term premium in the VAR system. In panels A, B, D, H, I, and J, we use the full sample to estimate parameters in the VAR system and then obtain the expected growth rate at time t using the data available until time t. All the predictive regressions are based on quarterly observations from 1947 to 2012. The short-run business condition is measured as the six-month expected growth rate, and the long-run business condition is measured as the five-year expected growth rate. Panel A repeats panel C in Table 3 by replacing IP with GDP. In the remaining panels, IP growth is used. Panel B repeats the analysis in panel C of Table 3 by using data from 1947 to 2012 to estimate parameters in the VAR system. Panel C uses expected growth rates based on recursively estimated parameters in a real-time fashion. Panels D and E repeat the regressions in panel C of Table 3 and panel C of this table at a monthly frequency. Panels F and G repeat the regressions in panels E and C by using vintage IP data (i.e., the data that have not been subsequently revised, so at each point in time the data are available to the investor), respectively. Panel H repeats panel C of Table 3 by controlling for the default premium, the term premium, the interest rate, the inflation rate, and the surplus ratio. Panels I and J perform a subsample analysis by dividing the sample into two subsamples using the same control variables as in panel H. Panel K repeats panel C in Table 3 by using lag 4 for the VAR system. Panel L uses the method of principal component analysis and extracts the first two components as the two instrumental variables that are used in the VAR system. Panel M reports the analysis using monthly data from 1927–2012. Panel N performs the out-of-sample analysis. The GMM t-statistics with Newey–West correction (with lag $h+6$, denoted by t-GMM) are reported. When the GMM method is not applicable, we report the Newey–West t-statistics (with lag $h+6$, denoted by t-NW). All the regressions use quarterly data if not stated otherwise.

potentially lead to large biases in long-run growth because of the compounding effect. Thus, to alleviate this potential problem and still keep a reasonably large number of observations, we use quarterly IP data to estimate short-run and long-run IP growth in our main analysis. Nonetheless, in panels D and E, we repeat the regressions in panel C of Table 3 and panel C of Table 4, respectively, using monthly IP data. The results are quite similar, and our key predictors retain significant predictive power.

The data on IP tend to be subsequently revised by the Federal Reserve. Since our main purpose is to perform in-sample analysis as in Lettau and Ludvigson (2001) and Baker and Wurgler (2006), we use the revised IP data so far. With revised IP data, the estimation of the expected growth should be more precise. If investors have rational expectations, the estimation based on the revised data should be closer to their true corresponding values, and thus we can estimate a more precise relation between expected growth and the risk premia. However, to truly perform real-time analysis, one should use the raw and unrevised IP data. In panels F and G in Table 4, we repeat the predictive regressions using vintage data (i.e., the data that have not been subsequently revised, so at each point in time the data are available to investors). The results of these robustness tests, despite being slightly weaker,[8] confirm the findings in panel C of Table 3.

One potential explanation for our findings is that the short- and long-run expected economic growth obtained from the VAR system is correlated with some commonly used predictive variables. For example, Fama and Schwert (1977), Keim and Stambaugh (1986), Campbell and Shiller (1988), Fama and French (1988, 1989), Campbell (1991), Ferson and Harvey (1991), Kothari and Shanken (1997), Lettau and Ludvigson (2001), and Li (2001) find evidence that the stock market can be predicted by variables related to the business cycle, such as the default spread, term spread, interest rate, inflation rate, dividend yield, consumption–wealth ratio, and surplus ratio.

Since our predictive variables have a clear economic interpretation, this is not a big concern. Moreover, economic growth has to be correlated with other business cycle variables. Nonetheless, it is still interesting to see whether the predictive power of short- and long-run expected growth is subsumed by other variables. In panel H of Table 4, we reexamine the relation between future market returns and short- and long-run expected economic growth by controlling for business cycle fluctuations. In addition to the traditional variables such as the term premium, the default premium, the interest rate, and the inflation rate, we also control for the consumption–surplus ratio, a proxy for effective risk aversion of the representative agent in the economy.[9]

The results in panel H of Table 4 show that the predictive ability of our short- and long-run expected growth is robust to the inclusion of predictor variables that have been used in earlier studies. After controlling for these variables simultaneously, short-run expected growth retains its predictive power with roughly the same coefficient size and same level of statistical significance. However, the statistical significance for long-run expected growth becomes weaker.[10]

In panels I and J of Table 4, we perform the standard subsample analysis. The whole sample is divided into two equal subsamples. The results are robust in two subsamples, despite slightly lower t-statistics, which are expected as a result of a smaller number of observations.

For parsimony, we have chosen the lag to be 2 in the VAR system. The number of the lag may not be optimal under an information criterion. We calculate the Akaike information criterion and Schwarz Bayesian criterion for our VAR system in Equation (1). The Akaike information criterion values with lags of 2, 3, 4, 5, 6, 7, and 8 are −18.12, −18.24, −18.47, −18.51, −18.49, −18.47, and −18.47, respectively. The Schwarz Bayesian criterion values with lags of 2, 3, 4, 5, 6, 7, and 8 are −17.88, −17.90, −18.03, −17.96, −17.84, −17.72, and −17.61, respectively. This suggests that 4 or 5 may be the optimal lag. However, the difference with the case of lag 2 is very small. As a robustness check, we also use lag = 4 and lag = 5 for the VAR system and find that the results remain similar. In particular, we report the results with lag = 4 in panel K. It can be seen that the results are slightly more significant with lag = 4, compared with panel C of Table 3.

In our base model, we choose the DP ratio and the term premium to be the two predictors of future economic growth rates for the parsimony concern and the fact that the empirical studies have documented that these two variables can predict growth rates very well. However, one may still be concerned that these two predictors are too specific. Thus, we perform a robustness check by using 14 variables (used in Goyal and Welch 2008) as the predictors of economic growth. These 14 variables are the DP ratio, dividend yield, earnings price ratio, dividend payout ratio, stock variance, book–market ratio, net equity expansion, T-bill rate, long-term yield, long-term return, term spread, default yield spread, default return spread, and inflation. For our parsimony concern, we standardize the 14 variables and use principal component analysis to extract the first several components. We choose the first two components (which have explained 48.4% of the variance) and use them in the VAR system to estimate the economic growth. Then we conduct the predictive regressions as in the base model. The results are reported in panel L. The results show that the coefficients retain the same sign with a slightly lower significance level.

So far, we have been focusing on the post-WWII sample period. We also perform the same analysis using pre-WWII data. Panel M of Table 4 shows that the signs of the coefficients remain the same, but the statistical significance becomes weaker. However, in untabulated analysis, we find that the key result that the short- and long-run expected growth have opposite predictive power in forecasting returns is still there and remains statistically significant. There are two potential reasons that could lead to weaker results. First, the pre-WWII macro data are less accurately measured (see, e.g., Romer 1986). Several studies also focus on post-WWII data, including Fama and French (1990). Fama and French (1990) argues that they want to avoid the weak wartime relations between stock returns and real activity as reported by Kaul (1987) and Shah (1989). Indeed, in the pre-1947 period, there is a long period of WWII and the great depression. The usual economic forces may not work well during those special episodes. For example, it is possible that the key underlying economic mechanisms driving our empirical pattern may not be present during the war period.

Second, in the monthly frequency, the short- and long-run expected growth are formed by aggregating 6- and 60-month growth rates, respectively. Thus, small measurement errors in coefficient estimations of the VAR system could potentially lead to large biases in long-run expected growth as a result of the compounding effect. Because of these concerns, our main analysis focuses on the postwar return predictability with quarterly frequency data.

Next we turn to out-of-sample analysis by following Clark and McCracken (2001) and Goyal and Welch (2008). The general procedure is as follows: we first run a regression $r_{t+1} = a + bx_t + \epsilon_{t+1}$ using data up to time τ, and we use $\hat{r}_{\tau+1} = \hat{a} + \hat{b}x_\tau$ to forecast the return at time $\tau + 1$. We then compare the mean squared error of the forecast $\hat{r}_{\tau+1}$ with that of the other forecast, the sample mean return, $\bar{r}_\tau$, up to time τ. The out-of-sample R^2 is defined as

$$R^2_{\text{OOS}} = 1 - \frac{\sum_{\tau=1}^{T}(r_\tau - \hat{r}_\tau)}{\sum_{\tau=1}^{T}(r_\tau - \bar{r}_\tau)}.$$

A positive R^2_{OOS} means that the forecast from the model works better than that from a simple sample mean. We use the first 30 years as our initial estimation. The results are reported in panel N of Table 4.

The asymptotic critical value (with 5% significance level) for ENC-T and ENC-REG is 1.413, and for ENC-NEW, it is 2.234. These critical values are taken from Clark and McCracken (2001). At the one- and two-quarter horizons, all of the three tests do not reject the null hypothesis that the forecast from sample mean encompasses the forecast from the model with short- and long-run growth. At the one-year, two-year, three-year, and four-year horizons, only the ENC-NEW test rejects the null hypothesis; the other two tests do not. At the five-year horizon, all of the three tests reject the null hypothesis. Overall, the OOS tests are pretty weak, especially at shorter horizons.

Campbell and Thompson (2008) show that the OOS R^2 can be improved by imposing sensible restrictions on the out-of-sample forecasting exercise. We thus follow Campbell and Thompson (2008) by imposing two restrictions for our OOS analysis: (1) a nonnegative constraint on the predictive returns and (2) that the coefficient on the short-run growth is nonpositive, and the coefficient on the long-run growth is nonnegative. Consistent with Campbell and Thompson (2008), we also find that these restrictions improve the OOS performance of our model. Most of the OOS R^2 values are now indeed positive after adding those restrictions. However, we admit that these OOS results are still relatively weak.

On the other hand, we believe that these relatively weak OOS results are not critical for the main purpose of our paper. There are two main reasons. First, the main purpose of this paper is not examining the out-of-sample (real-time) predictive power of the short-run and long-run economic growth. Instead, similar in spirit to Lettau and Ludvigson (2001) and Baker and Wurgler (2006), we mainly investigate the in-sample properties of our predictors. These in-sample properties would still be interesting for macro-asset pricing models to match. Second, and more important, Cochrane (2008) shows through simulation that a small or even negative OOS R^2 is expected even if returns are truly forecastable. He shows that a poor out-of-sample R^2 is exactly what we expect given the persistence of our regressors and the relatively short samples we have for estimating the relation between returns and our predictors. Hence, a small (or even negative) OOS R^2 does not necessarily reject the hypothesis that returns are predictable by our variables (see, e.g., Inoue and Kilian 2004, Cochrane 2008). Overall, the OOS tests are not statistically more powerful than the traditional in-sample tests, although they do certainly have practical uses, and good OOS results can also alleviate our concern of overfitting.

In sum, the robustness tests in Table 4 confirm our findings that short- and long-run expected economic growth rates have distinct predictive power.[11] However, we would like to acknowledge that there are possible overfitting issues. For example, our model implies that expected excess returns are negative for about 24.8% of the whole time period, and the negative magnitude sometimes can be large. This suggests possible overfitting of our model, or possible overpricing of the aggregate market, or both. Below we provide more tests based on international data and survey data to further alleviate the concern on the overfitting of our model.

3.3. International Evidence

To provide additional support for our results, we also repeat our main analysis for the remaining G7 countries: Canada, France, Germany, Italy, Japan, and the United Kingdom. Following Cooper and Priestley (2009), the excess stock returns are computed as the difference between the Morgan Stanley capital market total return index and the local short-term interest rate.[12] The DP ratio is also constructed from the Morgan Stanley capital market total return index (with and without dividends). Dictated by data availability, the term premium is calculated from long-term (10-year) government bond yield minus short-term (three-month) yield. The data for Canada, Germany, France, and the United Kingdom are from the St. Louis Fed, and the data for Italy and Japan are from Datastream. Industrial production is the production of total industry in each country. The data were collected from Datastream and the St. Louis Fed, with a sample period from the first quarter of 1970 to the fourth quarter of 2012. For these six countries, we have only the revised data, and thus we focus on in-sample predictability.

Table 5 presents the cross-country evidence on long-horizon regressions of excess market returns on short- and long-run expected economic growth. The signs of coefficients are mostly correct; the statistical significance is slightly weaker in general and becomes better at longer horizons (more than one year). This

Table 5. International Evidence

Horizon	1 quarter	2 quarters	1 year	2 years	3 years	4 years	5 years
			A: Canada				
Short run	0.22	−0.89	−2.51	−3.26	−2.66	−2.01	−2.36
t-GMM	0.30	−0.57	−1.05	−0.87	−0.58	−0.50	−0.61
Long run	0.26	1.04	2.19	2.80	3.36	2.88	2.24
t-GMM	0.74	1.31	1.59	1.39	1.36	1.28	1.13
R^2	0.01	0.05	0.11	0.12	0.17	0.11	0.04
			B: France				
Short run	0.45	−0.43	−0.42	0.46	1.01	−3.39	−11.13
t-GMM	0.53	−0.26	−0.16	0.13	0.30	−0.71	−1.61
Long run	0.30	0.78	1.15	1.27	1.71	2.79	2.99
t-GMM	0.60	0.78	0.78	0.68	0.84	0.89	0.82
R^2	0.01	0.01	0.01	0.01	0.02	0.01	0.04
			C: Germany				
Short run	0.39	−1.36	−2.68	−5.19	−7.67	−16.72	−22.85
t-GMM	0.47	−1.02	−1.24	−1.89	−2.18	−2.20	−2.72
Long run	0.40	1.50	2.71	4.35	5.37	7.19	5.92
t-GMM	1.10	2.24	2.52	3.12	4.04	2.90	1.76
R^2	0.02	0.04	0.07	0.08	0.08	0.08	0.15
			D: Italy				
Short run	−1.42	−1.53	−3.46	−5.82	−9.35	−16.54	−16.75
t-GMM	−1.22	−0.67	−0.77	−0.81	−1.23	−1.62	−1.43
Long run	1.17	1.20	1.99	3.46	6.68	10.73	8.28
t-GMM	1.49	0.70	0.52	0.52	1.04	2.09	1.63
R^2	0.00	−0.00	−0.00	−0.00	0.02	0.05	0.03
			E: Japan				
Short run	−0.18	−0.71	−2.08	−5.38	−5.31	−8.54	−14.61
t-GMM	−0.35	−0.73	−1.04	−1.47	−1.39	−1.60	−2.19
Long run	0.54	1.19	2.50	3.86	3.06	4.41	7.84
t-GMM	1.30	1.56	1.61	1.39	1.05	1.21	1.54
R^2	0.02	0.04	0.06	0.06	0.02	0.04	0.10
			F: United Kingdom				
Short run	−2.16	−3.17	−8.60	−13.12	−20.23	−25.40	−33.93
t-GMM	−0.55	−0.60	−0.75	−0.98	−1.02	−1.00	−1.37
Long run	0.76	1.19	3.08	4.89	7.50	8.76	10.18
t-GMM	0.76	0.89	1.03	1.54	1.52	1.47	1.60
R^2	−0.00	0.00	0.03	0.05	0.09	0.12	0.19

Notes. This table reports long-horizon regressions of excess market returns on short- and long-run expected economic growth for Canada, France, Germany, Italy, Japan, and the United Kingdom. For each country, we use the data on production of total industry to construct IP growth rates. The expected IP growth rates are estimated based on Equations (1) and (2) with IP growth, the DP ratio, and the term premium in the VAR system. We use the full sample to estimate parameters in the VAR system and then obtain the expected growth rate at time t using the data available until time t. All the predictive regressions are based on quarterly observations from 1970 to 2012. The short-run business condition is measured as the six-month expected growth rate, and the long-run business condition is measured as the five-year expected growth rate. The GMM t-statistics with Newey–West correction (with lag $h+6$) are reported.

is expected given the shorter sample period in these regressions. Overall, the evidence from international data is supportive and consistent with that based on U.S. data.

3.4. Predicting Future Uncertainty

Typically, a variable can predict risk premia for two reasons: either it is a proxy for the expected amount of risk or it is a proxy for the price of risk. To understand why short- and long-run business conditions have predictive power for stock returns and why there are different signs in predicting returns, we further investigate the relation between business conditions and future aggregate stock market variance, which is a proxy for the amount of risk rather than the price of risk. From the return predictability results in Table 3, we expect that short-run expected growth is negatively related to future variance, whereas long-run expected growth is positively related to future variance. In panel A of Table 6, we find that short-run growth tends to have stronger predictive power for variance at shorter horizons than at longer horizons, whereas long-run growth has stronger predictive power at longer horizons than at shorter horizons. In general, the results in predicting future market variance are not very strong. Moreover, the signs on the coefficients in panel A are sometimes opposite to our prediction. For example, long-run expected growth should be positively

Table 6. Predicting Future Uncertainty

Horizon	1 quarter	2 quarters	1 year	2 years	3 years	4 years	5 years
			A: Predicting stock variance with short- and long-run growth				
Short run	−0.12	−0.18	−0.23	−0.14	−0.01	0.34	0.88
t-GMM	−1.39	−1.35	−0.92	−0.39	−0.02	0.58	1.51
Long run	0.01	0.01	−0.02	−0.18	−0.31	−0.44	−0.53
t-GMM	0.59	0.24	−0.47	−2.15	−2.15	−2.23	−2.16
R^2	0.02	0.02	0.03	0.11	0.16	0.18	0.19
			B: Predicting IP variance with short- and long-run growth				
Short run	−1.11	−1.87	−2.49	−4.30	−4.22	−5.30	−6.24
t-GMM	−2.19	−2.17	−1.68	−1.73	−1.49	−1.53	−1.63
Long run	0.20	0.35	0.52	0.95	1.27	2.04	2.86
t-GMM	1.53	1.30	0.98	0.97	1.01	1.32	1.55
R^2	0.05	0.05	0.04	0.05	0.03	0.06	0.08

Notes. Panel A reports long-horizon regressions of future stock market variance on short- and long-run expected economic growth. We use expected IP growth to measure expected economic conditions. Panel B reports long-horizon regressions of future IP growth variance on short- and long-run expected economic growth. We use expected IP growth to measure expected economic conditions. Expected IP growth rates are estimated based on Equations (1) and (2) with IP growth, the DP ratio, and the term premium in the VAR system. We use the full sample to estimate parameters in the VAR system and then obtain the expected growth rate at time t using the data available until time t. Stock market variances are calculated from daily return data in each quarter and then summed up in corresponding periods. We follow Segal et al. (2015) and use monthly data on IP to construct the quarterly IP growth variance. The long-horizon IP variances are the sums of the quarterly variances in the corresponding periods. The IP growth variance are in basis points. The GMM t-statistics with Newey–West correction (with lag $h+6$) are reported.

associated with future stock variance, whereas our evidence shows the opposite.

Besides predicting future stock market variance, we also investigate the link between expected growth and future economic uncertainty, another proxy for the expected amount of risk. Following Segal et al. (2015), we measure economic uncertainty with IP growth variance. Indeed, panel B of Table 6 shows that short-run expected growth is strongly negatively related to future economic uncertainty, whereas long-run expected growth is positively related to future economic uncertainty. Thus, the evidence based on economic uncertainty lends support to the notion that the expected business condition captures the variation in the amount of risk in the economy, and thus predicts stock market returns.

Turning to the issue of how short- and long-run expected growth rates are related to the price of risk, we use the surplus ratio as a proxy for the inverse of effective risk aversion (e.g., Campbell and Cochrane 1999). Panel B of Table 1 shows that the surplus ratio is negatively correlated to both short-run and long-run expected growth (−0.27 versus −0.41). This is also true in a multivariate regression of the surplus ratio on short-run and long-run expected growth. Thus, both short- and long-run expected growth are positively correlated to the effective risk aversion. Hence, the evidence suggests that the negative predictive power of short-run growth is unlikely because short-run growth is a proxy for effective risk aversion. However, the stronger positive association between long-run growth and effective risk aversion might partially explain the positive relation between long-run growth and the risk premium. On the other hand, panel H of Table 4 shows that even after controlling for the surplus ratio, the predictive power of both short- and long-run growth remains.

In sum, we find relatively weak evidence regarding the association between expected growth and future return variance. On the other hand, we find a stronger link between expected growth and economic uncertainty. Thus, it seems worthwhile to develop a macroeconomic model to further our understanding of the exact underlying mechanism linking expected growth to economic uncertainty, and hence to the risk premium.[13]

3.5. Predicting Excess Bond Returns

Our previous analysis shows that expected economic growth is related to risk premia in the equity market. Thus, a natural step is to investigate whether these two economic variables can also predict bond returns in both the short term and the long term. The existing literature (with a few recent exceptions, such as Ludvigson and Ng 2009, Cooper and Priestley 2009, Joslin et al. 2014, and Bansal and Shaliastovich 2013, among others) typically relies on yield and prices to predict excess bond returns. We show that our fundamental variables can also forecast excess bond returns.

We regress excess bond returns on our short- and long-run expected economic growth. Since excess bond returns are monthly, we use monthly data on IP growth, the DP ratio, and the term premium to estimate short- and long-run expected economic growth. Panel A of Table 7 shows that short- and long-run expected economic growth conditions still have distinct predictive power for bond returns, although the GMM t-statistics with Newey–West correction are insignificant.

Table 7. Predicting Excess Bond Returns

	2-year bond	3-year bond	4-year bond	5-year bond
		A: Excess bond returns		
Short run	−0.31	−0.46	−0.59	−0.70
t-GMM	−1.29	−0.95	−0.79	−0.72
Long run	0.13	0.22	0.34	0.45
t-GMM	1.23	0.97	0.95	0.97
R^2	0.03	0.03	0.04	0.05
		B: Excess bond returns (controlled for the CP factor)		
Short run	−0.31	−0.46	−0.59	−0.70
t-GMM	−1.65	−1.21	−1.01	−0.87
Long run	0.13	0.22	0.34	0.45
t-GMM	1.66	1.32	1.28	1.23
R^2	0.18	0.19	0.22	0.19

Notes. The table reports the regression of future excess bond returns on short- and long-run expected economic growth. We use expected IP growth rates as measures of expected economic conditions. Data for bond returns span from 1952m6 to 2012m12. Excess bond returns are obtained by borrowing at the one-year rate and buying a two-, three-, four-, or five-year bond and then selling it after one year. All variables are at a monthly frequency. We use monthly data on IP growth, the DP ratio, and the term premium to obtain short-run and long-run expected economic conditions for each month. In particular, expected IP growth rates are estimated based on Equations (1) and (2) with IP growth, the DP ratio, and the term premium in the VAR system. We use the full sample to estimate parameters in the VAR system and then obtain the expected growth rate at time t using the data available until time t. In panel A, we regress excess bond returns on short-run (6-month) and long-run (60-month) expected IP growth without control variables. In panel B, we control for the CP factor in the regression. The GMM t-statistics with Newey–West correction (with lag 12) are reported.

Table 7 reports the results. The signs on the regression coefficients are the same as in the stock return predictive regressions; that is, when long-run (short-run) economic growth is high, the long-term bond risk premium is also high (low). In panel A, we see that the R^2 values range from 3% to 5%. We also regress the excess bond returns on Cochrane and Piazzesi's (2005) forward rate predictor variable (CP) along with expected economic growth. Because the CP factor and expected economic growth variables are highly correlated,[14] following Cooper and Priestley (2009), we first orthogonalize them by regressing the CP factor on expected economic growth. We then regress the excess bond returns on the expected economic growth variables and the orthogonalized component of the CP factor. The results in panel B show that after controlling for the CP factor, the GMM t-statistics with Newey–West correction for short- and long-run expected economic growth are slightly larger.

The evidence (admittedly, relatively weak) that short- and long-run economic growth can forecast excess bond returns suggests that traditional affine term structure models, in which all bond return predictability is attributed to yields or forward rates, are unlikely to fully describe bond price dynamics. Again, it seems worthwhile to develop a macro term structure model to link bond price dynamics to both short- and long-run expected business conditions.

4. Comparisons with Survey-Based Economic Growth Forecasts

As mentioned earlier, in an intriguing study, Campbell and Diebold (2009) use predictors that are closely related to our expected economic growth. In particular, they use both the Livingston Survey and the Survey of Professional Forecasters (SPF) and show that future economic growth forecasts are negatively correlated with risk premia. This result is consistent with the contrarian predictive power of our short-run economic growth. Indeed, the main predictor variable in Campbell and Diebold (2009) is the six-month-ahead economic growth forecast. However, the stand-alone predictive power of short-run growth in our study is weak and insignificant without controlling for long-run growth, whereas the survey-based variable can predict returns even without controlling for any other variables.

Table 8 extends the analysis in Campbell and Diebold (2009) to two additional survey-based variables, the Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index. These surveys are based on responses from individuals rather than professionals. Specifically, we use both the Conference Board survey and the Michigan survey on expected future business conditions to forecast excess market returns. Both surveys ask questions regarding future business conditions. In the Conference Board survey on business conditions, individuals are asked to provide their views on business prospects up to six months ahead. By contrast, in the Michigan survey, individuals are asked to provide their views on business conditions from one year to five years ahead. The constructed index is a combination of those forecasts. Thus, the Michigan survey is on longer-term business conditions, whereas the Conference Board survey is on short-term business conditions. It appears that survey data on near-future business conditions (i.e., the

Table 8. Using Survey Data to Predict Stock Returns

Horizon	1 month	3 months	1 year	2 years	3 years	4 years	5 years
			A: CB survey: 1967–2012				
Coeff.	−0.02	−0.05	−0.18	−0.35	−0.47	−0.56	−0.78
t-NW	−1.67	−1.82	−2.40	−3.14	−3.96	−4.46	−6.62
R^2	0.01	0.02	0.06	0.13	0.17	0.20	0.30
			B: Michigan survey: 1959–2012				
Coeff.	−0.00	−0.02	−0.08	−0.20	−0.22	−0.32	−0.64
t-NW	−0.23	−0.45	−0.63	−1.09	−0.93	−1.29	−2.20
R^2	−0.00	−0.00	0.00	0.01	0.01	0.03	0.08
			C: CB survey + Michigan survey: 1967–2012				
CB	−0.04	−0.09	−0.30	−0.53	−0.73	−0.81	−0.91
t-NW	−2.66	−2.80	−2.72	−3.73	−3.80	−3.72	−4.04
Michigan	0.05	0.11	0.30	0.42	0.61	0.56	0.32
t-NW	1.83	1.47	1.18	1.47	1.71	1.71	0.94
R^2	0.01	0.03	0.08	0.16	0.21	0.23	0.31

Notes. This table reports the long-horizon regressions of future stock returns on survey data. We use both the Conference Board (CB) survey and the Michigan survey to forecast future market returns. Data for the CB survey span from February 1967 to December 2012, and data for the Michigan survey span from November 1959 to December 2012. The Newey and West (1987) (NW) t-statistics (with lag $h+6$) are reported.

Conference Board survey) have significant negative power in predicting returns. Similar results hold for the Livingston Survey on GDP growth, since they are six-month-ahead and one-year-ahead forecasts (see Campbell and Diebold 2009). However, the predictive ability of the Michigan survey is much weaker, probably because of the longer-term feature of these expectation forecasts and the potential misperception component in survey data we shall discuss below.

Forecasts based on survey data could be contaminated by investors' optimism and pessimism. Indeed, Campbell and Sharpe (2009) and Malmendier and Nagel (2016) show that both expert forecasts and individual consumer forecasts exhibit systematic biases, respectively. The contrarian predictive power of the survey-based forecast can be potentially, at least partially, due to misperception. For example, if a high expected business condition reflects optimism, then the predictive power on returns can also be obtained as a result of the subsequent correction of mispricing. In addition, if the forecasts are influenced by investor optimism/pessimism, then the forecast errors should be predictable. Thus, in Table 9, we examine whether forecast errors are predictable. Since we cannot measure forecast errors for the Michigan survey and the Conference Board survey, we instead use the SPF and the Livingston Survey on GDP growth forecasts. Campbell and Diebold (2009) show that both forecasts can predict future excess market returns, although the predictive power of the SPF forecasts is slightly weaker than that based on the Livingston Survey. We regress forecast errors on past forecast levels. Indeed, a higher forecast level tends to be followed by negative forecast errors (i.e., the difference between realized and forecasted growth over the same period), suggesting optimism (pessimism) when the forecast level is high (low).

On the other hand, estimated short-run economic growth based on actual data cannot predict forecast errors, and the sign is opposite. Thus, the contrarian predictive power of short-run economic growth based on actual data is not driven by systematic estimation error in short-run expected growth. In addition, the regression coefficient of forecast errors on long-run expected growth has a negative sign. Given the positive correlation between GDP growth and stock returns, this negative sign for long-run economic growth tends to weaken the procyclical predictive power of long-run growth that we documented in this study. Thus, the procyclical predictive power of long-run economic growth based on actual data is not driven by systematic estimation error either.

In this light, we can also understand why the survey-based expected long-horizon business condition has

Table 9. Regressions of Forecast Errors on Macro Predictors

	γ	R^2
Livingston (6-month, 1952–2012)	−0.34	0.02
	(−1.96)	—
Livingston (10-year, 1991–2012)	−3.00	0.88
	(−14.48)	—
SPF (1-year, 1969–2012)	−0.09	0.00
	(−0.51)	—
Short run (1947–2012)	0.17	0.01
	(0.89)	—
Long run (1947–2012)	−0.43	0.07
	(−2.29)	—

Notes. This table reports the regression of forecast errors on several predictors. The predictors are obtained from three sources: (1) the Livingston Survey from the Philadelphia Fed (there are only 24 observations for the Livingston (10-year) regression), (2) the SPF from the Philadelphia Fed, and (3) our short- and long-run expected IP growth. The forecast errors are defined as realized GDP or IP growth minus forecast GDP or IP growth in the corresponding periods. The Newey–West t-statistics are reported in parentheses.

little to no power in predicting returns, even if the true expected long-run growth has procyclical predictive power. A high expectation of long-run economic growth could reflect either investor optimism or a genuinely high future long-run growth rate. According to our findings based on actual growth data, these two forces have opposite implications for future market returns, thus weakening the predictive power of long-run growth forecasts based on survey data. If the misperception component is large enough in survey-based forecasts, the association between long-run growth forecasts based on survey data and future stock returns could be very weak or even negative even if genuine long-run growth is positively associated with the expected return.[15] On the other hand, for survey forecasts on short-run business conditions, the contrarian predictive power of objective short-run growth and the misperception channel reinforce each other, increasing the predictive power of the survey-based short-run business condition forecasts in a countercyclical fashion. Thus, considering the potential misperception in the survey data, the overall evidence based on survey data is consistent with our findings that although the short-run business condition is negatively related to the risk premium, the long-run business condition is positively related to the risk premium.

Last, existing studies linking direct measures of business conditions and other macro variables to risk premia provide somewhat mixed evidence on the relation between expected business conditions and future stock returns. For example, using output gap (which is negatively related to expected future growth by construction), Cooper and Priestley (2009) find a positive association between economic growth and stock returns, the opposite of the finding of Campbell and Diebold (2009). Our findings help reconcile the seemingly contradictory findings on the relation between expected business conditions and expected returns. The output gap in Cooper and Priestley (2009) and the forecasted GDP growth in Campbell and Diebold (2009) capture different aspects of business conditions. Indeed, the negative output gap is more closely correlated with long-run growth than with short-run growth (0.61 versus 0.37). On the other hand, Campbell and Diebold (2009) focus largely on the short-term survey measures of economic growth.

To some extent, our current study complements Campbell and Diebold (2009) by directly estimating the expected growth rate using actual growth data, and thus our variable is less subject to the influence of investor misperception. The general message of existing studies (e.g., Fama and French 1989, Campbell and Diebold 2009) is that expected returns are lower when economic conditions are strong and higher when conditions are weak. However, the further analysis based on additional survey data appears to confirm our previous evidence that the relation between expected returns and expected business conditions depends on the duration of the expected business condition.

5. Conclusion

Many existing studies argue that when expected future business conditions are bad, the expected risk premium is high. This stylized fact has been a key feature of many state-of-the-art asset pricing models. Our study shows that it is important to distinguish the short-run and long-run business conditions. Although it is indeed true that short-run business conditions are negatively associated with future excess returns, the opposite is true for long-run economic growth. Considered together, short-run and long-run economic growth can significantly predict excess stock market returns with opposite signs.

One possible avenue for future research is to investigate the underlying economic mechanism that could explain why the predictive power of short-run and long-run growth extends in opposite directions. In addition, it would also be interesting to develop structural economic models to further our understanding of the higher-frequency variations in the risk premium in both equity and bond markets, since most existing models feature only lower-frequency variations in expected excess returns.

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Endnotes

[1] Our results are not sensitive to this choice. For example, the results remain similar if we choose $T_s = 1$ year and $T_l = 8$ years.

[2] In addition, Cochrane (2008) shows through simulation that even if returns are genuinely forecastable by persistent predictors, poor out-of-sample forecast power is expected. He shows that this poor out-of-sample behavior is due to the persistence of the regressors and the relatively short samples we have for estimating the relation between returns and predictors. Hence, Cochrane (2008) concludes that pure out-of-sample R^2 is not a statistic that gives us better power to distinguish alternatives than conventional full-sample hypothesis tests. As a result, we focus our analysis on full-sample analysis.

[3] We thank an anonymous referee for this suggestion.

[4] It is worth noting that the opposite signs of regression coefficients on short- and long-run expected growth are not a mechanical result because of their positive correlation. If the true data-generating process for returns is predictable by a state variable and both short- and long-run expected growth are positively correlated to this state variable, then the coefficients for both short- and long-run expected growth would likely carry the same sign, rather than opposite signs, despite their positive correlation. Only if the true data-generating process for returns is predictable by (proxies of) both short- and long-run growth with opposite signs, we can obtain opposite signs

for the coefficients on short- and long-run growth in the multiple regression. This is exactly the classical example of the omitted variable regression.

[5] See Lettau and Ludvigson (2001) and Boudoukh et al. (2007).

[6] These results are reminiscent of the findings in Guo and Savickas (2006, 2008) and Li and Yu (2012). Guo and Savickas (2006, 2008) show that the correlation between market volatility and average idiosyncratic volatility is large and positive. In predicting future market excess returns individually, neither has significant power. However, when jointly predicting future excess stock market returns, both variables have strong predictive power. Although idiosyncratic volatility carries a negative sign, stock market volatility is positively related to stock market returns. Li and Yu (2012) show a similar pattern for nearness to the 52-week high and nearness to the historical high. In particular, they can jointly predict excess returns with opposite signs, but with much weaker stand-alone power.

[7] In this recursive setting, we only report Newey–West t-statistics without the GMM adjustment for the generated regressors since the standard GMM does not apply to this recursive setting. As a result, these t-statistics might overstate the true significance.

[8] Since the GMM method is not applicable for rolling window estimation, we report Newey–West t-statistics for panels C, E, F, and G of Table 4. The t-statistics of panel F should be compared with those of panel E, and the t-statistics of panel G should be compared with those of panel C.

[9] Since the sample period for the consumption–wealth ratio of Lettau and Ludvigson (2001) is shorter than for other control variables, we do not include it in our control list in panel G. In untabulated analysis, we show that adding the consumption–wealth ratio to our control list changes our results only marginally. In particular, the GMM t-statistics with Newey–West correction for short-run growth are −0.34, −1.20, −1.98, −1.97, −1.74, −1.69, and −1.67 for one-quarter, two-quarter, one-year, two-year, three-year, four-year, and five-year horizons, respectively. The GMM t-statistics with Newey–West correction for long-run growth are 1.27, 1.39, 1.50, 1.51, 1.51, 1.51, and 1.50 for one-quarter, two-quarter, one-year, two-year, three-year, four-year, and five-year horizons, respectively.

[10] Since we use the DP ratio and the term premium in the VAR system to estimate expected economic growth, the multicollinearity issue may arise when controlling for both variables in the regressions. Indeed, the VIFs are 38.07, 484.65, 146.20, and 347.25 for short-run expected growth, long-run expected growth, the DP ratio, and the term premium, respectively. These VIFs are much larger than the critical cutoff of 10 suggested by Kutner et al. (2004). On the other hand, if the DP ratio is excluded from the regressors, the VIFs are only 2.21, 4.40, and 4.83 for short-run expected growth, long-run expected growth, and the term premium, respectively. Finally, the opposing predictive power of short- and long-run growth survives if we only control for the DP ratio without the term premium.

[11] Recently, the partial least squares (PLS) approach developed in Kelly and Pruitt (2013) has become more and more popular in finance. For example, Huang et al. (2015) adopted the PLS approach to estimate the unobserved investor sentiment and found that the sentiment index estimated by the PLS approach has greater power in predicting aggregate returns. In an unreported tabulation, we also adopt the PLS approach to estimate the short- and long-run growth and obtain similarly significant results.

[12] The short-term interest rates are the three-month T-bill rate in Canada, France, and the United Kingdom; the three-month euromark rate in Germany; the three-month interbank deposit rate in Italy; and the overnight money market rate in Japan.

[13] Recent attempts along these lines include Bansal et al. (2014) and Segal et al. (2015), among others.

[14] The correlation coefficient is 0.42 for short-run expected economic growth and the CP factor, and 0.60 for long-run expected economic growth and the CP factor. A regression of the CP factor on short- and long-run expected economic growth produces an R^2 of 37%.

[15] Indeed, Table 9 shows that the misperception component in long-run forecasts based on the Livingston Survey is very large. The correlation between long-run growth forecasts and realized growth in corresponding periods is actually negative (−87%). This might explain why Campbell and Diebold (2009) find a negative association between long-run growth forecasts based on survey data and future stock returns, whereas we find a strong positive association between long-run expected growth based on VAR estimation and future stock returns.

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