Long-run economic uncertainty*

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November 17, 2018

Abstract

Higher levels of long-run economic uncertainty are shown to predict larger risk premia as well as lower inflation rates, lower consumption growth and lower output growth over business-cycle to "generational" horizons. When seen through an asset pricing lens, the relation between long-run uncertainty and future inflation rates is a necessary by-product of three conditions: the (near) orthogonality of long-run uncertainty with respect to the dividend-to-price ratio, the ability of long-run uncertainty to strongly predict future risk premia, and its inability to predict nominal cash flows and real interest rates. A general class of equilibrium models with price rigidities is used to provide an economic channel.

JEL classification: C22, E32, E44, G12, G17

Keywords: financial uncertainty, policy uncertainty, macro uncertainty, the long run, the real economy

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* **Preliminary draft: comments welcome.** We are grateful to Sydney Ludvigson for helpful communications and to A. Rebucci, B. Kelly (discussant), and N. Bloom for valuable comments. We thank conference and seminar participants at the SITE 2018 Conference (Stanford), the 2018 Toulouse Financial Econometrics Conference, the 11th Annual SoFiE Conference in Lugano, Universitá di Verona and LSE Finance.

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1 Introduction

The impact on the real economy of shocks to alternative notions of uncertainty has been the subject of a successful recent literature. Bloom (2009) discusses a transmission mechanism leading to lower output growth and lower employment (before sharp rebounds) given sudden increases in uncertainty, as proxied by stock market volatility.[1] Bloom et al. (2018) document a negative relation between uncertainty, proxied by the cross-sectional dispersion in plant-level total factor productivity, and real activity. Baker et al. (2016) employ a newly designed index of policy-related economic uncertainty to show that increases in uncertainty of the magnitude experienced during the financial crisis would lead to considerable declines in real DGP and aggregate employment. This non-exhaustive summary of influential contributions has a common theme: economic uncertainty, irrespective of its proxy, is a precursor of economic contractions.

Methodologically, econometric studies on the response of economic activity to surprise changes in uncertainty have largely relied on vector autoregressions, e.g., Bloom (2009), Baker et al. (2016), Bachmann et al. (2013), Bekaert et al. (2013) and Jurado et al. (2015).

We contribute to the literature along three dimensions. First, our focus is on *levels of uncertainty* rather than on shocks to uncertainty. In particular, emphasis is placed on slow-moving, long-run, uncertainty levels. Second, we are interested in the *medium-frequency* to *low-frequency* links between (long-run) notions of uncertainty, the financial sector and the real economy. Thus, we devote particular attention to business-cycle prediction horizons as well as to longer horizons which may be defined as being "generational" in nature. Finally, methodological, we use economic restrictions from a present value identity (Campbell and Shiller (1988), CS henceforth), instead of iterated vector autoregressions, as a revealing financial lens to understand business-cycle as well as generational dependencies.

On the financial side, we show that long-run uncertainty has strong predictive ability for future long-run market risk premia. On the real side, higher long-run levels of uncertainty are associated with lower long-run levels of inflation, consumption growth and output growth. In order to link financial and real outcomes, we discuss a key implication of the CS present value identity: given

[1]The countercyclical behavior of U.S. stock market volatility is an established empirical fact. See, for example, Schwert (1989a,b).

the (near) orthogonality between long-run uncertainty and the dividend-to-price ratio and the inability of long-run uncertainty to predict either nominal cash flows or real interest rates, the strong predictive ability of long-run uncertainty for future risk premia (with a positive sign) and future inflation (with a negative sign) represent the two sides of the same coin.[2]

We illustrate how a broad class of dynamic stochastic general equilibrium (DSGE) models with price rigidities provides a framework to reconcile these effects. The intuition is simple: shocks to the productivity variance (a natural measure of uncertainty within these models) lead to lower consumption, increased precautionary savings and increased (precautionary) labour supply. In the presence of nominal price rigidities, downward wage pressure due to higher labour supply leads to increased markups and decreased labour demand. In equilibrium, the interaction between positive shifts in labour supply and negative shifts in labour demand may lead to falling wages, lower employment, lower output, and lower prices.

We simulate from a specific model within this class, that of Basu and Bundick (2017). Contrary to Basu and Bundick (2017), however, our specification allows for stochastic volatility in productivity growth. On the real side, *model-implied* regressions of future inflation rates, consumption growth and output growth onto long-run uncertainty (i.e., the long-run variance of productivity growth) yield the qualitative outcomes described in this Introduction over similarly long future horizons. So do, on the financial side, regressions of excess market returns on long-run uncertainty.

The literature on whether uncertainty is an endogenous response or an exogenous impulse is still in its infancy (e.g., Bachmann et al. (2013), Baker and Bloom (2013), Cesa-Bianchi et al. (2018), Carriero et al. (2018), Ludvigson et al. (2015) and Berger et al. (2017)).[3] We view the

[2]A large body of literature has documented a negative relation between stock returns and measures of *expected* or *unexpected* inflation (e.g., Lintner (1975), Bodie (1976), Fama and Schwert (1977), Nelson (1976), Fama (1981), Schwert (1981) and Pindyck (1984)). The result has been hard to justify economically (see, e.g., the discussion in Fama and Schwert (1977)): Fisher's classical decomposition, in fact, expresses expected nominal returns as the sum of expected real returns and expected inflation rates. We offer a novel economic justification for the negative relation (mediated by long-run uncertainty) between stock returns and inflation, in the long run. We document that higher long-run uncertainty is associated with future decreases in real activity coupled with prolonged lower inflation rates. At the same time, higher long-run uncertainty leads to a higher future compensation for uncertainty risk and lower asset prices.

[3]Bachmann et al. (2013) employ cross-sectional dispersion in analysts' or firms' subjective expectations (using a survey of German firms) as a measure of uncertainty and argue that uncertainty appears to be more an outcome of recessions than a cause. Baker and Bloom (2013) identify the causal link between uncertainty and economic activity using an instrumental variable approach. Ludvigson et al. (2015) adopt an external instrumental variable approach to identify structural dynamic causal effects. Carriero et al. (2018) use a large vector autoregression in which

question of whether long-run uncertainty is a source of medium-term to long-term fluctuations or, rather, an endogenous response to more fundamental economic shocks with a persistent impact as an important direction for future research, one on which we do not take a position in this work.

The paper is organized as follows. Because we rely on CS's present value identity to sharpen the detection of the long-run dependencies between long-run uncertainty and (aspects of) the real economy, we begin with empirical evidence on the predictive ability of long-run uncertainty for market risk premia (Section 2). We then turn to the identity, its logic and its implied *economic restrictions* (Section 3). We will show that an orthogonal (to the dividend-to-price ratio) predictor of market risk premia will necessarily also predict nominal cash flows (with a positive sign), inflation (with a negative sign), real risk free rates (with a positive sign), or a combination of them. Orthogonalized (with respect to the dividend-to-price ratio) long-run uncertainty mainly predicts inflation as a counterpart of its predictive ability for market risk premia. Section 4 is devoted to a discussion of the adopted notion of long-run uncertainty and a comparison across proxies. In order to arrive at informative long-run uncertainty proxies, we rely on the notion of *scale-wise predictability*, and its mapping with aggregation, recently introduced in the work of Bandi et al. (2018). Section 5 returns to the predictive ability of long-run uncertainty for market risk premia in Section 2 and positions it further in the context of the economic restrictions imposed by the present value identity. After careful examination of the link between long-run uncertainty and future inflation through the lens of the identity, Section 6 reports (outside of the identity) on the predictive ability of long-run uncertainty for future consumption rates (with a negative sign) and future output growth (also, with a negative sign). Section 7 discusses robustness. Section 8 turns to a justification of the reported real effects within a class of DSGE models with price rigidities. Section 9 concludes.

A thorough discussion of the data is provided in Appendix A. Appendix B and C provide technical details on some econometric implications of the long-run CS identity and on the construction of the long-run uncertainty measures, respectively.

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the uncertainty measures reflect changes in both the conditional mean and the conditional volatility of the relevant variables. Berger et al. (2017) argue that shocks to uncertainty have no significant effect on the economy.

2 Predicting risk premia: preliminary evidence

In order to set the stage for further analysis, we report a graphical representation analogous to that provided by Cochrane (2011) in his Figs. 3 and 4. Fig. 1,[4] Panel A through Panel C below, plots excess (market) returns over three different horizons (1 year, 7 years and 10 years) as well as excess return forecasts based on the dividend-to-price ratio *alone*, on an orthogonalized (with respect to the dividend-to-price ratio) proxy for long-run uncertainty (long-run market variance, in this case[5]) *alone* and on the dividend-to-price ratio and (orthogonalized) long-run market variance, *jointly*.[6]

The impact of long-run uncertainty is apparent. As we transition to longer horizons, uncertainty captures more and more of the slow-moving adjustments in long-run excess returns failed to be captured by the dynamics of the dividend-to-price ratio. The numbers (provided in Table 2) are remarkable. At 1 year, the dividend-to-price ratio captures 6.5% of the variability in excess returns, long-run uncertainty less than 3%. At 7 years, the R^2 associated with the dividend-to-price ratio reaches 34% and that associated with long-run uncertainty is about 32%, at 10 years the corresponding numbers are near 43% and 37%, respectively.[7] Said differently, given the orthogonality between long-run uncertainty and the dividend-to-price ratio, the joint R^2 from a regression of 10-year excess returns on *both* variables is close to 80%.

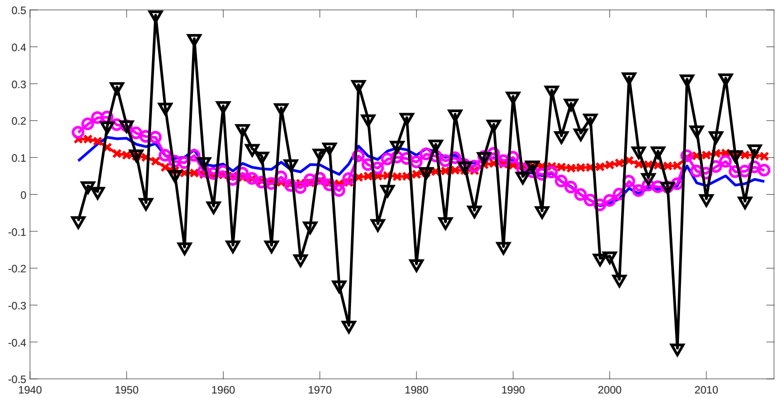
Long-run uncertainty serves as a powerful *long-run* excess return predictor, but improves predictability at *all* horizons. To highlight only a few more numbers (using market variance, once more), the joint use of the dividend-to-price ratio and long-run uncertainty leads to R^2 values

[4] Our data sample spans the period 1930-2016. Because 16 years of data are used to estimate long-run uncertainty, the initial time on the horizontal axis of all figures, here and below, is 1945. A detailed description of the data and its sources is contained in Appendix A.

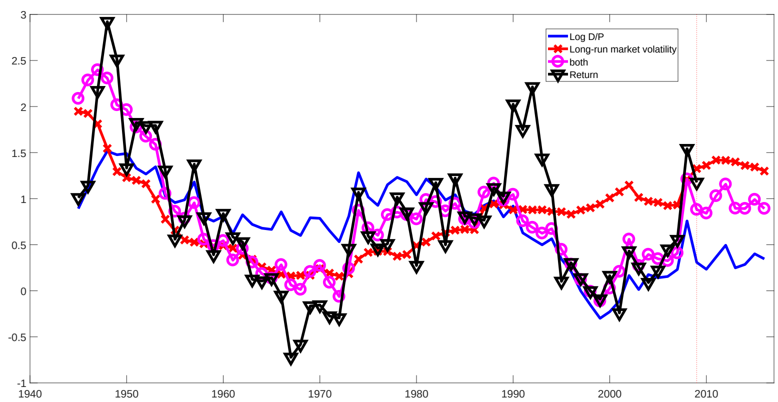
[5] The uncertainty measures used in this paper are *market variance* and a proxy for *economic policy uncertainty* (Baker et al., 2016) dubbed EPU. The long-run notions of both proxies are defined in Section 4. In Section 7 we also employ the measure of macroeconomic uncertainty in Jurado et al. (2015). Because it is only available over a shorter time period, less conducive to assessing low frequency dynamics, this third proxy is, however, solely invoked to evaluate robustness.

[6] Our adopted proxies for long-run uncertainty are *nearly orthogonal* to the dividend-to-price ratio (explicit figures are provided in Section 5). While, for reasons of theoretical and empirical accuracy discussed below, we employ their *exactly orthogonal* (to the dividend-to-price ratio) components in what follows, all reported findings would apply to the raw measures.

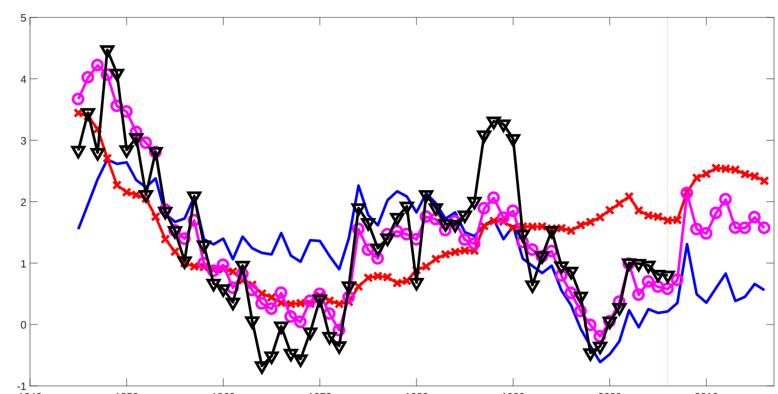
[7] Over the 10 year horizon, we observe an almost perfect fit for about 45 years, until the mid-80s. Both the price-to-dividend ratio and long-run uncertainty miss somewhat the surge in valuations around the 90s. Long-run uncertainty does not add much to the explanatory power of the dividend-to-price ratio between 1995 and 2000. Its (orthogonal) contribution, however, becomes important, again, between 2000 and 2006. (2006 is the last year in this exercise, the one corresponding to 10-year return forecasts over the horizon 2007-2016, c.f. the red vertical line in Panel C.)



(a) Actual and forecast 1-year returns



(b) Actual and forecast 7-year returns



(c) Actual and forecast 10-year returns

Figure 1: Plot of actual versus predicted excess nominal returns at the 1, 7 and 10 year horizons (h=1, 7, and 10): we plot $\alpha + \beta_{x,h} x_t$ along with $R_{t+1,t+h} - R^f_{t+1,t+h}$.

higher than 40% at the 4-year horizon, higher than 55% at the 6-year horizon, higher than 73% at the 8-year horizon and higher than 79% at the 9-year horizon (c.f., Table 2).

Below, we illustrate how the CS identity provides a conceptual framework to rationalize the predictive ability of long-run uncertainty. Any variable that is orthogonal to the dividend-to-price ratio, and predicts long-run excess returns, should lead to the prediction of (1) real dividend growth, (2) real short-term rates, or (3) a combination of these variables.

We show that long-run uncertainty predicts long-run inflation strongly. In the absence of effects on nominal cash flows and real short-term rates, the direction of predictability is constrained by the CS identity. Higher long-run certainty should lead to lower long-run inflation rates. This observation is consistent with data. Some figures using, again, market variance (see Table 4, Panel B): at 10 years and 15 years, the R^2s from regressions of inflation rates onto long-run uncertainty are 45% and about 60%, respectively. The corresponding numbers for the same regressions with the dividend-to-price ratio as the regressor are only 0.9% and 0.9%.

In sum, long-run uncertainty predicts long spells of low future inflation. When taken outside of the CS framework, we will show that it also predicts long-run reductions in *real* consumption growth and in *real* output growth (c.f., Section 6).

3 An asset pricing lens: the CS identity

The long-run predictive ability of the dividend-to-price ratio is by many, admittedly not all, thought to be a fact. Campbell and Shiller's present value identity (Campbell and Shiller, 1988), in particular, provides a natural framework to conceptualize it. In light of the identity, ignoring possible bubble terms, the dividend-to-price ratio should predict returns, dividend growth or both (Cochrane, 2008). If it does not predict returns, it ought to predict dividend growth, and vice versa. Cochrane (2008), in particular, stresses that the predictive ability of the dividend-to-price ratio for long-run returns is economically and statistically compelling, long-run dividend growth predictability being not so.

What the present value identity *does* is, by construction, attributing a key predictive role to the dividend-to-price ratio. When seen through the lens of the identity, alternative financial ratios are, in fact, often viewed as proxies for it. As an example, the earnings-to-price ratio (Campbell and Shiller, 2001), the book-to-market ratio (Kothari and Shanken, 1997, Pontiff and Shall, 1998), or linear combinations of financial ratios of various stock portfolios (Kelly and Pruitt, 2013) perform reasonably well in predicting stock returns. Like in the case of the dividend-to-price ratio, they all have "price" in the denominator. Low current prices imply high future expected returns, thereby justifying the predictive performance of these ratios as well as, of course, that of the more celebrated dividend-to-price ratio.

What the present value identity *does not* do is excluding the predictive ability of variables other than the dividend-to-price ratio. Yet, identifying variables capable to add to the predictive ability of the dividend-to-price ratio, particularly over the long run, is known not to be an easy task. The popular consumption-to-wealth ratio (see Lettau and Ludvigson, 2001), for instance, appears to impact short and medium-term return predictability, but does not lead to significant long-run return forecasts (Cochrane, 2011).

As shown in Section 2, long-run uncertainty adds considerably to the long-run predictive ability of the dividend-to-price ratio for excess returns. In what follows, we explore the economic implications of this predictability.

3.1 Economic restrictions: the role of the dividend-to-price ratio

The log-linearized CS identity implies the following expression:

$$d_t - p_t = r_{t+1} - \Delta d_{t+1} - c + \rho\left(d_{t+1} - p_{t+1}\right), \tag{1}$$

where d_t is log dividend, p_t is log price, $c = \log\left(1 + \exp\left\{\mathrm{E}\left[p - d\right]\right\}\right) - \rho \mathrm{E}\left[p - d\right]$ and $\rho = \frac{\exp\{\mathrm{E}[p-d]\}}{1+\exp\{\mathrm{E}[p-d]\}}$.

Eq. (1), and its forward iterations, are identities. They hold ex-post as well as in expectation (conditional on the dividend-to-price ratio or time-t information).[8] Ruling out the explosive

[8]We ignore the constant term (c) and interpret all variables from now on as being de-meaned.

behavior of stock prices, i.e., $\lim_{j\to\infty} \rho^j \left(d_{t+j} - p_{t+j}\right) = 0$, one easily obtains

$$
\begin{aligned}
d_t - p_t &= \sum_{j=1}^{\infty} \rho^{j-1} \left(r_{t+j} - \Delta d_{t+j}\right) \\
&= \mathrm{E}\left[\sum_{j=1}^{\infty} \rho^{j-1} \left(r_{t+j} - r^f_{t+j}\right) \middle| \, d_t - p_t\right] - \mathrm{E}\left[\sum_{j=1}^{\infty} \rho^{j-1} \left(\Delta d_{t+j} - r^f_{t+j}\right) \middle| \, d_t - p_t\right], \qquad (2)
\end{aligned}
$$

after adding and subtracting the risk-free rate, r^f_t.

In words, the quantity $d_t - p_t$ (i.e., the logarithmic dividend-to-price ratio) is informative about investor's expectations regarding either long-run dividend growth (in excess of the risk-free rate) or long-run excess returns, or *both*. This observation justifies the attention that the price-to-dividend ratio has received (see, e.g., Cochrane, 2008).

When taking the identity to data, the infinite sums ought to be truncated. We use the notation

$$
r^k_t = \sum_{j=1}^{k} \rho^{j-1} \left(r_{t+j} - r^f_{t+j}\right), \quad \Delta d^k_t = \sum_{j=1}^{k} \rho^{j-1} \left(\Delta d_{t+j} - r^f_{t+j}\right), \quad (d/p_t)^k = \rho^k \left(d_{t+k} - p_{t+k}\right), \qquad (3)
$$

where r^k_t, Δd^k_t, and $(d/p_t)^k$ define k-period (discounted) excess log returns, k-period (discounted) excess log dividend growth and the k-step ahead (discounted) log dividend-to-price ratio. When $k \to \infty$ (giving $(d/p_t)^k \to 0$), the symbols r^∞_t and Δd^∞_t are now well-defined. Naturally, we interpret r^∞_t and Δd^∞_t as notions of long-run (weighted, by ρ) returns and long-run (weighted, by ρ again) dividend growth.

When truncating, i.e., for a k insufficiently large, the bubble term may be empirically (and conceptually) important. Iterating Eq. (1) forward, write:

$$
\begin{aligned}
d_t - p_t &= \sum_{j=1}^{k} \rho^{j-1} \left(\left(r_{t+j} - r^f_{t+j}\right) - \left(\Delta d_{t+j} - r^f_{t+j}\right)\right) + \rho^k \left(d_{t+k} - p_{t+k}\right), \qquad (4) \\
&= r^k_t - \Delta d^k_t + (d/p_t)^k. \qquad (5)
\end{aligned}
$$

This expression readily implies that

$$\text{Cov}(d_t - p_t, d_t - p_t) = \text{Cov}(d_t - p_t, r_t^k) - \text{Cov}(d_t - p_t, \Delta d_t^k) + \text{Cov}(d_t - p_t, d/p_t^k) \ .$$

In terms of (univariate regression) βs, the restriction on the covariances becomes

$$1 = \beta^k_{r,dp} - \beta^k_{\Delta d,dp} + \beta^k_{d/p,dp}. \tag{6}$$

In the long run (i.e., for $k \to \infty$), the third equation can be ignored. As in Cochrane (2008), the restriction in Eq. (6), then, becomes

$$1 = \beta^\infty_{r,dp} - \beta^\infty_{\Delta d,dp}. \tag{7}$$

The dividend-to-price ratio should, therefore, predict long-run excess returns, long-run excess dividend growth, or both. Because $\beta^\infty_{r,dp}$ and $\beta^k_{\Delta d,dp}$ are found to be economically (and statistically) close to 1 and 0, Cochrane (2008) emphasizes that it predicts discount rates, rather than cash flows.[9]

3.2 Further economic restrictions: the role of *orthogonal* predictors.

An immediate implication of the same logic applies: if a variable x_t, *orthogonal* to the dividend-to-price ratio, were to forecast long-run excess returns r_t^∞, the same variable would also have to forecast long-run excess dividend growth Δd_t^∞. These forecasts would "offset" each other so that, given $d_t - p_t$, the forecast of the entire right hand side of the present value identity is not altered (c.f., Eq. (5) with $k \to \infty$). This is easy to see. Write

$$\text{Cov}(x_t, d_t - p_t) = \text{Cov}(x_t, r_t^k) - \text{Cov}(x_t, \Delta d_t^k) + \text{Cov}\left(x_t, (d/p_t)^k\right),$$

[9] Cochrane (2008) uses real returns and real dividend growth, rather than excess log return ($r_{t+1} - r^f_{t+1}$) and dividend growth less the interest rate ($\Delta d_{t+1} - r^f_{t+1}$).

where $\text{Cov}(x_t, d_t - p_t) = 0$, due to the assumed *orthogonality* between x_t and $d_t - p_t$. In terms of (univariate regression) βs, the previous restriction on the covariances now becomes:

$$0 = \beta^k_{r,x} - \beta^k_{\Delta d,x} + \beta^k_{d/p,x}. \tag{8}$$

In the long run ($k \to \infty$), the third equation can, again, be ignored and the restriction becomes

$$\beta^\infty_{r,x} = \beta^\infty_{\Delta d,x}. \tag{9}$$

This restriction is solely a by-product of (1) the CS identity and (2) the orthogonality of the predictor. In other words, for a large enough k, any orthogonal variable would satisfy it, irrespective of its predictive ability for long-run excess returns and excess dividend growth. This said, any orthogonal variable which predicts long-run excess returns (resp. long-run excess dividend growth) in a *statistically significant* manner should also represent a *statistically significant* predictor of long-run excess dividend growth (resp. long-run excess returns).

3.3 From nominal to real: a more granular CS identity

A decomposition written in terms of excess (nominal) dividend growth may hide important economic effects. We, therefore, add and subtract inflation rates and re-write the expression in Eq. (4) in terms of *real* dividend growth and *real* nominal rates:

$$d_t - p_t = \sum_{j=1}^{k} \rho^{j-1} \left(\left(r_{t+j} - r^f_{t+j} \right) - \left(\Delta d_{t+j} - \pi_{t+j} \right) + \left(r^f_{t+j} - \pi_{t+j} \right) \right) + \rho^k \left(d_{t+k} - p_{t+k} \right), \tag{10}$$

$$= r^k_t - \Delta d^{\text{real},k}_t + r^{f,\text{real},k}_t + (d/p_t)^k, \tag{11}$$

where the symbols $\Delta d^{\text{real},k}_t$ and $r^{f,\text{real},k}_t$ have a natural interpretation in terms of k-period real dividend growth and k-period aggregates of real short-term rates.

Eq. (9) would now become

$$\beta^\infty_{r,x} = \beta^\infty_{\Delta d^{\text{real}},x} - \beta^\infty_{r^{f,\text{real}},x}, \tag{12}$$

where $\beta^{\infty}_{\Delta d^{\text{real}},x}$ and $\beta^{\infty}_{rf,\text{real},x}$ are, respectively, the regression coefficient of long-run real dividend growth and long-run aggregates of real short-term rates on the orthogonal predictor x_t.

Equivalently, by breaking $\beta^{\infty}_{\Delta d^{\text{real}},x}$ into a nominal component and the contribution of inflation, one could write

$$\beta^{\infty}_{r,x} = \beta^{\infty}_{\Delta d,x} - \beta^{\infty}_{\pi,x} - \beta^{\infty}_{rf,\text{real},x}. \tag{13}$$

In this paper, the variable x_t is the orthogonal (to the dividend-to-price ratio) component of long-run uncertainty. By Eq. (12), because this component predicts long-run excess returns (see Section 2), it ought to either predict long-run real cash flows or long-run aggregates of real short-term rates, or both. Similarly, by Eq. (13), it should predict long-run nominal cash flows, long-run inflation, or long-run aggregates of real short-term rates. We will show that it predicts long-run real cash flows, the key channel being the predictability of long-run inflation (and, therefore, aggregates of short-term nominal interest rates).

4 *Long-run* uncertainty: defining the measure

Stock market variance and economic policy uncertainty (Baker et al., 2016), or EPU, are our main uncertainty proxies.[10] While the former represents, by definition, financial uncertainty, the latter is designed to capture key aspects of macro policy uncertainty.

Our adopted notion of *long-run* uncertainty is purposely simple. It is an H-year sum of 1-year values of the corresponding uncertainty proxy.

Using standard econometric logic, this construction is easily justifiable for market variance. Under an assumption of uncorrelatedness of the market return process, variance aggregates linearly. Hence, an H-year sum of yearly variance measures would amount to H-year market variance.[11]

More generally than in the case of market variance, linear aggregation is formally justified by Bandi et al. (2018) as a way to extract slow-moving components (of the uncertainty process, in our case) which may be brought to bear to forecast long-run risk premia effectively. To this extent,

[10] As mentioned, we also use the measure of macroeconomic uncertainty proposed by Jurado et al. (2015). Since the sample is considerably shorter, and our interest is in long-run effects, we do so in a robustness section.

[11] Because of return predictability with persistent regressors, the market return process is not uncorrelated. However, its noise-to-signal features are such that linear aggregation of variance is a very reasonable approximation.

we follow the logic in Bandi et al. (2018) and construct 16-year aggregates by setting H equal to 16,[12] as they do, in order to arrive at a revealing predictor for long-run risk premia.[13] Appendix B discusses the methods in Bandi et al. (2018) and the selection of H. Robustness to the choice of H is evaluated in Section 7.

Leaving methodology aside, our proposed notion of long-run uncertainty has an appealing economic interpretation. Using the logic in Asness (2000), 16-year aggregates capture (near) "generational" uncertainty. If, as Asness (2000) writes, "each generation's perception of the relative risk of stocks ... is shaped by the volatility it has experienced," then one should expect long spells of high excess returns following long spells of high uncertainty, something which we find strongly in the data.

The evidence from micro and survey data in Malmendier and Nagel (2011) and Malmendier and Nagel (2015) also strongly points to individuals learning from lifetime experiences. In Malmendier and Nagel (2011) and Malmendier and Nagel (2015), more recent data carries a larger informational content than past data, something which may be captured by forms of exponential smoothing (as in the weighted averages underlying the definition of "experienced real returns" in Nagel and Xu (2018)). Our 16-year aggregates may, of course, be interpreted as placing equal weights on observations within the past 16 years and zero weights before then. While this simple aggregates are successful in providing a persistent predictive signal, we are not excluding the possibility that forms of smooth decay would lead to an even stronger signal. From an econometric standpoint, however, aggregates with smooth decay may be harder to justify as a filter for slow-moving, persistent components (c.f., Bandi et al. (2018)).

4.1 Consistency between the long-run uncertainty proxies

Market variance and EPU share similar low-frequency dynamics. The correlation between yearly market variance and yearly EPU is 40%. It is twice as large after aggregating both measures to a 16-year horizon.

[12] All prediction problems in Fig. 1, for instance, are conducted using $H = 16$.

[13] The justification for using 16 years, rather than 15 years say, hinges on the dyadic nature of the cycles captured by the construction in Bandi et al. (2018). Because one can decompose any time series into components (indexed by j) with fluctuations between 2^{j-1} and 2^j periods, filtering through aggregation is naturally conducted using dyadic aggregation horizons.

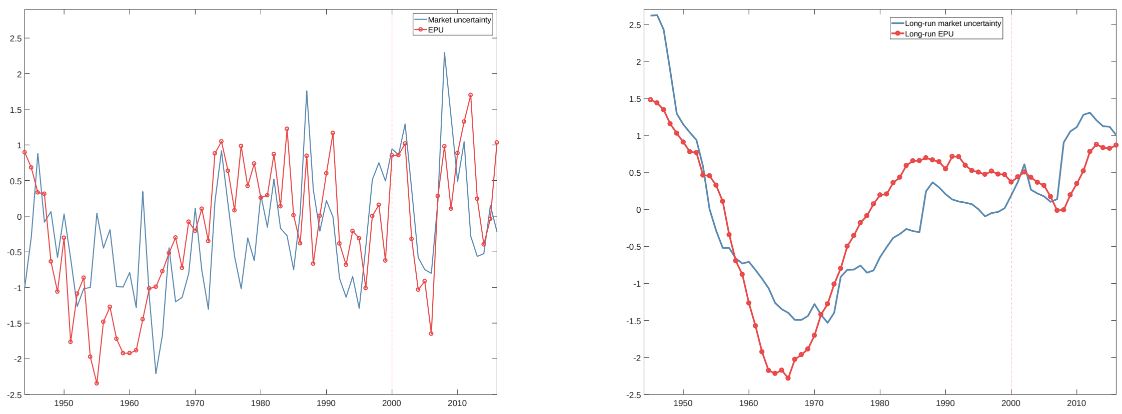
We further substantiate this observation by computing the long-run co-variability of the two series, as described in Muller and Watson (2018). Table 1 reports both the long-run correlation ($\rho_{x,y} = \text{Cov}_{x,y}/\left(\text{Std}_x \text{Std}_y\right)$) and the linear regression coefficient ($\beta_{x,y} = \text{Cov}_{xy}/\text{Var}_x$) obtained from long-run components of the two proxies. The results indicate that market variance and EPU are strongly correlated, and more so at lower frequencies. For instance, the median correlation is 54% for periods longer than 11 years (Panel A) and 70% for periods longer than 15 years (Panel B). As expected, the confidence intervals widen (the correlation's 90% credible sets are $0.40 \leq \rho \leq 0.78$ at 11-years and $0.19 \leq \rho \leq 0.81$ at 15-years). Despite the increase in estimation uncertainty, the estimates are statistically significant at standard confidence levels.[14]

	ρ	β
	Market variance and EPU, longer than 11-years	
Median estimate	0.54	0.85
67% CI	0.43,0.80	0.48,1.37
90% CI	0.35,0.92	0.33,1.52
67% Bayes CS	0.43,0.78	0.59,1.09
90% Bayes CS	0.40,0.78	0.40,1.25
	Market variance and EPU, longer than 15.5-years	
Median estimate	0.70	0.89
67% CI	0.43,0.85	0.45,1.31
90% CI	0.19,0.94	0.19,1.62
67% Bayes CS	0.43,0.78	0.58,1.18
90% Bayes CS	0.19,0.81	0.34,1.39

Table 1: **Long-run co-variability estimates, confidence intervals and credible sets using the Muller and Watson (2018) framework**. We compute long-run co-variability between market variance and squared EPU. EPU is divided by 1000 (before being squared) to obtain a final series that is on the same scale as market variance. The estimated values of ρ and β are the medians of the posteriors using the I(d)-model prior. "CI" denotes confidence interval. "Bayes CS"are Bayes equal-tailed credible sets derived from the parameter's posterior distribution. **Panel A: Periods longer than 11 years ($q = 11$). Panel B: Periods longer than 15.5 years ($q = 15$).** Quarterly data, 1932:Q1-2016:Q4.

[14] The analysis of Muller and Watson (2018) is helpful to compute *contemporaneous* comovement between two series at low frequencies. It may, however, not be immediately applicable to long-run lead/lag relationships, i.e., the main focus of this paper (c.f., in particular, Section 5).

Fig. 2 reports a graphical representation of the dynamics of the raw uncertainty series (Panel A) as well as those of 16-year aggregates proxying for their low-frequency components (Panel B).



(a) Short-run uncertainty. (b) Long-run uncertainty.

Figure 2: **Uncertainty measures**. Panel A displays the (log) market variance (solid line) and the (log) EPU (solid line with circles). Panel B displays the log of long-run market uncertainty (solid line) and the log of long-run EPU (solid line with circles). Long-run market uncertainty is market variance aggregated over $H = 16$ years. Long-run EPU is (squared) EPU aggregated over $H = 16$ years. For ease of comparison, all uncertainty measures are standardized. The red vertical line corresponds to 2000/12, the last available year for the 16-year ahead forecasts of macroeconomic and financial quantities over the horizon 2001-2016.

Should one view true uncertainty about economic fundamentals as a latent process, standard proxies may display short- to medium-term deviations from the latent, true uncertainty. Jurado et al. (2015), for example, have stressed how classical proxies, like market variance or measures of dispersions in firm-level earnings or productivity, may change in the absence of updates to true uncertainty. We do not focus on *innovations* in uncertainty, but on uncertainty *levels*. In addition, due to aggregation, our emphasis is on *low-frequency* levels of uncertainty. In this sense, we believe that the proposed measures are effective in capturing common (low-frequency) variation in true uncertainty, something which is important for uncertainty-based justifications of economic cycles (see, e.g., Jurado et al. (2015) for a discussion). In light of their analogous low-frequency dynamics, the similar predictive ability of the assumed long-run proxies is unsurprising. We now return to predictability.

5 Long-run uncertainty and predictability: a closer look

Our empirical work is largely conducted using simple returns. We, however, use continuously-compounded returns when evaluating, directly, the implications of the CS identity (as in Table 3, 6, 13, and 16, for instance).

Over the period 1930 to 2016, the correlation between 1-year market variance (resp. 1-year EPU) and the dividend-to-price ratio is 0.204 (resp. 0.209). Both correlations diminish during the post-war period (-0.138 for market variance and -0.082 for EPU). The correlations between 16-year market variance and 16-year EPU (computed, due to aggregation, over the period 1945-2016 only) are -0.077 and 0.141, respectively. Even though the latter figures are low, thereby providing evidence of near orthogonality between long-run uncertainty and the dividend-to-price ratio, we work with exactly *orthogonalized* long-run uncertainty proxies for reasons of technical accuracy and interpretability discussed earlier.

5.1 Market variance

In Section 1, we commented on the long-run predictive ability of market variance for returns (with a positive sign) and inflation (with a negative sign) (c.f. Table 2, Panel B and C, and Table 4, Panel B). We now investigate the same issue from a different perspective.

Table 3 contains univariate regressions of k-period (weighted, by powers of ρ) log excess returns, k-period (weighted) log dividend growth, k-period (weighted) log inflation rates, k-period (weighted) aggregates of log risk-free rates and the k-period ahead (weighted) log dividend-to-price ratio onto (1) the dividend-to-price ratio and (2) long-run market variance. The value of ρ is estimated to be equal to 0.9677.[15]

Given the CS identity, the prediction slopes associated with the dividend-to-price ratio should sum up to 1 whereas the prediction slopes associated with long-run market variance should sum up

[15]We recall the expression $\rho = \frac{\exp\{\mathrm{E}(p-d)\}}{1+\exp\{\mathrm{E}(p-d)\}}$. The quantity $\mathrm{E}(p-d)$ is estimated using the full sample 1930-2016. We also considered the case in which ρ is estimated using the *effective* sample 1945-2016. Results do not change.

to zero:

$$\beta^k_{r,x} - \beta^k_{\Delta d,x} + \beta^k_{\pi,x} + \beta^k_{rf,\text{real},x} + \beta^k_{dp,x} = 1 \quad \textit{if} \quad x = p - d$$
$$\beta^k_{r,x} - \beta^k_{\Delta d,x} + \beta^k_{\pi,x} + \beta^k_{rf,\text{real},x} + \beta^k_{dp,x} = 0 \quad \textit{if} \quad x = \text{long-run uncertainty.}$$

In addition, for a long enough horizon (k^*, say), the slope from a regression of the k-period ahead (weighted) log dividend-to-price ratio onto either the dividend-to-price ratio or long-run market variance ($\beta^{k^*}_{dp,x}$) should be effectively negligible. The latter phenomenon will be called *closure.*

While these two results should apply by construction, the time of *closure* k^* does provide information about the horizon k^* over which "the long run" begins to show up in the data. A careful evaluation of the economic and statistical significance of the remaining slopes at that horizon k^* will, therefore, be revealing and provide guidance about the economics of long-run predictability.

Table 3 reports two panels. Panel A refers to an horizon of $k = 16$ years, Panel B refers to an horizon of $k = 18$ years. At both horizons, and for both predictors, the coefficient associated with the k-period ahead (weighted) log dividend-to-price ratio is economically small (particularly over the longer horizon) and statistically insignificant. As expected, the dividend-to-price ratio has predictive ability for long-run (weighted) excess returns with a slope which is statistically equal to 1. Long-run uncertainty also has predictive ability for long-run returns, but return predictability is coupled with the predictability of long-run inflation rates. The corresponding slopes are 0.58 and -0.36 (with t-statistics of 2.63 and -3.60) over the 16-year horizon and 0.59 and -0.38 (with t-statistics of 2.72 and -4.35) over the 18-year horizon.

The superior statistical significance of the slope estimates from regressions of long-run inflation rates onto uncertainty is not surprising. It is easy to show that, given the nature of the return predictability of the dividend-to-price ratio, *indirect* regressions of dividend growth (in excess of the risk-free rate) on uncertainty are statistically *more* informative about the return predictability of uncertainty than *direct* regressions of returns on uncertainty (See Appendix B).

5.2 EPU

Using EPU, in place of market variance, does not modify the above findings. If anything, some figures are slightly strengthened. For example, the combined use of the dividend-to-price ratio and EPU in predicting excess returns at the 10-year horizon leads to an R^2 value of about 83% (43.22% is attributable to the dividend-to-price ratio and 39.99% is attributable to EPU) (Table 5). The corresponding numbers for market variance are marginally lower, the combined R^2 being 79.8% and the number associated with market variance being 36.58% (Table 2). Similarly, EPU's ability to predict inflation rates is slightly enhanced over the long run (Table 7, Panel B). Analogous conclusions can be reached when investigating the implications of the CS representation directly (Table 6). We note, however, that contrary to the market variance case, the horizon $k = 18$ may not be sufficient for *closure* in that the impact of the term $(d/p_t)^k$ appears to be economically and statistically sizeable in this case.

6 Long-run uncertainty and the real economy

When viewed through the lens of the CS identity, the return predictability of long-run uncertainty is justifiable by its ability to predict (lower) future inflation rates.

When taken outside of the CS framework, long-run uncertainty also predicts lower levels of future real consumption growth. Table 8, Panel A, provides a detailed numerical assessment of consumption forecasts for horizons up to 16 years. We report a monotonically increasing (negative) impact of long-run uncertainty on consumption growth as the horizon lengthens.

Identical considerations apply to the relation between long-run uncertainty and future long-run output growth. Table 8, Panel B, provides numerical results for forecasting horizons ranging from 1- to 16-years. Again, the partial effects of long-run uncertainty on future output growth are negative and decrease as the horizon becomes longer.

As emphasized by Basu and Bundick (2017), a robust prediction of neoclassical models subject to uncertainty fluctuations is that output, investments and hours worked will increase as a response to uncertainty shocks lowering consumption. In Section 8, we instead consider a class of models with price frictions yielding positive correlation between fluctuations in consumption growth and output growth. This class of models with generate decreases in both consumption and output growth, as a response to uncertainty shocks and persistently higher uncertainty levels, through increases in price markups.

7 Robustness...

7.1 ... to aggregation

Long-run uncertainty was defined by aggregating single-period proxies over a 16-year time period. As discussed earlier, the work of Bandi et al. (2018) on scale-wise return predictability associated with slow-moving components of the return and predictor process justifies this choice.

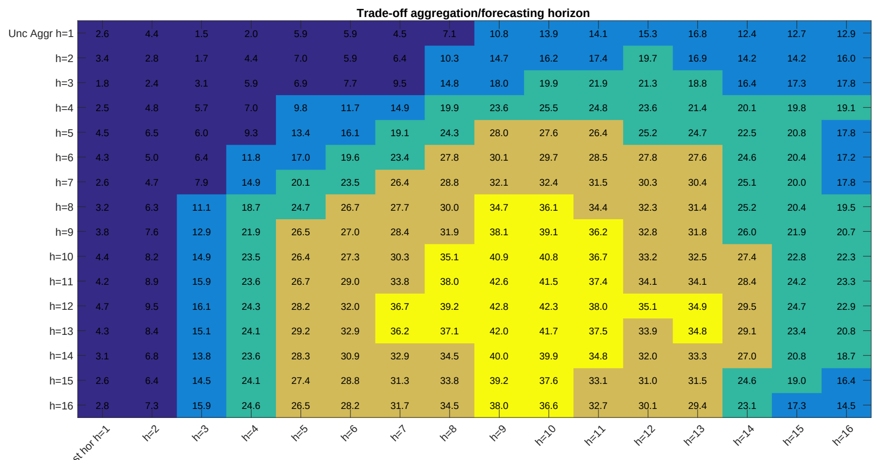
The Bandi et al. (2018) framework, however, relies on a bi-variate (component-wise) specification for returns and uncertainty. Hence, it does not account for the dividend-to-price ratio. In light of this observation, we revisit the choice of aggregation horizon when additional predictors (the dividend-to-price ratio, in our case) are accounted for.

We begin by examining an alternative 10-year aggregation period. Tables 10 and 11 show that aggregating uncertainty over a decadal time frame does not modify the findings reported in Tables 2 and 5 in any relevant fashion.

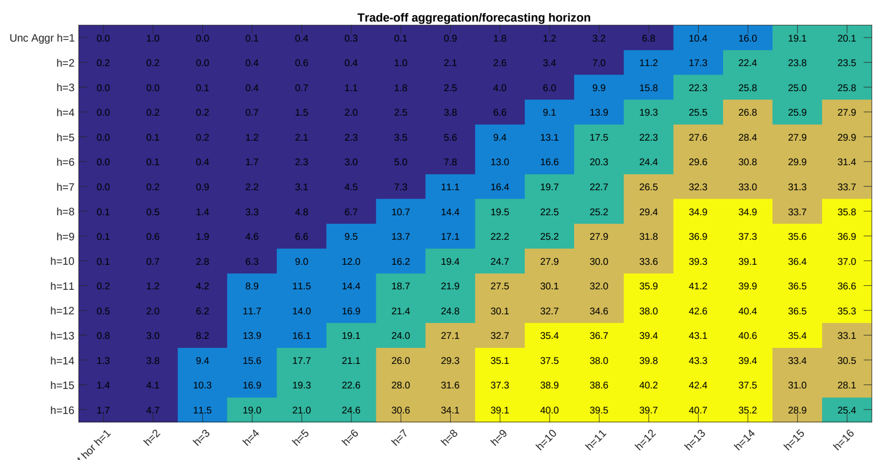
At a more granular level, one may be interested in selecting the best (in terms of R^2) aggregation time frame h_u (u for uncertainty) for *any* given forecasting horizon h_r (r for returns). To this end, Fig. 3 displays the heat-map of the R^2s obtained from regressions of h_r-year ahead returns (x-axis) on both uncertainty measures aggregated over the past h_u years (y-axis) and orthogonalized with respect to the dividend-to-price ratio. The figures on the rows associated with $h_u = 10$ and $h_u = 16$ correspond to the R^2s reported in Panel B of Tables 10 and 2 (for market variance) and Tables 11 and 5 (for EPU).

Panel 3(a) shows that, in the case of market variance, an aggregation horizon of $h_u = 12$ years delivers the largest R^2s for a wide range of forecasting horizons ($h_r \geq 7$ years). It is important to aggregate market uncertainty beyond business-cycle frequencies to uncover interesting low-frequency co-movements with returns. Panel 3(b) indicates that, for EPU, an aggregation horizon of $h_u = 16$

years attains the highest R^2s for forecasting horizons ranging from 1 to 12 years, thereby further validating the choice (of h_u) made throughout this paper. Comparing Panel 3(a) to Panel 3(b), we observe that EPU requires longer aggregation horizons to achieve high R^2s. Further, its co-movement with returns is localized at lower frequencies than the co-movement between market variance and returns.



(a) Market uncertainty.



(b) EPU.

Figure 3: **Uncertainty measures at different levels of aggregation**. The Figure displays the coefficients of determination from a regression of h_r-years holding period excess returns on the portion of the (log of) h_u-years past uncertainty which is orthogonal to the dividend-to-price ratio.

Overall, Fig. 3 suggests that, once we control for the dividend-to-price ratio, aggregating over a 10 to 12-year horizon is sufficient to extract an economically-relevant (for the long run) signal from uncertainty proxies.

7.2 ... to transformations

For both financial uncertainty and EPU, we used logarithmic transformations. Dispensing with the logarithm, or using the squared root, would not affect the reported results meaningfully.

7.3 ... to the time period

Restricting the horizon to the post-war 1967-2016 time period is not influential. It does, however, augment the short-term predictive ability of long-run uncertainty, as documented in Tables 12 and 13.

Long-run uncertainty adds to the predictive ability of the dividend-to-price ratio even when using a longer annual sample spanning the period between 1885 and 2016 (Table 14). For instance, the 12- and 13-year R^2 values from predictive regressions on long-run uncertainty and the dividend-to-price ratio are virtually twice as large as the values from regressions solely inclusive of the dividend-to-price ratio.

Interestingly, Panel A in Table 14 shows reduced return forecasting ability for the dividend-to-price ratio over this longer horizon. This finding is consistent with Golez and Koudijs (2018) who find that cash-flow news were an important driver of the dividend-to-price ratio before 1945, something which diminished the ability of the ratio to predict changes in discount rates before 1945.

7.4 ... to an alternative uncertainty proxy (macroeconomic uncertainty)

In Tables 15, 16 and 17, we report findings based on the measure of macroeconomic uncertainty suggested by Jurado et al. (2015). The sample length is shorter and covers the 1967-2016 time period. In order to obtain a long-run uncertainty proxy, the series is aggregated over an 8-year horizon (c.f., Appendix C for details). Analogous findings, however, apply to horizons of aggregation between 8 and 12 years.

The correlation between the 1-year measure and the dividend-to-price ratio is 0.2761. It is 0.5851 between its 8-year aggregate and the dividend-to-price ratio. Hence, orthogonalizing the series is more important in this case than in the case of market variance and EPU.

As earlier, long-run uncertainty predicts future excess returns (with a positive sign) and future inflation rates (with a negative sign). We also witness some predictability (with a positive sign) for real interest rates and for nominal cash flow growth, the latter over short time horizons. As in the case of EPU, the horizon $k = 18$ is not sufficient for *closure* since the impact of the term $(d/p_t)^k$ is both statistically and economically sizable. This notion of long-run (macroeconomic) uncertainty, therefore, displays some predictive ability for future (discounted) dividend-to-price ratios.

7.5 ... to the choice of the risk-free rate

In Table 18, we use the logarithm of long-run market variance to forecast market returns in excess of the yield on a zero-coupon bond with maturity equal to the forecasting horizon. Earlier, market returns were evaluated in excess of rolled-over short rates. Again, due to data availability on suitable bonds, the sample is the shorter 1967 to 2016 sample.

Consistent with previous results over the same data span, long-run uncertainty predicts excess market returns. Since returns are now computed in excess of the yield on a long-term bond with exposure to inflation, predictability is unlikely to be driven by the rolling-over of short rates whose evolution is linked to inflation adjustments.

7.6 ... to the use of international data

We work, once more, with a shorter sample of data from the UK. The effective sample is annual and spans the period 1960-2016 (dictated by the availability of macroeconomic quantities, like GDP).[16] In spite of the reduced data length, the UK data supports our previous conclusions.

We use EPU for the UK. Differently from the US data, the correlation between the long-run uncertainty measure (i.e., EPU aggregated over 16 years) and the dividend-to-price ratio is about 20%. Orthogonalizing the measure with respect to the dividend-to-price ratio reduces its predictive ability. This reduction notwithstanding, Table 19 shows that long-run uncertainty continues to predict future excess returns (with a positive sign). Table 20 provides evidence for predictability of future consumption growth (with a negative sign) and future output growth (also with a negative sign). Interestingly, both in the case of output growth and in the case of consumption growth, we

[16] Another challenge preventing the use of a long sample is the lack of a uniform measure for EPU. See Appendix A.2 for a detailed discussion of the data used in this section.

observe a hump-shaped pattern in R^2s with maximum predictability localized around the 10-year horizon.

In spite of the reported similarities, there is an interesting difference between the UK data and the US data. For the UK, the impact of uncertainty on future inflation rates is weaker than in the US (not reported). Given the CS identity, this effect is compensated by the stronger predictability of future real interest rates, as documented in Table 20-Panel C.[17]

8 An economic channel: DSGE models with price rigidities

With the reported empirical evidence as a background, we now ask whether long-lasting uncertainty shocks (leading to persistently high levels of uncertainty) have the potential to lead to persistently high market risk premia. We also ask whether the real implications of these shocks are consistent with prolonged (negative) impacts of uncertainty on real consumption and output growth as well as on inflation rates.

Because neoclassical models would deliver reductions in consumption, but *increases* in output, as a robust response to uncertainty shocks, in order to answer these questions, we employ the logic of DSGE models with price rigidities. Within this class of models, shocks to the variance of productivity growth lead to lower consumption, increased precautionary savings and increased precautionary labour supply. In the presence of nominal price rigidities, downward wage pressure due to higher labour supply leads to increased markups and decreased labour demand. In equilibrium, the interaction between positive shifts in labour supply and negative shifts in labour demand may lead to falling wages, lower employment, *lower* output, and lower prices.

[17]Because we do not have access to a reliable and consistent measure of dividends for the UK, we cannot implement the analysis in, e.g., Tables 3 and 6.

As in Basu and Bundick (2017), the main intuition can be provided with four equations:

$$Y_t = C_t + I_t, \quad (14)$$

$$Y_t = F(K_t, Z_t N_t) \quad (15)$$

$$\frac{W_t}{P_t} U_1(C_t, 1 - N_t) = U_2(C_t, 1 - N_t), \quad (16)$$

$$\mu_t \frac{W_t}{P_t} = Z_t F_2(K_t, Z_t N_t), \quad (17)$$

where Y_t is output, C_t is consumption, I_t is investment, N_t is hours worked, Z_t is technology, K_t is capital stock, $\frac{W_t}{P_t}$ is real wage, μ_t is a markup, U is a utility function (with derivatives with respect to the first and the second argument given by U_1 and U_2) and F is a production function. Eq. (14) is the income accounting identity in a closed-economy. Eq. (15) defines production given inputs. Eq. (16) and Eq. (17) are optimality conditions for households and firms, respectively, yielding labour demand and labour supply.

Uncertainty shocks lead to lower consumption levels and, hence, a higher marginal utility of consumption $U_1(C_t, 1-N_t)$. Because of Eq. (16), an increase in the marginal utility of consumption generates an increase in labour supply (N_t) for each wage level W_t (i.e., an outward shift in the labour supply schedule). The downward pressure on nominal wages, along with a slowly-adjusting price level P_t, will induce an increase in the markup μ_t. Such an increase would lead to an inward shift in the labour demand schedule. The interaction between the shift in labour supply and the shift in labour demand may generate a decrease in hours worked, lower wages, lower output (through Eq. (15)), lower investment (through Eq. (14) and, eventually, lower prices.

We simulate from the equilibrium conditions of a widely-accepted model in this class. The specification is that of Basu and Bundick (2017) with one important exception: the source of uncertainty is, in our case, the stochastic volatility of productivity growth.[18] We employ the parameter estimates in Table I of Basu and Bundick (2017). Given equilibrium observations, we run *model-implied* regressions of long-run uncertainty (proxied by the long-run variance of productivity growth) onto future excess returns, inflation rates, and real consumption growth (c.f., Table 9).

[18] In the notation of Basu and Bundick (2017), we allow for a subscript t in the shocks to productivity σ^Z_{t-1} but set $\sigma^a_{t-1} = \sigma^a$.

The model yields the previous qualitative findings over similarly long future horizons. While, in terms of magnitudes and statistical relevance, the model-implied predictability of risk premia is mild (a typical outcome of DSGE models), the predictive ability of long-run uncertainty for future inflation rates is statistically strong. Long-run uncertainty, also, has predictive ability for future real consumption growth and future real output growth.

We believe that, within the model, the reported magnitudes may be improved by, e.g., adding memory to the impact of the shocks to productivity or improving the modeling of risk aversion. Work on this issue is under way and will be reported in later drafts.

9 Conclusions

Long-run uncertainty has forecasting ability for long term future risk premia above and beyond that of the dividend-to-price ratio.

After casting this empirical finding within the CS framework, we show that it must be the case that long-run uncertainty predicts - in the long run - at least one between nominal cash flows, real interest rates, and inflation rates. We find support for the latter result: long-run uncertainty is associated with a persistent fall in future inflation rates.

We rationalize the relation between long-run uncertainty and inflation in a New Keynesian model with price rigidities: in the model, shocks to uncertainty (and higher uncertainty levels) reduce the long-run demand for consumption goods and, through markups, hours worked, employment, inflation and output over the long haul. The data supports these implications.

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Panel A: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.11	0.22	0.29	0.40	0.60	0.82	1.04	1.34	1.58	1.89	2.27	2.58	2.91	3.48	4.20	4.92
	(2.25)	(2.52)	(2.70)	(3.09)	(3.64)	(3.58)	(3.64)	(3.78)	(4.09)	(3.98)	(3.78)	(3.64)	(3.63)	(3.51)	(3.50)	(3.73)
R^2(%)	[6.55]	[11.77]	[13.79]	[16.51]	[22.20]	[29.38]	[34.18]	[39.17]	[41.42]	[43.22]	[43.87]	[42.12]	[41.26]	[42.69]	[44.74]	[45.46]

Panel B: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	0.06	0.15	0.27	0.42	0.57	0.71	0.90	1.13	1.37	1.56	1.73	1.90	2.11	2.15	2.18	2.23
	(1.48)	(2.02)	(2.83)	(3.82)	(4.51)	(4.33)	(4.17)	(4.19)	(4.19)	(3.95)	(3.50)	(2.97)	(2.47)	(1.98)	(1.60)	(1.35)
R^2(%)	[2.77]	[7.31]	[15.88]	[24.55]	[26.49]	[28.18]	[31.73]	[34.45]	[37.99]	[36.58]	[32.69]	[30.11]	[29.41]	[23.14]	[17.33]	[14.50]

Panel C: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \beta_{h,v} v_{t-h+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.11	0.22	0.29	0.40	0.60	0.82	1.04	1.34	1.58	1.89	2.27	2.58	2.91	3.48	4.20	4.92
	(2.23)	(2.59)	(3.28)	(4.63)	(6.54)	(8.92)	(16.40)	(26.35)	(13.82)	(11.95)	(9.61)	(8.68)	(7.72)	(6.41)	(5.72)	(5.54)
$v_{t-15,t}$	0.06	0.15	0.27	0.42	0.57	0.71	0.90	1.13	1.37	1.56	1.73	1.90	2.11	2.15	2.18	2.23
	(1.42)	(1.76)	(2.39)	(3.08)	(3.30)	(3.59)	(4.04)	(4.46)	(5.24)	(5.09)	(4.86)	(5.43)	(6.88)	(6.29)	(5.75)	(5.25)
R^2(%)	[9.32]	[19.08]	[29.67]	[41.06]	[48.69]	[57.55]	[65.91]	[73.62]	[79.41]	[79.80]	[76.56]	[72.23]	[70.67]	[65.83]	[62.07]	[59.96]

Table 2: **Excess nominal returns and Long-run market uncertainty. Panel A: log DP-only.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio. **Panel B: Long-run market uncertainty only.** Linear regressions (with an intercept) of excess returns on log of long-run market uncertainty. **Panel C: Multiple regressions of excess returns on log dividend-price and long-run market uncertainty.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio and log of long-run market variance. $R_{t+1,t+h}$ represents the total return from time t to time $t+h$. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times$ (horizon $-$ 1) lags. We use overlapping observations for the full sample. Long-run market uncertainty is market variance aggregated over $H = 16$ years. The sample is annual and spans the period 1945-2016.

Panel A: Direct regression, $k = 16$

Right-Hand Variable	Coefficients $\sum_{j=1}^{k}\rho^{j-1}r^{ex}_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\Delta d_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\pi_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\text{rrf}_{t+j}$	$\rho^k dp_{t+k}$	$b_r^{(k)} - b_d^{(k)} + b_\pi^{(k)} + b_{rrf}^{(k)} + b_{dp}^{(k)}$
dp_t	1.18	-0.03	-0.26	0.14	-0.11	0.989
	(3.00)	(-0.74)	(-0.90)	(1.19)	(-0.67)	
$R^2(\%)$	[52.46]	[0.34]	[9.97]	[8.64]	[1.65]	
$v_{t-h,t}$	0.58	-0.04	-0.36	-0.13	-0.10	0.038
	(2.63)	(-0.36)	(-3.60)	(-2.93)	(-1.44)	
$R^2(\%)$	[33.46]	[1.45]	[48.86]	[17.28]	[4.05]	

Panel B: Direct regression, $k = 18$

Right-Hand Variable	Coefficients $\sum_{j=1}^{k}\rho^{j-1}r^{ex}_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\Delta d_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\pi_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\text{rrf}_{t+j}$	$\rho^k dp_{t+k}$	$b_r^{(k)} - b_d^{(k)} + b_\pi^{(k)} + b_{rrf}^{(k)} + b_{dp}^{(k)}$
dp_t	1.10	-0.09	-0.27	0.16	-0.10	0.989
	(2.66)	(-1.81)	(-0.88)	(1.31)	(-0.63)	
$R^2(\%)$	[47.64]	[2.87]	[9.85]	[10.05]	[1.61]	
$v_{t-h,t}$	0.59	-0.03	-0.38	-0.15	-0.05	0.037
	(2.72)	(-0.27)	(-4.35)	(-4.25)	(-1.05)	
$R^2(\%)$	[35.44]	[0.62]	[52.67]	[23.31]	[1.10]	

Table 3: **Long-Run Regression Coefficients: Market uncertainty.** Direct regressions on log DP and the component of log of market variance aggregated over $H = 16$ years orthogonal to log D/P. "Direct" regression estimates are calculated using k-year ex post excess returns, nominal dividend growth, Δd_t, inflation, π_t, real risk free rate (nominal 1-year rate minus realized inflation), rrf_t, and dividend yields, dp_t, as left-hand variables. **Panel A: Direct regression, $k = 16$. Panel B: Direct regression , $k = 18$.** Table entries are long-run regression coefficients, for example, $b_r^{(k)}$ in $\sum_{j=1}^{k}\rho^{j-1}r^{ex}_{t+j} = a + b_r^{(k)}dp_t + \varepsilon^r_{t+k}$, where $r^{ex} = \log R_{t+1,t+h} - \log R^f_{t+1,t+h}$. Annual CRSP data, 1945-2016.

Panel A: $D_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	0.04	0.08	0.12	0.15	0.17	0.14	0.10	0.07	0.06	0.06	0.05	0.02	-0.02	-0.05	-0.10	-0.14
	(2.17)	(2.62)	(2.51)	(2.31)	(2.06)	(1.47)	(0.91)	(0.50)	(0.41)	(0.38)	(0.26)	(0.08)	(-0.08)	(-0.21)	(-0.41)	(-0.56)
R^2(%)	[5.82]	[11.39]	[13.29]	[13.01]	[11.89]	[7.19]	[3.64]	[1.49]	[1.00]	[0.84]	[0.36]	[0.04]	[0.03]	[0.23]	[0.96]	[1.79]

Panel B: $\Pi_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	-0.01	-0.03	-0.06	-0.10	-0.14	-0.19	-0.25	-0.33	-0.40	-0.48	-0.55	-0.63	-0.72	-0.80	-0.89	-0.98
	(-0.41)	(-0.95)	(-1.36)	(-1.58)	(-1.62)	(-1.75)	(-1.96)	(-2.13)	(-2.25)	(-2.37)	(-2.45)	(-2.57)	(-2.76)	(-3.01)	(-3.27)	(-3.61)
R^2(%)	[0.74]	[4.80]	[10.64]	[16.51]	[19.34]	[23.72]	[29.86]	[35.27]	[39.97]	[44.24]	[47.67]	[50.83]	[53.79]	[56.36]	[58.40]	[59.68]

Panel C: $\frac{R^f_{t+1,t+h}}{\Pi_{t+1,t+h}} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	-0.03	-0.05	-0.06	-0.07	-0.08	-0.09	-0.09	-0.09	-0.09	-0.10	-0.11	-0.12	-0.13	-0.15	-0.16	-0.18
	(-2.38)	(-2.10)	(-1.92)	(-1.65)	(-1.47)	(-1.30)	(-1.17)	(-1.10)	(-1.05)	(-1.09)	(-1.17)	(-1.26)	(-1.37)	(-1.49)	(-1.63)	(-1.83)
R^2(%)	[16.76]	[15.11]	[14.58]	[13.90]	[12.81]	[10.77]	[8.82]	[7.48]	[6.57]	[6.94]	[7.59]	[8.34]	[9.24]	[10.36]	[11.57]	[13.81]

Table 4: **Panel A: Dividend growth and Long-run market uncertainty.** Linear regressions (with an intercept) of dividend growth on log of long-run market variance. **Panel B: Inflation and Long-run market uncertainty.** Linear regressions (with an intercept) of inflation on log of long-run market uncertainty. **Panel C: Real risk free rate and Long-run market uncertainty.** Linear regressions (with an intercept) of real risk free rate on log of long-run market uncertainty. $D_{t+1,t+h}$ and $\Pi_{t+1,t+h}$ represent the growth rate of dividends and the inflation rate from time t to time $t+h$, respectively. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times$ (horizon $-$ 1) lags. We use overlapping observations for the full sample. Long-run market uncertainty is market variance aggregated over $H = 16$ years. The sample is annual and spans the period 1945 - 2016.

Panel A: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.11	0.22	0.29	0.40	0.60	0.82	1.04	1.34	1.58	1.89	2.27	2.58	2.91	3.48	4.20	4.92
	(2.25)	(2.52)	(2.70)	(3.09)	(3.64)	(3.58)	(3.64)	(3.78)	(4.09)	(3.98)	(3.78)	(3.64)	(3.63)	(3.51)	(3.50)	(3.73)
R^2(%)	[6.55]	[11.77]	[13.79]	[16.51]	[22.20]	[29.38]	[34.18]	[39.17]	[41.42]	[43.22]	[43.87]	[42.12]	[41.26]	[42.69]	[44.74]	[45.46]

Panel B: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	0.04	0.11	0.20	0.33	0.45	0.58	0.76	0.95	1.17	1.37	1.59	1.83	2.07	2.21	2.33	2.43
	(1.23)	(2.01)	(2.52)	(2.88)	(3.12)	(3.32)	(3.67)	(3.90)	(3.94)	(3.97)	(3.93)	(3.74)	(3.41)	(2.99)	(2.55)	(2.16)
R^2(%)	[1.67]	[4.68]	[11.55]	[18.98]	[21.02]	[24.60]	[30.65]	[34.11]	[39.12]	[39.99]	[39.47]	[39.72]	[40.70]	[35.19]	[28.87]	[25.38]

Panel C: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \beta_{h,v} v_{t-h+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.11	0.22	0.29	0.40	0.60	0.82	1.04	1.34	1.58	1.89	2.27	2.58	2.91	3.48	4.20	4.92
	(2.26)	(2.60)	(3.03)	(3.85)	(5.10)	(5.93)	(7.48)	(10.29)	(13.29)	(17.34)	(20.19)	(19.85)	(15.42)	(11.51)	(9.16)	(8.23)
$v_{t-15,t}$	0.04	0.11	0.20	0.33	0.45	0.58	0.76	0.95	1.17	1.37	1.59	1.83	2.07	2.21	2.33	2.43
	(1.26)	(2.02)	(2.63)	(3.17)	(3.79)	(4.94)	(6.76)	(9.49)	(13.20)	(17.84)	(21.41)	(23.84)	(21.85)	(20.70)	(17.03)	(13.65)
R^2(%)	[8.23]	[16.45]	[25.34]	[35.49]	[43.21]	[53.98]	[64.83]	[73.28]	[80.54]	[83.21]	[83.33]	[81.84]	[81.96]	[77.87]	[73.61]	[70.84]

Table 5: **Excess nominal returns and Long-run Economic Policy Uncertainty (EPU, see Baker, Bloom and Davis, 2016). Panel A: log DP-only.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio. **Panel B: Long-run EPU only.** Linear regressions (with an intercept) of excess returns on log of long-run EPU. **Panel C: Multiple regressions of excess returns on log dividend-price and long-run EPU.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio and log EPU. $R_{t+1,t+h}$ represents the total return from time t to time $t+h$. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times (\text{horizon} - 1)$ lags. We use overlapping observations for the full sample. Long-run EPU is EPU aggregated over $H = 16$ years. The sample is annual and spans the period 1945-2016.

Panel A: Direct regression, $k = 16$

Right-Hand Variable	Coefficients $\sum_{j=1}^{k}\rho^{j-1}r^{ex}_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\Delta d_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\pi_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\text{rrf}_{t+j}$	$\rho^k dp_{t+k}$	$b_r^{(k)} - b_d^{(k)} + b_\pi^{(k)} + b_{rrf}^{(k)} + b_{dp}^{(k)}$
dp_t	1.18	-0.03	-0.26	0.14	-0.11	0.989
	(3.00)	(-0.74)	(-0.90)	(1.19)	(-0.67)	
$R^2(\%)$	[52.46]	[0.34]	[9.97]	[8.64]	[1.65]	
$v_{t-h,t}$	0.52	-0.07	-0.33	0.04	-0.27	0.033
	(2.56)	(-1.20)	(-9.24)	(0.72)	(-5.45)	
$R^2(\%)$	[39.51]	[6.06]	[59.99]	[2.28]	[41.66]	

Panel B: Direct regression, $k = 18$

Right-Hand Variable	Coefficients $\sum_{j=1}^{k}\rho^{j-1}r^{ex}_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\Delta d_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\pi_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\text{rrf}_{t+j}$	$\rho^k dp_{t+k}$	$b_r^{(k)} - b_d^{(k)} + b_\pi^{(k)} + b_{rrf}^{(k)} + b_{dp}^{(k)}$
dp_t	1.10	-0.09	-0.27	0.16	-0.10	0.989
	(2.66)	(-1.81)	(-0.88)	(1.31)	(-0.63)	
$R^2(\%)$	[47.64]	[2.87]	[9.85]	[10.05]	[1.61]	
$v_{t-h,t}$	0.52	-0.07	-0.36	0.01	-0.22	0.034
	(2.81)	(-1.49)	(-12.36)	(0.25)	(-5.96)	
$R^2(\%)$	[41.36]	[7.17]	[68.19]	[0.21]	[30.82]	

Table 6: **Long-Run Regression Coefficients: Economic Policy Uncertainty (EPU, see Baker, Bloom and Davis, 2016).** Direct regressions on log DP and the component of log of EPU aggregated over $H = 16$ years orthogonal to log D/P. "Direct" regression estimates are calculated using k-year ex post excess returns, nominal dividend growth, Δd_t, inflation, π_t real risk free rate (nominal 1-year rate minus realized inflation), rrf_t, and dividend yields, dp_t, as left-hand variables. **Panel A: Direct regression, $k = 16$. Panel B: Direct regression , $k = 18$.** Table entries are long-run regression coefficients, for example, $b_r^{(k)}$ in $\sum_{j=1}^{k}\rho^{j-1}r^{ex}_{t+j} = a + b_r^{(k)} dp_t + \varepsilon^r_{t+k}$, where $r^{ex} = \log R_{t+1,t+h} - \log R^f_{t+1,t+h}$. Annual CRSP data, 1945-2016.

Panel A: $D_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	0.03	0.06	0.08	0.09	0.10	0.08	0.07	0.06	0.06	0.06	0.04	0.01	-0.03	-0.08	-0.15	-0.21
	(2.39)	(1.92)	(1.70)	(1.60)	(1.52)	(1.18)	(0.89)	(0.69)	(0.60)	(0.49)	(0.29)	(0.05)	(-0.20)	(-0.53)	(-0.95)	(-1.42)
$R^2(\%)$	[4.46]	[6.34]	[6.34]	[5.59]	[5.07]	[3.45]	[2.45]	[1.79]	[1.38]	[0.91]	[0.33]	[0.01]	[0.15]	[0.99]	[3.01]	[6.18]

Panel B: $\Pi_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	-0.00	-0.01	-0.03	-0.06	-0.09	-0.13	-0.18	-0.24	-0.31	-0.39	-0.47	-0.55	-0.64	-0.74	-0.83	-0.93
	(-0.00)	(-0.59)	(-1.02)	(-1.29)	(-1.49)	(-1.78)	(-2.19)	(-2.71)	(-3.33)	(-4.00)	(-4.72)	(-5.51)	(-6.52)	(-7.89)	(-9.78)	(-12.59)
$R^2(\%)$	[0.00]	[0.82]	[3.27]	[6.91]	[10.25]	[14.73]	[20.59]	[26.93]	[34.20]	[41.65]	[48.76]	[55.48]	[62.12]	[68.48]	[74.56]	[79.95]

Panel C: $\frac{R^f_{t+1,t+h}}{\Pi_{t+1,t+h}} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	-0.01	-0.01	-0.01	-0.00	0.01	0.01	0.02	0.03	0.04	0.05	0.05	0.06	0.06	0.05	0.05	0.04
	(-1.27)	(-0.70)	(-0.32)	(-0.06)	(0.12)	(0.28)	(0.43)	(0.54)	(0.61)	(0.63)	(0.66)	(0.68)	(0.68)	(0.65)	(0.59)	(0.44)
$R^2(\%)$	[2.45]	[1.12]	[0.31]	[0.01]	[0.06]	[0.37]	[0.90]	[1.48]	[1.98]	[2.31]	[2.53]	[2.54]	[2.39]	[2.06]	[1.61]	[0.90]

Table 7: **Panel A: Dividend growth and long-run economic policy uncertainty (EPU, see Baker, Bloom and Davis, 2015) aggregated over $H = 16$ years.** Linear regressions (with an intercept) of dividend growth on log of long-run EPU. **Panel B: Inflation and long-run EPU.** Linear regressions (with an intercept) of inflation on log of long-run EPU. **Panel C: Real risk free rate and long-run EPU.** Linear regressions (with an intercept) of real risk free rate on log of long-run EPU. $D_{t+1,t+h}$ and $\Pi_{t+1,t+h}$ represent the growth rate of dividends and the inflation rate from time t to time $t+h$, respectively. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times$ (horizon $-$ 1) lags. We use overlapping observations for the full sample. Long-run EPU is EPU aggregated over $H = 16$ years. The sample is annual and spans the period 1930 - 2016.

Panel A: $\frac{C_{t+h}}{C_t} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MKT Unc																
	-0.01	-0.02	-0.03	-0.04	-0.05	-0.06	-0.06	-0.07	-0.08	-0.08	-0.09	-0.09	-0.10	-0.10	-0.10	-0.10
	(-2.17)	(-4.12)	(-3.99)	(-3.53)	(-3.02)	(-2.72)	(-2.57)	(-2.51)	(-2.57)	(-2.64)	(-2.78)	(-2.93)	(-2.96)	(-2.87)	(-2.83)	(-2.70)
R^2(%)	[13.07]	[23.23]	[26.18]	[28.50]	[28.07]	[27.97]	[28.46]	[28.74]	[28.55]	[29.70]	[31.22]	[31.88]	[31.30]	[29.59]	[27.53]	[25.53]
EPU																
	-0.01	-0.02	-0.03	-0.03	-0.04	-0.05	-0.06	-0.06	-0.07	-0.08	-0.08	-0.08	-0.09	-0.09	-0.09	-0.10
	(-2.53)	(-3.71)	(-3.93)	(-4.02)	(-3.94)	(-3.93)	(-3.97)	(-4.10)	(-4.27)	(-4.26)	(-4.20)	(-4.03)	(-3.78)	(-3.52)	(-3.34)	(-3.18)
R^2(%)	[8.31]	[16.44]	[20.81]	[24.74]	[26.64]	[28.61]	[30.16]	[31.13]	[33.57]	[35.76]	[37.45]	[37.98]	[37.88]	[36.98]	[36.58]	[36.61]

Panel B: $\frac{GDP_{t+h}}{GDP_t} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MKT Unc																
	-0.02	-0.03	-0.03	-0.04	-0.04	-0.05	-0.06	-0.07	-0.08	-0.09	-0.10	-0.11	-0.11	-0.11	-0.11	-0.11
	(-2.01)	(-1.86)	(-1.92)	(-1.99)	(-1.87)	(-1.86)	(-2.03)	(-2.23)	(-2.53)	(-2.77)	(-3.10)	(-3.19)	(-3.02)	(-2.71)	(-2.50)	(-2.23)
R^2(%)	[12.13]	[11.53]	[10.52]	[10.31]	[10.33]	[12.14]	[15.59]	[18.44]	[20.43]	[23.06]	[26.91]	[28.16]	[27.32]	[25.45]	[22.99]	[20.66]
EPU																
	-0.01	-0.02	-0.03	-0.04	-0.04	-0.05	-0.05	-0.06	-0.07	-0.07	-0.08	-0.08	-0.09	-0.09	-0.09	-0.10
	(-1.90)	(-1.94)	(-2.06)	(-2.18)	(-2.16)	(-2.25)	(-2.48)	(-2.74)	(-3.01)	(-3.04)	(-2.98)	(-2.83)	(-2.68)	(-2.55)	(-2.47)	(-2.35)
R^2(%)	[5.87]	[8.41]	[10.08]	[11.56]	[13.03]	[14.78]	[17.01]	[18.38]	[20.35]	[22.22]	[24.17]	[24.13]	[23.73]	[23.81]	[23.96]	[24.04]

Table 8: **Panel A: Consumption growth and Long-run uncertainty.** Linear regressions (with an intercept) of real consumption growth on either (i) log of market variance; or (ii) log of EPU, both aggregated over $H = 16$ years. **Panel B: Output growth and Long-run uncertainty.** Linear regressions (with an intercept) of real output growth on either (i) log of market variance; or (ii) log of EPU, both aggregated over $H = 16$ years. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times (\text{horizon} - 1)$ lags. We use overlapping observations for the full sample. The sample is annual and spans the period 1945-2016.

Panel A: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h v_{t-h+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	0.02	0.03	0.05	0.06	0.07	0.07	0.08	0.08	0.09	0.09	0.10	0.10	0.10	0.11	0.12	0.12
(5^{th}, 95^{th})	(0.01,0.03)	(0.02,0.07)	(0.03,0.10)	(0.03,0.12)	(0.04,0.16)	(0.05,0.20)	(0.06,0.23)	(0.06,0.26)	(0.07,0.29)	(0.07,0.32)	(0.07,0.33)	(0.07,0.34)	(0.08,0.35)	(0.08,0.37)	(0.08,0.39)	(0.08,0.41)
R^2(%)	[2.09]	[3.83]	[5.9]	[7.6]	[7.9]	[8.9]	[9.5]	[10.9]	[11.0]	[12.1]	[13.9]	[13.6]	[14.1]	[14.5]	[15.7]	[15.9]

Panel B: $\Pi_{t+1,t+h} = \alpha_h + \beta_h v_{t-h+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	0.01	0.01	0.01	0.00	-0.00	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.03	-0.04	-0.05	-0.05	-0.06
(5^{th}, 95^{th})	(-0.01, 0.01)	(-0.04, 0.02)	(-0.04, 0.02)	(-0.05,0.01)	(-0.05, 0.01)	(-0.05, 0.02)	(-0.05, 0.02)	(-0.06, 0.02)	(-0.06, 0.02)	(-0.07, 0.03)	(-0.07, 0.02)	(-0.08, 0.02)	(-0.09, 0.02)	(-0.10, 0.03)	(-0.10, 0.04)	(-0.11, 0.05)
R^2(%)	[28.71]	[33.50]	[37.44]	[41.06]	[43.76]	[45.36]	[46.13]	[46.40]	[46.76]	[47.28]	[47.78]	[48.20]	[48.56]	[48.78]	[48.88]	[48.98]

Panel C: $\frac{C_{t+h}}{C_t} = \alpha_h + \beta_h v_{t-h+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	-0.02	-0.03	-0.03	-0.04	-0.05	-0.06	-0.06	-0.06	-0.07	-0.07	-0.08	-0.08	-0.07	-0.08	-0.08	-0.09
(5^{th}, 95^{th})	(-0.07, -0.02)	(-0.08, -0.01)	(-0.08, 0.01)	(-0.09, 0.01)	(-0.10, 0.01)	(-0.11, 0.01)	(-0.11, 0.04)	(-0.11, 0.03)	(-0.12, -0.02)	(-0.12, -0.01)	(-0.13, 0.01)	(-0.13, 0.03)	(-0.12, 0.02)	(-0.13, 0.04)	(-0.13, 0.09)	(-0.14, 0.09)
R^2(%)	[1.39]	[3.28]	[3.59]	[4.86]	[6.75]	[9.11]	[11.20]	[11.98]	[12.39]	[12.97]	[14.44]	[15.55]	[16.18]	[16.59]	[16.70]	[17.39]

Panel D: $\frac{GDP_{t+h}}{GDP_t} = \alpha_h + \beta_h v_{t-h+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	-0.13	-0.17	-0.19	-0.21	-0.22	-0.25	-0.27	-0.28	-0.29	-0.31	-0.31	-0.31	-0.31	-0.32	-0.32	-0.33
(5^{th}, 95^{th})	(-0.18, -0.07)	(-0.22, -0.07)	(-0.24, -0.08)	(-0.26, -0.06)	(-0.27, -0.05)	(-0.30, -0.03)	(-0.32, 0.00)	(-0.33, 0.02)	(-0.34, 0.03)	(-0.36, 0.06)	(-0.36, 0.13)	(-0.36, 0.20)	(-0.36, 0.21)	(-0.37, 0.26)	(-0.37, 0.30)	(-0.38, 0.3
R^2(%)	[21.58]	[18.70]	[17.09]	[16.62]	[17.95]	[20.53]	[23.28]	[24.85]	[25.44]	[25.94]	[27.08]	[28.77]	[30.26]	[30.84]	[30.87]	[30.88]

Table 9: **Model-implied regressions. Panel A: Excess returns and Long-run productivity uncertainty.** Linear regressions (with an intercept) of excess returns on log of long-run productivity risk. **Panel B: Inflation and Long-run productivity uncertainty.** Linear regressions (with an intercept) of inflation on log of long-run productivity risk. **Panel C: Real Consumption growth and Long-run productivity uncertainty.** Linear regressions (with an intercept) of real consumption growth on log of long-run productivity risk over $H = 16$ years. **Panel D: Real Output growth and Long-run productivity uncertainty.** Linear regressions (with an intercept) of real output growth on log of long-run productivity risk over $H = 16$ years. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times (\text{horizon} - 1)$ lags. We use overlapping observations for the full sample. Long-run productivity uncertainty is uncertainty aggregated over $H = 16$ years. The regression coefficients (median and $5\% - 95\%$ percentile) are from 100 samples of equivalent length to the data (70 years). R^2 are from a long simulation of 2000 quarterly observations.

Panel A: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.11	0.22	0.29	0.40	0.60	0.82	1.04	1.34	1.58	1.89	2.27	2.58	2.91	3.48	4.20	4.92
	(2.25)	(2.52)	(2.70)	(3.09)	(3.64)	(3.58)	(3.64)	(3.78)	(4.09)	(3.98)	(3.78)	(3.64)	(3.63)	(3.51)	(3.50)	(3.73)
R^2(%)	[6.55]	[11.77]	[13.79]	[16.51]	[22.20]	[29.38]	[34.18]	[39.17]	[41.42]	[43.22]	[43.87]	[42.12]	[41.26]	[42.69]	[44.74]	[45.46]

Panel B: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-9,t}$	0.08	0.17	0.28	0.45	0.63	0.77	0.98	1.30	1.67	1.95	2.19	2.42	2.73	2.92	3.13	3.47
	(1.90)	(2.49)	(3.08)	(3.67)	(3.91)	(3.70)	(3.78)	(4.10)	(4.25)	(4.48)	(4.31)	(3.45)	(2.75)	(2.31)	(2.06)	(1.98)
R^2(%)	[4.36]	[8.20]	[14.92]	[23.54]	[26.41]	[27.26]	[30.34]	[35.08]	[40.91]	[40.80]	[36.67]	[33.22]	[32.55]	[27.39]	[22.75]	[22.32]

Panel C: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \beta_{h,v} v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.11	0.22	0.29	0.40	0.60	0.82	1.04	1.34	1.58	1.89	2.27	2.58	2.91	3.48	4.20	4.92
	(2.23)	(2.57)	(2.95)	(3.51)	(4.22)	(4.60)	(5.36)	(6.59)	(10.11)	(11.54)	(11.16)	(10.30)	(10.81)	(8.17)	(6.90)	(7.23)
$v_{t-9,t}$	0.08	0.17	0.28	0.45	0.63	0.77	0.98	1.30	1.67	1.95	2.19	2.42	2.73	2.92	3.13	3.47
	(1.88)	(2.33)	(3.10)	(4.08)	(4.61)	(5.03)	(6.00)	(7.85)	(10.83)	(12.85)	(11.65)	(8.87)	(6.03)	(4.91)	(4.69)	(4.83)
R^2(%)	[10.91]	[19.97]	[28.71]	[40.06]	[48.61]	[56.64]	[64.52]	[74.24]	[82.33]	[84.02]	[80.54]	[75.35]	[73.81]	[70.08]	[67.49]	[67.78]

Table 10: **Excess nominal returns and Long-run (i.e. decadal) market uncertainty. Panel A: log DP-only.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio. **Panel B: Long-run market uncertainty only.** Linear regressions (with an intercept) of excess returns on log of long-run market uncertainty. **Panel C: Multiple regressions of excess returns on log dividend-price and long-run market uncertainty.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio and log of long-run market variance. $R_{t+1,t+h}$ represents the total return from time t to time $t+h$. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times (\text{horizon} - 1)$ lags. We use overlapping observations for the full sample. Long-run market uncertainty is market variance aggregated over $H = 10$ years. The sample is annual and spans the period 1945-2016.

Panel A: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.11	0.22	0.29	0.40	0.60	0.82	1.04	1.34	1.58	1.89	2.27	2.58	2.91	3.48	4.20	4.92
	(2.25)	(2.52)	(2.70)	(3.09)	(3.64)	(3.58)	(3.64)	(3.78)	(4.09)	(3.98)	(3.78)	(3.64)	(3.63)	(3.51)	(3.50)	(3.73)
R^2(%)	[6.55]	[11.77]	[13.79]	[16.51]	[22.20]	[29.38]	[34.18]	[39.17]	[41.42]	[43.22]	[43.87]	[42.12]	[41.26]	[42.69]	[44.74]	[45.46]

Panel B: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-10,t}$	0.01	0.04	0.09	0.16	0.26	0.35	0.48	0.63	0.82	1.01	1.22	1.48	1.80	2.06	2.30	2.58
	(0.34)	(0.94)	(1.40)	(1.65)	(1.88)	(2.11)	(2.53)	(3.00)	(3.54)	(4.03)	(4.39)	(4.48)	(4.45)	(4.30)	(3.95)	(3.64)
R^2(%)	[0.12]	[0.72]	[2.77]	[6.25]	[8.98]	[12.03]	[16.20]	[19.44]	[24.74]	[27.86]	[29.98]	[33.63]	[39.26]	[39.10]	[36.39]	[37.02]

Panel C: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \beta_{h,v} v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.11	0.22	0.29	0.40	0.60	0.82	1.04	1.34	1.58	1.89	2.27	2.58	2.91	3.48	4.20	4.92
	(2.25)	(2.53)	(2.76)	(3.24)	(3.97)	(4.16)	(4.55)	(5.19)	(6.39)	(6.99)	(7.82)	(8.89)	(11.66)	(12.62)	(11.27)	(12.57)
$v_{t-10,t}$	0.01	0.04	0.09	0.16	0.26	0.35	0.48	0.63	0.82	1.01	1.22	1.48	1.80	2.06	2.30	2.58
	(0.35)	(0.95)	(1.46)	(1.78)	(2.11)	(2.49)	(3.12)	(4.07)	(5.88)	(8.29)	(10.65)	(12.68)	(14.21)	(16.90)	(21.43)	(23.42)
R^2(%)	[6.68]	[12.49]	[16.56]	[22.76]	[31.18]	[41.41]	[50.38]	[58.61]	[66.16]	[71.08]	[73.85]	[75.75]	[80.52]	[81.79]	[81.13]	[82.48]

Table 11: **Excess nominal returns and Long-run (i.e. decadal) Economic Policy Uncertainty (EPU, see Baker, Bloom and Davis, 2016). Panel A: log DP-only.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio. **Panel B: Long-run EPU only.** Linear regressions (with an intercept) of excess returns on log of long-run EPU. **Panel C: Multiple regressions of excess returns on log dividend-price and long-run EPU.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio and log EPU. $R_{t+1,t+h}$ represents the total return from time t to time $t+h$. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times (\text{horizon} - 1)$ lags. We use overlapping observations for the full sample. Long-run EPU is EPU aggregated over $H = 10$ years. The sample is annual and spans the period 1945-2016.

Panel A: $R_{t+1,t+h} - R^f_{t,t+h} = \alpha_h + \beta_h dp_t + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.07	0.13	0.13	0.18	0.33	0.46	0.63	0.87	1.12	1.38	1.73	2.02	2.35	2.96	3.76	4.65
	(1.15)	(1.29)	(1.24)	(1.62)	(2.83)	(4.63)	(5.01)	(5.63)	(4.91)	(5.26)	(5.92)	(6.41)	(6.08)	(5.04)	(4.51)	(4.44)
R^2(%)	[2.40]	[3.74]	[2.73]	[3.20]	[6.62]	[10.77]	[15.60]	[23.19]	[28.86]	[33.18]	[35.63]	[36.24]	[37.86]	[40.33]	[45.29]	[50.56]

Panel B: $R_{t+1,t+h} - R^f_{t,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	0.20	0.41	0.58	0.82	1.13	1.35	1.59	1.92	2.37	2.72	3.05	3.09	2.95	2.98	3.01	2.89
	(3.38)	(5.27)	(7.89)	(9.11)	(8.77)	(8.30)	(6.70)	(6.02)	(5.18)	(5.97)	(7.67)	(8.47)	(5.27)	(3.17)	(2.34)	(1.86)
R^2(%)	[16.10]	[27.42]	[35.47]	[42.35]	[46.23]	[48.84]	[50.93]	[52.85]	[53.27]	[53.74]	[47.15]	[37.26]	[26.93]	[19.46]	[13.75]	[10.14]

Panel C: $R_{t+1,t+h} - R^f_{t,t+h} = \alpha_h + \beta_h dp_t + \beta_{h,v} v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.07	0.13	0.13	0.18	0.33	0.46	0.63	0.87	1.12	1.38	1.73	2.02	2.35	2.96	3.76	4.65
	(1.18)	(1.33)	(1.48)	(2.10)	(2.86)	(3.63)	(6.43)	(9.81)	(11.18)	(18.11)	(21.01)	(14.66)	(10.06)	(6.49)	(5.31)	(5.09)
$v_{t-15,t}$	0.20	0.41	0.58	0.82	1.13	1.35	1.59	1.92	2.37	2.72	3.05	3.09	2.95	2.98	3.01	2.89
	(3.42)	(5.35)	(8.22)	(10.25)	(10.23)	(9.93)	(9.67)	(10.75)	(10.54)	(14.59)	(22.37)	(10.86)	(5.15)	(3.24)	(2.57)	(2.23)
R^2(%)	[18.50]	[31.16]	[38.20]	[45.55]	[52.86]	[59.60]	[66.53]	[76.04]	[82.13]	[86.93]	[82.78]	[73.50]	[64.79]	[59.79]	[59.04]	[60.70]

Table 12: **Excess nominal returns and Market uncertainty (alternative sample). Panel A: log DP-only.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio. **Panel B: Long-run market uncertainty only.** Linear regressions (with an intercept) of excess returns on log of long-run market variance. **Panel C: Multiple regressions of excess returns on log dividend-price and long-run market uncertainty.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio and log of long-run market variance. $R_{t+1,t+h}$ represents the total return from time t to time $t+h$. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times$ (horizon $-$ 1) lags. We use overlapping observations for the full sample. Long-run market uncertainty is market variance aggregated over $H = 16$ years. The sample is annual and spans the period 1967-2016.

Panel A: Direct regression, $k = 16$

Right-Hand Variable	$\sum_{j=1}^{k} \rho^{j-1} r^{ex}_{t+j}$	$\sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j}$	$\sum_{j=1}^{k} \rho^{j-1} \pi_{t+j}$	$\sum_{j=1}^{k} \rho^{j-1} \text{rrf}_{t+j}$	$\rho^k dp_{t+k}$	$b_r^{(k)} - b_d^{(k)} + b_\pi^{(k)} + b_{rrf}^{(k)} + b_{dp}^{(k)}$
	Coefficients					
dp_t	0.71	0.03	0.15	0.38	-0.26	0.958
	(2.83)	(0.82)	(0.78)	(7.56)	(-2.37)	
$R^2(\%)$	[30.15]	[0.26]	[2.90]	[65.20]	[8.70]	
$v_{t-15,t}$	0.82	-0.40	-0.71	0.10	-0.55	0.057
	(4.49)	(-6.42)	(-30.35)	(0.94)	(-6.17)	
$R^2(\%)$	[54.88]	[49.11]	[87.37]	[6.13]	[56.08]	

Panel B: Direct regression, $k = 18$

Right-Hand Variable	$\sum_{j=1}^{k} \rho^{j-1} r^{ex}_{t+j}$	$\sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j}$	$\sum_{j=1}^{k} \rho^{j-1} \pi_{t+j}$	$\sum_{j=1}^{k} \rho^{j-1} \text{rrf}_{t+j}$	$\rho^k dp_{t+k}$	$b_r^{(k)} - b_d^{(k)} + b_\pi^{(k)} + b_{rrf}^{(k)} + b_{dp}^{(k)}$
	Coefficients					
dp_t	0.65	-0.03	0.15	0.42	-0.29	0.964
	(2.08)	(-0.78)	(0.79)	(12.96)	(-2.03)	
$R^2(\%)$	[28.15]	[0.26]	[2.79]	[72.77]	[15.36]	
$v_{t-15,t}$	0.76	-0.38	-0.73	0.04	-0.38	0.062
	(4.01)	(-8.37)	(-29.50)	(0.39)	(-3.42)	
$R^2(\%)$	[52.65]	[52.30]	[86.95]	[0.89]	[36.84]	

Table 13: **Long-Run Regression Coefficients: Market uncertainty (alternative sample).** Direct regressions on log DP and the orthogonal component of log of market variance aggregated over $H = 16$ years w.r.t. log DP. "Direct" regression estimates are calculated using k-year ex post excess returns, nominal dividend growth, Δd_t, inflation, π_t real risk free rate (nominal 1-year rate minus realized inflation), rrf_t, and dividend yields, dp_t, as left-hand variables. **Panel A: Direct regression, $k = 16$. Panel B: Direct regression , $k = 18$.** Table entries are long-run regression coefficients, for example, $b_r^{(k)}$ in $\sum_{j=1}^{k} \rho^{j-1} r^{ex}_{t+j} = a + b_r^{(k)} dp_t + \varepsilon^r_{t+k}$, where $r^{ex} = \log R_{t+1,t+h} - \log R^f_{t+1,t+h}$. Annual CRSP data, 1967-2016.

Panel A: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.07	0.17	0.21	0.33	0.47	0.58	0.72	0.94	1.05	1.22	1.48	1.72	2.01	2.42	2.92	3.27
	(1.88)	(2.38)	(2.06)	(2.44)	(2.93)	(2.86)	(3.01)	(3.15)	(2.97)	(2.69)	(2.59)	(2.45)	(2.25)	(2.10)	(2.20)	(2.22)
R^2(%)	[2.86]	[6.65]	[6.52]	[8.96]	[12.54]	[13.78]	[15.10]	[18.18]	[18.27]	[17.46]	[17.88]	[17.40]	[16.95]	[17.25]	[18.39]	[17.21]

Panel B: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	0.04	0.09	0.15	0.22	0.26	0.32	0.41	0.52	0.65	0.82	1.02	1.25	1.48	1.70	1.91	2.19
	(1.29)	(1.62)	(1.99)	(2.15)	(2.01)	(2.01)	(1.98)	(1.99)	(2.07)	(2.24)	(2.30)	(2.23)	(2.13)	(1.98)	(1.82)	(1.74)
R^2(%)	[1.41]	[2.59]	[5.19]	[6.14]	[5.73]	[6.64]	[7.73]	[8.90]	[10.87]	[12.71]	[13.99]	[15.57]	[16.39]	[15.80]	[15.18]	[15.87]

Panel C: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \beta_{h,v} v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.07	0.17	0.21	0.33	0.47	0.58	0.72	0.94	1.05	1.22	1.48	1.72	2.01	2.42	2.92	3.27
	(1.90)	(2.48)	(2.24)	(2.76)	(3.31)	(3.29)	(3.63)	(4.14)	(4.11)	(3.91)	(4.05)	(4.12)	(3.87)	(3.43)	(3.53)	(3.49)
$v_{t-15,t}$	0.04	0.09	0.15	0.22	0.26	0.32	0.41	0.52	0.65	0.82	1.02	1.25	1.48	1.70	1.91	2.19
	(1.31)	(1.59)	(1.91)	(2.00)	(1.89)	(2.01)	(2.13)	(2.31)	(2.67)	(3.16)	(3.46)	(3.40)	(3.19)	(2.90)	(2.62)	(2.35)
R^2(%)	[4.27]	[9.24]	[11.71]	[15.11]	[18.27]	[20.42]	[22.83]	[27.08]	[29.14]	[30.16]	[31.87]	[32.97]	[33.34]	[33.05]	[33.57]	[33.08]

Table 14: **Excess nominal returns and Long-run market uncertainty (alternative, long-run sample). Panel A: log DP-only.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio. **Panel B: Long-run market uncertainty only.** Linear regressions (with an intercept) of excess returns on log of long-run market uncertainty. **Panel C: Multiple regressions of excess returns on log dividend-price and long-run market uncertainty.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio and log of long-run market variance. $R_{t+1,t+h}$ represents the total return from time t to time $t+h$. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times$ (horizon $-$ 1) lags. We use overlapping observations for the full sample. Long-run market uncertainty is market variance aggregated over $H = 16$ years. The sample is annual and spans the period 1900-2016.

Panel A: $R_{t+1,t+h} - R^f_{t,t+h} = \alpha_h + \beta_h dp_t + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.07	0.13	0.13	0.18	0.33	0.46	0.63	0.87	1.12	1.38	1.73	2.02	2.35	2.96	3.76	4.65
	(1.15)	(1.29)	(1.24)	(1.62)	(2.83)	(4.63)	(5.01)	(5.63)	(4.91)	(5.26)	(5.92)	(6.41)	(6.08)	(5.04)	(4.51)	(4.44)
$R^2(\%)$	[2.40]	[3.74]	[2.73]	[3.20]	[6.62]	[10.77]	[15.60]	[23.19]	[28.86]	[33.18]	[35.63]	[36.24]	[37.86]	[40.33]	[45.29]	[50.56]

Panel B: $R_{t+1,t+h} - R^f_{t,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-7,t}$	0.03	0.24	0.65	1.24	1.67	2.32	2.89	3.25	3.93	5.56	7.57	10.41	12.86	14.56	14.92	15.18
	(0.11)	(0.52)	(0.89)	(1.20)	(1.26)	(1.60)	(1.72)	(1.84)	(2.22)	(3.50)	(5.40)	(6.64)	(7.01)	(7.28)	(5.78)	(4.41)
$R^2(\%)$	[0.02]	[0.51]	[2.43]	[5.55]	[6.30]	[9.86]	[12.02]	[11.35]	[12.53]	[19.09]	[24.57]	[35.35]	[42.79]	[38.80]	[29.41]	[24.32]

Panel C: $R_{t+1,t+h} - R^f_{t,t+h} = \alpha_h + \beta_h dp_t + \beta_{h,v} v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.07	0.13	0.13	0.18	0.33	0.46	0.63	0.87	1.12	1.38	1.73	2.02	2.35	2.96	3.76	4.65
	(1.15)	(1.26)	(1.18)	(1.50)	(2.39)	(3.18)	(4.30)	(5.68)	(6.25)	(7.76)	(11.67)	(16.05)	(20.87)	(11.66)	(7.83)	(7.00)
$v_{t-7,t}$	0.03	0.24	0.65	1.24	1.67	2.32	2.89	3.25	3.93	5.56	7.57	10.41	12.86	14.56	14.92	15.18
	(0.11)	(0.48)	(0.82)	(1.09)	(1.09)	(1.31)	(1.37)	(1.43)	(1.71)	(2.74)	(4.92)	(10.04)	(14.57)	(15.85)	(11.32)	(7.12)
$R^2(\%)$	[2.42]	[4.25]	[5.16]	[8.75]	[12.92]	[20.62]	[27.62]	[34.54]	[41.39]	[52.27]	[60.20]	[71.59]	[80.64]	[79.12]	[74.71]	[74.88]

Table 15: **Excess returns and Long-run Macroeconomic Uncertainty (Jurado, Ludvigson and Ng, 2015) aggregated over $H = 8$ years. Panel A: log DP-only.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio. **Panel B: Long-run macroeconomic uncertainty only.** Linear regressions (with an intercept) of excess returns on log of long-run macroeconomic uncertainty (squared). **Panel C: Multiple regressions of excess returns on log dividend-price and long-run macroeconomic uncertainty.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio and log of long-run macroeconomic uncertainty (squared). $R_{t+1,t+h}$ represents the total return from time t to time $t+h$. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times$ (horizon $-$ 1) lags. We use overlapping observations for the full sample. Long-run macroeconomic uncertainty is macroeconomic uncertainty aggregated over $H = 8$ years. The sample is annual and spans the period 1967 - 2016.

Panel A: Direct regression, $k = 16$

Right-Hand Variable	Coefficients $\sum_{j=1}^{k}\rho^{j-1}r^{ex}_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\Delta d_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\pi_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\text{rrf}_{t+j}$	$\rho^k dp_{t+k}$	$b_r^{(k)} - b_d^{(k)} + b_\pi^{(k)} + b_{rrf}^{(k)} + b_{dp}^{(k)}$
dp_t	0.71	0.03	0.15	0.38	-0.26	0.958
	(2.83)	(0.82)	(0.78)	(7.56)	(-2.37)	
$R^2(\%)$	[30.15]	[0.26]	[2.90]	[65.20]	[8.70]	
$v_{t-7,t}$	2.42	-1.04	-1.96	0.68	-2.11	0.086
	(4.09)	(-5.80)	(-8.20)	(3.89)	(-12.22)	
$R^2(\%)$	[36.74]	[25.68]	[50.90]	[21.53]	[62.20]	

Panel B: Direct regression, $k = 18$

Right-Hand Variable	Coefficients $\sum_{j=1}^{k}\rho^{j-1}r^{ex}_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\Delta d_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\pi_{t+j}$	$\sum_{j=1}^{k}\rho^{j-1}\text{rrf}_{t+j}$	$\rho^k dp_{t+k}$	$b_r^{(k)} - b_d^{(k)} + b_\pi^{(k)} + b_{rrf}^{(k)} + b_{dp}^{(k)}$
dp_t	0.65	-0.03	0.15	0.42	-0.29	0.964
	(2.08)	(-0.78)	(0.79)	(12.96)	(-2.03)	
$R^2(\%)$	[28.15]	[0.26]	[2.79]	[72.77]	[15.36]	
$v_{t-7,t}$	2.30	-1.03	-2.01	0.51	-1.70	0.120
	(4.30)	(-8.32)	(-8.75)	(3.18)	(-10.76)	
$R^2(\%)$	[37.09]	[29.06]	[50.23]	[11.16]	[55.32]	

Table 16: **Long-Run Regression Coefficients: Macroeconomic Uncertainty (Jurado, Ludvigson and Ng, 2014).** Direct regressions on log DP and the orthogonal component of log of Macroeconomic Uncertainty aggregated over $H = 8$ years w.r.t. log DP. "Direct" regression estimates are calculated using k-year ex post excess returns, nominal dividend growth, Δd_t, inflation, π_t real risk free rate (nominal 1-year rate minus realized inflation), rrf_t, and dividend yields, dp_t, as left-hand variables. **Panel A: Direct regression, $k = 16$. Panel B: Direct regression , $k = 18$.** Table entries are long-run regression coefficients, for example, $b_r^{(k)}$ in $\sum_{j=1}^{k}\rho^{j-1}r^{ex}_{t+j} = a + b_r^{(k)}dp_t + \varepsilon^r_{t+k}$, where $r^{ex} = \log R_{t+1,t+h} - \log R^f_{t+1,t+h}$. Annual CRSP data, 1967-2016.

Panel A: $D_{t+1,t+h} = \alpha_h + \beta_h v_{t-h+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-7,t}$	0.28	0.56	0.86	1.00	1.09	0.98	0.73	0.28	-0.19	-0.74	-1.10	-1.40	-1.59	-2.00	-2.31	-2.88
	(3.16)	(3.25)	(3.48)	(3.10)	(2.54)	(1.96)	(1.34)	(0.53)	(-0.34)	(-1.24)	(-1.64)	(-1.98)	(-1.98)	(-2.43)	(-2.72)	(-3.94)
R^2(%)	[7.91]	[11.73]	[14.85]	[13.63]	[12.30]	[8.93]	[4.85]	[0.72]	[0.28]	[3.12]	[5.47]	[6.90]	[7.27]	[10.19]	[13.18]	[20.19]

Panel B: $\Pi_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-7,t}$	-0.10	-0.24	-0.39	-0.55	-0.77	-1.06	-1.39	-1.70	-2.08	-2.57	-3.15	-3.71	-4.16	-4.51	-4.76	-5.07
	(-2.52)	(-2.30)	(-2.21)	(-2.13)	(-2.21)	(-2.38)	(-2.49)	(-2.58)	(-2.71)	(-2.88)	(-3.09)	(-3.32)	(-3.55)	(-3.87)	(-4.25)	(-4.75)
R^2(%)	[6.38]	[8.64]	[10.19]	[11.79]	[14.79]	[18.48]	[21.41]	[23.00]	[26.39]	[31.81]	[37.98]	[43.07]	[46.07]	[47.62]	[48.44]	[49.63]

Panel C: $\frac{R^f_{t+1,t+h}}{\Pi_{t+1,t+h}} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-7,t}$	0.09	0.18	0.27	0.38	0.50	0.64	0.77	0.89	0.99	1.10	1.16	1.17	1.13	1.08	1.02	0.97
	(1.67)	(1.24)	(1.14)	(1.22)	(1.36)	(1.56)	(1.79)	(2.06)	(2.14)	(2.28)	(2.36)	(2.47)	(2.51)	(2.63)	(2.64)	(2.79)
R^2(%)	[5.60]	[7.01]	[7.75]	[9.10]	[11.01]	[13.35]	[14.84]	[16.24]	[17.78]	[19.36]	[19.51]	[18.40]	[16.51]	[14.69]	[13.11]	[11.27]

Table 17: **Panel A: Dividend growth and Long-run Macroeconomic Uncertainty (Kurado, Ludvigson and Ng, 2014) aggregated over $H = 8$ years.** Linear regressions (with an intercept) of dividend growth on log of long-run macroeconomic uncertainty (squared). **Panel B: Inflation and Long-run Macroeconomic Uncertainty.** Linear regressions (with an intercept) of inflation on log of long-run macroeconomic uncertainty (squared). **Panel C: Real risk free rate and Long-run Macroeconomic Uncertainty.** Linear regressions (with an intercept) of real risk free rate on log of long-run macroeconomic uncertainty (squared). $D_{t+1,t+h}$ and $\Pi_{t+1,t+h}$ represent the growth rate of dividends and the inflation rate from time t to time $t+h$, respectively. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times$ (horizon $- 1$) lags. We use overlapping observations for the full sample. Long-run macroeconomic uncertainty is macroeconomic uncertainty aggregated over $H = 16$ years. The sample is annual and spans the period 1967 - 2016.

Panel A: $R_{t+1,t+h} - YTM_{t+1}^{(h)} = \alpha_h + \beta_h dp_t + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.07	0.20	0.27	0.40	0.65	0.89	1.15	1.51	1.89	2.27	2.74	3.16	3.60	4.31	5.21	6.21
	(1.18)	(2.16)	(3.16)	(4.77)	(8.43)	(15.77)	(16.60)	(14.89)	(12.07)	(11.36)	(10.38)	(9.96)	(9.21)	(7.20)	(6.24)	(6.09)
R^2(%)	[2.52]	[8.89]	[11.70]	[15.62]	[24.05]	[34.03]	[42.91]	[53.08]	[60.19]	[64.79]	[65.83]	[65.18]	[65.63]	[64.74]	[66.15]	[68.21]

Panel B: $R_{t+1,t+h} - YTM_{t+1}^{(h)} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	0.20	0.37	0.49	0.68	0.96	1.13	1.30	1.54	1.94	2.12	2.24	2.05	1.64	1.37	1.08	0.61
	(3.35)	(4.45)	(5.01)	(5.02)	(5.22)	(4.37)	(3.74)	(3.66)	(3.54)	(3.89)	(4.44)	(3.91)	(2.30)	(1.27)	(0.75)	(0.35)
R^2(%)	[15.90]	[22.51]	[25.86]	[28.91]	[30.99]	[29.51]	[27.43]	[26.01]	[25.88]	[23.63]	[18.86]	[12.07]	[6.17]	[3.11]	[1.34]	[0.35]

Panel C: $R_{t+1,t+h} - YTM_{t+1}^{(h)} = \alpha_h + \beta_h dp_t + \beta_{h,v} v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.07	0.20	0.27	0.40	0.65	0.89	1.15	1.51	1.89	2.27	2.74	3.16	3.60	4.31	5.21	6.21
	(1.21)	(2.14)	(3.42)	(4.96)	(5.77)	(6.73)	(11.90)	(17.85)	(25.54)	(28.03)	(17.18)	(13.46)	(11.24)	(7.92)	(6.58)	(6.26)
$v_{t-15,t}$	0.20	0.37	0.49	0.68	0.96	1.13	1.30	1.54	1.94	2.12	2.24	2.05	1.64	1.37	1.08	0.61
	(3.39)	(4.64)	(5.60)	(6.04)	(6.58)	(5.13)	(4.91)	(6.04)	(9.60)	(12.33)	(10.19)	(4.64)	(2.28)	(1.32)	(0.85)	(0.45)
R^2(%)	[18.42]	[31.40]	[37.55]	[44.53]	[55.05]	[63.54]	[70.34]	[79.09]	[86.07]	[88.42]	[84.69]	[77.25]	[71.79]	[67.85]	[67.50]	[68.56]

Table 18: **Excess nominal returns and Market uncertainty. Panel A: log DP-only.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio. **Panel B: Long-run market uncertainty only.** Linear regressions (with an intercept) of excess returns on log of long-run market variance. **Panel C: Multiple regressions of excess returns on log dividend-price and long-run market uncertainty.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio and log of long-run market variance. $R_{t+1,t+h}$ represents the total return from time t to time $t+h$. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times (\text{horizon} - 1)$ lags. We use overlapping observations for the full sample. Long-run market uncertainty is market variance aggregated over $H = 16$ years. The sample is annual and spans the period 1967-2016.

Panel A: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.07	0.13	0.20	0.26	0.37	0.52	0.68	0.89	1.14	1.49	1.79	2.17	2.52	2.87	3.79	4.04
	(4.10)	(4.18)	(6.49)	(6.31)	(5.91)	(5.65)	(5.33)	(4.61)	(4.28)	(3.93)	(4.19)	(3.96)	(4.22)	(5.08)	(5.13)	(6.74)
R^2(%)	[17.32]	[25.23]	[39.62]	[42.64]	[46.88]	[57.33]	[61.42]	[60.78]	[61.33]	[60.38]	[58.51]	[54.74]	[49.61]	[46.36]	[50.47]	[44.94]

Panel B: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-9,t}$	0.05	0.08	0.12	0.18	0.25	0.38	0.77	1.23	2.00	3.20	4.93	6.53	8.89	11.34	14.31	19.81
	(1.69)	(1.42)	(1.12)	(1.01)	(0.98)	(0.82)	(0.90)	(1.20)	(1.71)	(2.32)	(2.99)	(3.40)	(3.82)	(4.32)	(7.58)	(10.32)
R^2(%)	[1.79]	[2.24]	[2.32]	[2.48]	[1.99]	[1.78]	[2.86]	[3.29]	[4.47]	[6.31]	[10.03]	[11.58]	[14.69]	[17.60]	[16.79]	[24.64]

Panel C: $R_{t+1,t+h} - R^f_{t+1,t+h} = \alpha_h + \beta_h dp_t + \beta_{h,v} v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
dp_t	0.07	0.13	0.20	0.26	0.37	0.52	0.68	0.89	1.14	1.49	1.79	2.17	2.52	2.87	3.79	4.04
	(4.19)	(4.28)	(7.06)	(6.95)	(6.18)	(5.96)	(5.92)	(5.08)	(4.73)	(4.37)	(4.69)	(4.31)	(4.63)	(5.68)	(5.13)	(7.03)
$v_{t-9,t}$	0.05	0.08	0.12	0.18	0.25	0.38	0.77	1.23	2.00	3.20	4.93	6.53	8.89	11.34	14.31	19.81
	(2.10)	(2.31)	(2.30)	(2.24)	(2.26)	(1.77)	(1.87)	(2.34)	(3.25)	(6.11)	(7.42)	(7.90)	(6.17)	(5.83)	(10.55)	(8.54)
R^2(%)	[19.11]	[27.47]	[41.95]	[45.11]	[48.87]	[59.11]	[64.28]	[64.08]	[65.80]	[66.68]	[68.53]	[66.32]	[64.30]	[63.96]	[67.26]	[69.58]

Table 19: **(UK evidence) Excess nominal returns and Long-run Economic Policy Uncertainty (EPU, see Baker, Bloom and Davis, 2016). Panel A: log DP-only.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio. **Panel B: Long-run EPU only.** Linear regressions (with an intercept) of excess returns on log of long-run EPU. **Panel C: Multiple regressions of excess returns on log dividend-price and long-run EPU.** Linear regressions (with an intercept) of excess returns on log dividend-price ratio and log EPU. $R_{t+1,t+h}$ represents the total return from time t to time $t+h$. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times$ (horizon $-$ 1) lags. We use overlapping observations for the full sample. Long-run EPU is EPU aggregated over $H = 10$ years. The sample is annual and spans the period 1960/12-2016/12.

Panel A: $\frac{C_{t+h}}{C_t} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-9,t}$	-0.00	-0.00	-0.01	-0.01	-0.02	-0.04	-0.07	-0.11	-0.15	-0.16	-0.15	-0.14	-0.12	-0.09	-0.02	0.07
	(-1.12)	(-0.70)	(-0.72)	(-0.96)	(-1.57)	(-1.89)	(-1.86)	(-1.82)	(-1.81)	(-2.01)	(-2.27)	(-2.51)	(-2.64)	(-2.51)	(-0.92)	(2.79)
R^2(%)	[0.54]	[0.36]	[0.40]	[0.70]	[1.94]	[4.19]	[6.49]	[8.52]	[11.96]	[12.43]	[11.08]	[8.43]	[6.38]	[3.92]	[0.19]	[1.79]

Panel B: $\frac{GDP_{t+h}}{GDP_t} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-9,t}$	-0.00	-0.01	-0.01	-0.01	-0.02	-0.04	-0.08	-0.12	-0.16	-0.17	-0.17	-0.16	-0.15	-0.14	-0.07	0.01
	(-1.99)	(-1.13)	(-0.96)	(-0.97)	(-1.22)	(-1.49)	(-1.68)	(-1.75)	(-1.79)	(-1.94)	(-2.17)	(-2.46)	(-2.74)	(-2.70)	(-1.80)	(0.34)
R^2(%)	[1.46]	[0.85]	[0.57]	[0.73]	[1.71]	[4.19]	[7.26]	[10.79]	[16.02]	[15.66]	[13.50]	[12.50]	[11.54]	[10.53]	[3.19]	[0.08]

Panel C: $\frac{R^f_{t+1,t+h}}{\Pi_{t+1,t+h}} = \alpha_h + \beta_h v_{t-H+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-9,t}$	-0.03	-0.06	-0.10	-0.14	-0.19	-0.29	-0.43	-0.55	-0.62	-0.63	-0.64	-0.64	-0.61	-0.56	-0.49	-0.38
	(-6.59)	(-4.17)	(-3.72)	(-3.67)	(-3.76)	(-4.21)	(-4.27)	(-3.45)	(-2.79)	(-2.60)	(-2.43)	(-2.35)	(-2.21)	(-1.96)	(-1.57)	(-1.17)
R^2(%)	[25.67]	[25.53]	[24.38]	[23.26]	[22.27]	[22.54]	[23.41]	[22.45]	[19.44]	[16.34]	[13.56]	[11.45]	[9.14]	[6.65]	[4.17]	[2.18]

Table 20: **(UK evidence) Panel A: Consumption growth and Long-run uncertainty.** Linear regressions (with an intercept) of real consumption growth on log of EPU, both aggregated over $H = 10$ years. **Panel B: Output growth and Long-run uncertainty.** Linear regressions (with an intercept) of real output growth on log of EPU, both aggregated over $H = 10$ years. **Panel C: Real risk free rate and Long-run uncertainty.** Linear regressions (with an intercept) of real risk free rate on log of EPU, both aggregated over $H = 16$ years. For each regression, the table reports OLS estimates of the regressors, corrected t-stats in parentheses and R^2 statistics in square brackets at the different horizons. Standard errors are Newey–West with $2 \times (\text{horizon} - 1)$ lags. We use overlapping observations for the full sample. The sample is annual and spans the period 1960/12-2016/12.

Appendix

A Data

A.1 US data

The measure of economic policy uncertainty (EPU) is based on Baker et al. (2016). We use the News-Based Policy Uncertainty Index available on EPU's web site for the US. The series is monthly and spans the period 1985:1−2016:12. We convert it to annual values by taking the end of the year value. To go further back in time, we merge the News-Based Policy Uncertainty Index series with the US Index, a longer series available from the Historical EPU's web site. Although the News-Based US Historical Index is available from 1900:1 to 2014:10, we only use data from 1930:12 to 1984:12 in order to obtain a final series spanning the period 1930 to 2016.

The sample in Bandi et al. (2018) ended in 2014 and did not use the information in the News-Based Policy Uncertainty Index. Splicing together the US Historical Index with News-Based Policy Uncertainty Index results in even stronger findings than in Bandi et al. (2018).

The measure of macroeconomic uncertainty is an updated version of data used in Jurado et al. (2015) and Ludvigson et al. (2015). It is available on Sydney Ludvigson's home page. The macro uncertainty index is constructed using a monthly macro dataset consisting of 134 mostly macroeconomic time series taken from McCracken and Ng (2016). We use their 12-month ahead uncertainty series. The series spans the period 1960:07−2016:12. We take the end of the year value to construct annual series.

The excess stock return variance is from the Welch and Goyal (2008) dataset. Welch and Goyal (2008) measure stock return volatility using the sum of squared daily excess stock returns during the month. Understandably, many papers argue for the presence of a severe outlier in October 1987. By taking 16-year moving average, our long-run measure of market uncertainty is unaffected by the October crash. We square the EPU and macroeconomic uncertainty series to obtain a variance-like measure.

Finally, to construct long-run (financial, EPU, macroeconomic) uncertainty variable, we sum the H most recent years, from t too $t - H + 1$, and take logs.

Inflation is calculated from the Consumer Price Index (CPI) for all urban consumers, which is available from the Welch and Goyal (2008) dataset.[19]

The U.S. stock market return is the Center for Research in Security Prices (CRSP) value-weighted market return containing all NYSE, AMEX, and NASDAQ stocks. Our sample is January 1926 to December 2016. We start from monthly cum-dividend and ex-dividend returns. Their difference, multiplied by the lagged ex-dividend price, is the monthly dividend:

$$D_t = (R_t^{\text{cum}} - R_t^{\text{ex}})\, P_{t-1}.$$

The annual series is obtained by aggregating the dividends paid out over the year. One important question, recently highlighted by Chen (2009) and van Binsbergen and Koijen (2010), is what to assume regarding the reinvestment rate of these monthly dividends received within the year. Throughout the paper we assume that the dividends are reinvested at a zero rate. This amounts to adding up the dividends in the current month and the past 11 months. An alternative option (used, e.g., by Cochrane (2008)) is to re-invest the dividends at the cum-dividend stock market return. CRSP computes annual return series under the stock market re-investment assumption. We checked that using directly CRSP annual data on total returns and returns without dividends does not alter our results. For example, when using the market re-investment assumption, Table 4, Panel A, would look as reported below.

Table 14 uses the US stock market data starting in 1885 available from Amit Goyal's website. The starting point is restricted by the availability of the realized variance measure (stock market data would be available from 1871). For the period between 1871 and 1925, these data come from Cowles (1939), covering

[19] Updated data for the variables in Goyal and Welch (2008) are available from Amit Goyal's webpage at `http://www.hec.unil.ch/agoyal/`.

Panel A: $D_{t+1,t+h} = \alpha_h + \beta_h v_{t-h+1,t} + \epsilon_{t+h}$

	Horizon h (in years)															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$v_{t-15,t}$	0.05	0.11	0.15	0.19	0.20	0.14	0.12	0.12	0.09	0.06	0.02	0.02	0.00	-0.05	-0.12	-0.17
	(1.46)	(2.52)	(2.28)	(2.21)	(1.96)	(1.25)	(0.90)	(0.75)	(0.47)	(0.30)	(0.12)	(0.08)	(0.01)	(-0.18)	(-0.44)	(-0.59)
R^2(%)	[2.96]	[7.97]	[10.64]	[11.51]	[9.58]	[4.90]	[3.12]	[2.35]	[1.17]	[0.44]	[0.07]	[0.03]	[0.00]	[0.16]	[0.95]	[1.67]

Table A.1: **Panel A: Dividend growth and Long-run market uncertainty.** We run linear regressions (with an intercept) of dividend growth on the log of long-run market variance. We use overlapping observations for the full sample. Long-run market uncertainty is market variance aggregated over $H = 16$ years. The sample is annual and spans the period 1945−2016.

between 50 (1871) and 258 (1925) securities. From 1926, the data are based on the Standard and Poosr's (S&P) 500 index provided by the Center for Research in Security Prices (CRSP). Before 1957, this was actually the S&P 90.

To sum up, the annual nominal dividend and return growth series are obtained by summing the monthly observations within the year. To obtain real returns and dividends, we deflate these series by the CPI.

The risk-free is the 1-year (1-Year Treasury Constant Maturity Rate; series DGS1) Treasury yield from the FRED database at the Federal Reserve Bank of St. Louis. The series starts in 1962. We extend the series using annual data on the 1-year rate series for the United States which is available, from 1890, on Robert J. Shiller's website.

Output is GDP in line 1 of NIPA Table 1.1.5. We deflate the series by the GDP deflator in line 1 of Table 1.1.9 and by the civilian population ages 16+. The series go back to 1948. We complement the series with GDP from Barro and Ursua's Macroeconomic Data for the years 1945-1947 (Barro and Ursua (2008)). Using the Barro and Ursua series (which ends in 2009), and extending it with the GDP from NIPA, does not alter our results.

Total household consumption of nondurables and services in millions is constructed by adding the series for consumption of nondurables and for consumption of services both from the NIPA. The data is annualized and seasonally adjusted in nominal terms. We make the standard "end-of-period" timing assumption that consumption during period t takes place at the end of the period. Growth rates are constructed by taking the first difference of the corresponding log series.

A consumption deflator for total nondurables and services consumption is based on data from NIPA. The deflator is constructed from two consumption deflators, one for total services consumption and one for total nondurables consumption. Data on real consumption expenditures from NIPA is also used in the construction of the deflator. The first step is to calculate the inflation rate for each type of consumption:

$$INFserv_t = \frac{Defserv_t}{Defserv_{t-1}} - 1 \quad INFndur_t = \frac{Defndur_t}{Defndur_{t-1}} - 1,$$

where $Defserv$ and $Defndur$ are the deflators for nondurables and services respectively. $INFserv$ and $INFndur$ are the calculated inflation rates for each of these deflators. The consumption deflator is defined as:

$$Def_t = Def_{t-1} \times [(1 + INFserv_t) \times Wserv_t + (1 + INFndur_t) \times Wndur_t],$$

where $Wserv$ and $Wndur$ are the proportions of total real nondurables and services consumption in each of the respective categories.

Table 18 uses Treasury yield data from Gurkaynak et al. (2007) (data are available for download on the website `http://www.federalreserve.gov/Pubs/feds/2006/200628/feds200628.xls`).

A.2 UK data

The data for Table 19 are from Global Financial Data. Stock returns are derived from the "Total Return Indices–Stocks" series in Global Financial Data's Total Return Database. Excess returns are computed relative to the country's three-month Treasury bill rate. Following convention, a smoothed dividend series (an average of dividends from month $t-11$ through month t) is used to compute the dividend-to-price ratio. Importantly, the stocks comprising the index trade on well-known exchanges that have been in existence for a century. The inflation measure in Table 20 is core CPI; prior to 1970 we use all-items CPI; both are from the OECD. GDP data are obtained from the Office of National Statistics (ONS). Specifically, we use the chained volume, seasonally-adjusted, GDP series. The measure of UK policy-related economic uncertainty is available on EPU's web site. The UK series is monthly and spans the period 1997:1−2016:12. This index draws from two newspapers: The Times of London and The Financial Times. To go further back in time, we splice this series with the measure of European policy-related economic uncertainty (starting in 1987:1). Finally, we merge this series with the UK Historical News-Based Policy Index, a longer series available from the Historical EPU's web site. This index reflects data from two major newspapers from the UK: the Times of London and the Guardian. Although the UK Historical Index is available from 1900:01 to 2008:12, we only use data from 1950:01 to 1986:12 in order to obtain a final series spanning the period 1950 to 2017. We convert it to annual values by taking the end of the year value. The starting date for the EPU series is dictated by our availability of macro data (which start in 1960) and the fact that we need 10-years of past data to construct our assumed long-run uncertainty proxy. Alternatively, one could have merged the UK policy-related economic uncertainty directly with the UK Historical News-Based Policy Index (thus, avoiding the European EPU). This procedure would lead to similar conclusions, with slightly weaker results for Table 19 and stronger results for Table 20.

B Some econometric implications of CS

Whether one obtains more signal from either a regression of long-run returns on the assumed predictor or from a regression of long-run dividend growth (in excess of the risk-free rate) on the assumed predictor depends on testable restrictions. This is easy to see. Write

$$r_t^{\infty} = \beta_{r,x}^{\infty} x_t + \epsilon_{r,t+\infty}, \tag{B.1}$$

Eq. (B.1)) and Eq. (2), with $k \to \infty$, imply that

$$\Delta d_t^{\infty} = \beta_{r,x}^{\infty} x_t + \epsilon_{r,t+\infty} - (d_t - p_t).$$

Hence, we have $\mathrm{E}[\Delta d_t^{\infty}|x_t] = \mathrm{E}[r_t^{\infty}|x_t] = \beta_{r,x}^{\infty} x_t$ since $\mathrm{E}[d_t - p_t|x_t] = \mathrm{E}[d_t - p_t] = 0$. The first equality derives from the orthogonality of $d_t - p_t$ and x_t and the second equality derives from the fact that $d_t - p_t$ is de-meaned. *For a large enough k, the true beta can be estimated consistently both from long-run returns and from long-run dividend growth. Both regressions are correctly specified.*

Importantly, however, the relative signal of a regression of long-run dividend growth on x_t or long-run returns on x_t depends on the relation between $\mathrm{var}(\epsilon_{r,t+\infty} - (d_t - p_t))$ and $\mathrm{var}(\epsilon_{r,t+\infty})$.

Immediately, the signal from the former regression is stronger than that from the latter when

$$\rho_{\epsilon_r,pd} \geq \frac{\sigma_{pd}}{2\sigma_{\epsilon_r}},$$

where $\rho_{\epsilon_r,pd}$ is the correlation between shocks to long-run returns and $d_t - p_t$, σ_{ϵ_r} is the standard deviation of shocks to long-run returns, and σ_{pd} is the standard deviation of the price-to-dividend ratio.

Now, notice that $\epsilon_{r,t+\infty}$ is positively correlated with $d_t - p_t$ since the latter has predictive ability for long-run returns and is orthogonal to the new variable x_t. In fact, by orthogonality, the correlation $\rho_{\epsilon_r,pd}$ is proportional to $\beta_{r,dp}^{\infty}$ from the univariate regression of long-run returns (or, equivalently, the errors $\epsilon_{r,t+\infty}$)

onto the dividend-to-price ratio:

$$\epsilon_{r,t+\infty} = \beta^{\infty}_{r,dp}(d_t - p_t) + \epsilon^*_{r,t+\infty}.$$

Hence,

$$\rho_{\epsilon_r,pd} = \beta^{\infty}_{r,dp}\frac{\sigma_{pd}}{\sigma_{\epsilon_r}},$$

which implies

$$\beta^{\infty}_{r,dp} \geq 1/2.$$

In other words, should the slope associated with the classical long-run predictive regression on the dividend-to-price ratio be larger than 1/2, an *indirect* long-run dividend-growth regression provides more signal to detect the predictability of alternative predictors than a *direct* long-run return regression. *This is like saying that, should the dividend-to-price ratio display more predictability, economically, for long-run returns than for long-run dividend growth ($\beta^{\infty}_{r,dp} \geq 1/2$), then long-run dividend growth should be, statistically, more informative about the predictive ability of an orthogonal regressor than long-run returns.* Since the condition $\beta^{\infty}_{r,dp} \geq 1/2$ is easily satisfied in the data, we expect the standard errors of the slope estimates derived from long-run dividend growth regressions on x_t to be smaller. Indirect long-run dividend growth regressions are, therefore, more powerful to detect the predictability of orthogonal regressor(s) than direct long-run return regressions.

More can be said. Should one agree with Cochrane's view that $\beta^{\infty}_{r,dp} = 1$, the signal about additional predictability from a regression of long-run dividend growth onto the orthogonal predictor would be as large as the signal about additional predictability from a full model in which long-run returns are regressed onto *both* the orthogonal regressor and the dividend-to-price ratio. This is again easy to see.

Using the same notation as before, the *full* specification would read:

$$r^{\infty}_t = \beta^{\infty}_{r,x}x_t + \underbrace{\beta^{\infty}_{r,dp}(d_t - p_t) + \epsilon^*_{r,t+\infty}}_{\epsilon_{r,t+\infty}}.$$

Given the definition of $\epsilon_{r,t+\infty}$ with $\beta^{\infty}_{r,dp} = 1$, the long-run dividend growth regression would now be:

$$\begin{aligned}\Delta d^{\infty}_t =& \beta^{\infty}_{r,x}x_t + \epsilon_{r,t+\infty} - (p_t - d_t)\\ =& \beta^{\infty}_{r,x}x_t + \epsilon^*_{r,t+\infty}.\end{aligned}$$

By the orthogonality of $d_t - p_t$ and x_t and the fact that the two regressions have the same error terms, running a long-run dividend growth regression on the assumed predictor yields the same standard error (for the quantity of interest, $\hat{\beta}^{\infty}_{r,x}$) as working with the completely-specified, full model.

C *Long-run* uncertainty: a technical justification

A generic uncertainty proxy u_t, like any covariance-stationary economic time series, can be expressed as a linear aggregate of orthogonal, mean-zero, *components* $u^{(j)}_t$ in addition to a mean term π_u, i.e., $u_t = \pi_u + \sum_{j=1}^{\infty} u^{(j)}_t$. The components $u^{(j)}_t$ are elements of the uncertainty process generated by *scale-specific* (with j denoting scale, in years) and *time-specific* shocks. In particular, the component associated with the j-th scale captures economic cycles between 2^{j-1} and 2^j years. Lower scales are associated with higher resolution, higher frequencies, and lower calendar-time persistence. Higher scales, on the other hand, are affected by shocks which are relatively smaller in size but persist in the system longer, as is typical of medium and long-run shocks (Bandi et al., 2018).

The presumed dependence between risk premia ($y_{t+1} = R_{t+1} - R^f_{t+1}$) and uncertainty (often proxied by market variance) is known to be hard to detect. However, stronger evidence of dependence has been found for a specific scale, frequency, or level of resolution j. More explicitly, while the classical predictive regression

$$y_{t+1} = \alpha + \beta u_t + \varepsilon_{t+1} \tag{C.1}$$

has lead to ambiguous outcomes, the *scale-wise regression*

$$y^{(j)}_{k2^j+2^j} = \alpha + \beta u^{(j)}_{k2^j} + \varepsilon^{(j)}_{k2^j+2^j}, \tag{C.2}$$

with $k \in \mathbb{Z}$, has been shown to result, for a suitable j, in a clearer predictive link between hidden layers of the excess return process and the uncertainty process. In particular, a component (with $j = 4$) of the uncertainty process with cycles between 8 years (2^{j-1} with $j = 4$) and 16 years (2^j with $j = 4$) has been shown to predict itself as well as a low-frequency component of the excess return process with, again, cycles between 8 and 16 years (Bandi et al., 2018).[20]

In Table C.1, we report the same scale-wise regressions for our data and confirm previous findings. We refer to Bandi et al. (2018) for details on the extraction of the components.

Panel A: Market Variance

	Scale j			
	1	2	3	4
$v^{(j)}_t$	0.45	-0.12	-0.84	0.78
	(0.17)	(-0.18)	(-0.76)	(1.78)
R^2(%)	[2.71]	[1.36]	[6.09]	[35.21]

Panel B: Economic Policy Uncertainty

	Scale j			
	1	2	3	4
$v^{(j)}_t$	-0.01	-0.01	-0.01	0.04
	(-0.33)	(-0.19)	(-0.32)	(2.35)
R^2(%)	[4.15]	[1.09]	[2.49]	[70.02]

Panel B: Macroeconomic Uncertainty

	Scale j			
	1	2	3	4
$v^{(j)}_t$	0.23	0.11	0.08	0.07
	(0.52)	(0.29)	(0.23)	(1.31)
R^2(%)	[1.64]	[7.19]	[3.54]	[25.48]

Table C.1: **Component-wise predictive regressions of the components of excess stock market returns on the components of market variance.** The specification is $r^{(j)}_{k2^j+2^j} - rf^{(j)}_{k2^j+2^j} = \beta_j v^{(j)}_{k2^j} + \epsilon_{k2^j+2^j}$. For each regression, the table reports OLS estimates of the regressors, Newey-West t-statistics with $2 * (\text{horizon} - 1)$ lags (in parentheses), and R^2 (in square brackets). For each j we can use 2^j possible start years. We calculate statistics using decimated (nonoverlapping) observations for each year-end $(1, \ldots, 2^j)$ and report the the median of estimates, t-statistics, and R^2.

[20] We note that Eq. (C.2) is defined in scale time rather than in calendar time.

Because it represents a spectral property of the return and uncertainty process, one which applies to individual components of the two series, Bandi et al. (2018) define this form of component-wise predictability as *scale-wise predictability.*

Scale-wise predictability amounts to a broadening of the scope of classical predictability. It is shown that classical predictability (as in Eq. (C.1)) can be viewed as a highly-restricted form of scale-wise predictability (intuitively, if predictability applies to the raw series it also applies, in a highly-parametrized fashion, to all of their components). Conversely, scale-wise predictability may translate into rich dynamic patterns of predictability on the raw series, well beyond those that would be implied by the regressive structure of order 1 of classical predictability as implied by Eq. (C.1).

A theoretical implication of exact $j = 4$ scale-wise predictability (in the absence of predictability at alternative scales) applied to excess return and uncertainty series is that backward-aggregates of uncertainty over 16 years have maximum predictive ability for future excess returns over a 16-year horizon. The intuition is simple: because components of the uncertainty and excess return processes with cycles between 8 and 16 years are linked by (scale-wise) predictability, aggregating returns forward and uncertainty backward, before running predictive regressions on the aggregated series, is an effective way to wash out uncorrelated components operating at higher frequencies. Thus, conversely, achieving maximum predictability on the aggregated series over an horizon of aggregation equal to 16-years is a reflection of the scale over which the connected low-frequency components operate and interact (i.e., 8 to 16 years) (c.f., Proposition I in Bandi et al. (2018)).

In order to verify this logic, Table C.2 reports slope estimates, t-statistics and R^2 values for regressions of the three uncertainty proxies aggregated over the past h years onto excess returns aggregated over the future h years. In the case of market variance and EPU, maximum predictability upon two-way forward/backward aggregation is reached over horizons of 14 to 16 years. Macroeconomic uncertainty has, also, predictive ability when aggregated over shorter 10 to 12 years horizons. The spillovers between the $j = 3$ and the $j = 4$ scale in Table C.1 justifies this finding.

Panel A: Market Variance

	Horizon h (in years)									
	2	4	6	8	10	12	14	16	18	20
$v_{t-h+1,t}$	0.52	0.49	1.19	1.83	2.70	2.98	2.87	2.65	1.73	0.56
	(0.83)	(0.74)	(2.10)	(3.10)	(5.34)	(6.31)	(6.16)	(5.42)	(4.21)	(1.85)
$R^2(\%)$	[1.32]	[1.81]	[11.27]	[22.87]	[40.03]	[47.05]	[50.50]	[50.16]	[27.86]	[3.23]

Panel B: Economic Policy Uncertainty

	Horizon h (in years)									
	2	4	6	8	10	12	14	16	18	20
$v_{t-h+1,t}$	0.02	0.01	0.02	0.04	0.05	0.05	0.05	0.05	0.04	0.02
	(1.67)	(0.87)	(1.38)	(4.09)	(8.84)	(17.68)	(35.44)	(15.52)	(8.10)	(7.53)
$R^2(\%)$	[3.03]	[1.54]	[4.36]	[24.37]	[39.32]	[54.11]	[61.63]	[59.13]	[47.33]	[24.28]

Panel C: Macroeconomic Uncertainty

	Horizon h (in years)									
	2	4	6	8	10	12	14	16	18	20
$v_{t-h+1,t}$	-0.04	0.14	0.23	0.25	0.27	0.24	0.22	0.17	-0.03	-0.24
	(-0.44)	(1.34)	(1.99)	(2.53)	(6.18)	(9.39)	(8.82)	(6.05)	(-0.76)	(-1.51)
$R^2(\%)$	[0.22]	[4.69]	[16.58]	[27.16]	[44.11]	[42.43]	[48.05]	[28.65]	[0.90]	[8.17]

Table C.2: **Forward Backward Regressions.** We run linear regressions of h-period continuously compounded market returns on the CRSP value-weighted index in excess of a 1-year Treasury bill rate on h-period past market variance (Panel A), Economic Policy Uncertainty (EPU, see Baker, Bloom and Davis, 2016) (Panel B), and Macroeconomic Uncertainty (Jurado, Ludvigson and Ng, 2015) (in Panel C). The specification is $(r_{t+1,t+h} - rf_{t+1,t+h}) = \alpha_h + \beta_h v_{t-h+1,t} + \epsilon_{t+h}$. For each regression, the table reports OLS estimates of the regressors, Newey-West t-statistics with $2 * (\text{horizon} - 1)$ lags (in parentheses), and R^2 (in square brackets).

In light of these observations, in order to extract a strong slow-moving signal about future *long-run* excess returns, we aggregate market variance and EPU over a 16-year horizon. Macroeconomic uncertainty is aggregated over a shorter 8-year horizon.

Methodologically, we depart from Bandi et al. (2018) along two main dimensions. First, we work with the exact orthogonal (with respect to the dividend-to-price ratio) component of long-run economic uncertainty for conceptual reasons laid out in the main text. Second, we do not solely focus on prediction horizons equal to the aggregation horizon of the predictor, but evaluate the predictive ability of the assumed long-run uncertainty proxies over alternative horizons, ranging from 1 year to 16 years.

Regarding the last issue, the adopted long-run measures are theoretically justified in the sense that they are meant to provide a strong, slow-moving signal about long-run returns. Yet, as said, they are also shown to represent an effective signal about future returns over shorter (than "generational") horizons. Having made this point, we do not make claims about optimality across horizons. Alternative long-run uncertainty measures may perform satisfactorily over specific (short) time frames. The discussion on robustness to aggregation in Subsection 7.1 expands on this issue.