Journal of Financial Economics 150 (2023) 103724

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Return predictability with endogenous growth ☆

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ARTICLE INFO

Dataset link: https://doi.org/10.17632/5939yh85bh.5

JEL classification:
C22
E32
E44
G12
G17

Keywords:
TFP volatility
Uncertainty trends
Endogenous growth
Price rigidities

ABSTRACT

The component of the volatility of total factor productivity (TFP) that is orthogonal to the dividend price ratio is shown to have long-run predictive ability for excess market returns. This finding implies that TFP volatility should also predict real cash flows and/or real interest rates: it is found to mainly predict real cash flows through inflation. A model with endogenous growth, Epstein-Zin preferences and price rigidities reconciles both TFP volatility-driven long-run predictability and its real implications. Within the model, we justify the similar (to that of TFP volatility) predictive ability of a *low-frequency* notion of market volatility as well as the cross-sectional pricing of TFP volatility risk in alternative asset classes.

1. Introduction

The impact on the real economy of shocks to alternative notions of uncertainty has been the subject of a successful literature.[1] The literature has a common theme: uncertainty, irrespective of its proxy, is a precursor of economic contractions.[2] For a recent review, a rich list of references, and novel perspectives, we refer the reader to Fernández-Villaverde and Guerrón-Quintana (2020).

Against this backdrop, this article focuses on the relation between uncertainty and asset prices. First, we document a strong link between future excess market returns and current TFP volatility, our main notion of uncertainty.[3] We do so by progressively building a body of evidence by way of reduced-form and structural modeling on both financial and real variables. The reduced-form modeling includes economic restrictions from the *real* Campbell and Shiller (1988, CS, henceforth) identity. This evidence speaks to the relation between risk premia and TFP

☆ We thank Nick Roussanov (the Editor) and an anonymous reviewer for their very constructive comments. We are grateful to Nicholas Bloom, Bryan Kelly (discussant), Sydney Ludvigson, Lasse Heje Pedersen, Alessandro Rebucci, Christian Schlag (discussant) and Nancy Xu (discussant) for their feedback and suggestions. We also thank conference and seminar participants at Copenhagen Business School, London School of Economics, the 2018 SITE Conference (Stanford), the 2018 Toulouse Financial Econometrics Conference, the 11th Annual SoFiE Conference (Lugano), the 2021 Conference of the Midwest Finance Association (virtual) and the 2021 SGF Conference (virtual) for helpful discussions.

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[1] The countercyclical behavior of stock market volatility is an established empirical fact with a long tradition (e.g., Schwert, 1989a,b, for early evidence, and Berger et al., 2020, for recent work). 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. Baker et al. (2016) employ a news-based index of economic policy uncertainty to show that increases in uncertainty of the magnitude experienced during the financial crisis may lead to considerable declines in real GDP and aggregate employment. 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. In a recent article, Bansal et al. (2020) study a multi-sector production economy in which uncertainty leads to reallocations away from R&D-intensive capital resulting in a negative relation between uncertainty shocks and medium-term growth.

[2] The relative causal role of economic and financial uncertainty is evaluated in, e.g., Ludvigson et al. (2021).

[3] Consistent with a large portion of the literature, we use the convention of defining all of our *realized* volatility measures, including TFP volatility, as “uncertainty”. There are exceptions to this norm. For example, in Berger et al. (2020) the term “uncertainty” is reserved for forward-looking volatility measures, e.g. the VIX.

https://doi.org/10.1016/j.jfineco.2023.103724
Received 30 August 2021; Received in revised form 25 September 2023; Accepted 26 September 2023

Available online 23 October 2023

volatility but, also, to the real counterparts of this relation. Second, we motivate our empirical findings in the context of a model in which the pricing of endogenous long-run growth risks gives rise to meaningful high-, medium- and low-frequency risk premia. Third, we show that the model accounts for (i) the limited predictive ability of alternative macroeconomic uncertainty measures (i.e., consumption and GDP volatility) relative to TFP volatility and (ii) the similar - to TFP volatility - predictive ability of a low-frequency notion of market volatility, an *uncertainty trend*. Using model-based counterfactuals, we document that the predictive ability of *low-frequency market volatility* may be viewed as being linked to the persistence of TFP volatility, an *uncertainty trend* itself. Finally, turning from time-series to cross-sectional analysis, we employ the model to justify the pricing of (innovations to) TFP volatility in meaningful cross sections of stocks and bonds.

We begin with the dependence between TFP volatility and risk premia across horizons (cf. Section 2). We show that the component of TFP volatility *orthogonal* with respect to the dividend price ratio has significant predictive ability for market risk premia. Adding TFP volatility to the dividend price ratio generates large R^2 increases with long-run effects in excess of 60%. In light of the well-known inability of popular predictors to yield predictability over the long run beyond that delivered by the dividend price ratio, and because of the economic appeal of predictability driven by a central element of macroeconomic uncertainty (like TFP volatility), this finding is striking and worth a thorough exploration.

A key implication of the real CS identity is that any orthogonal (to the dividend price ratio) predictor of future risk premia should forecast real cash flows and/or real interest rates. We show that TFP volatility predicts neither nominal cash flows nor real interest rates (particularly over the long run). As a consequence, it ought to predict inflation as the flip side of its predictive ability for future excess returns. This is what our evidence suggests, thereby - in effect - implying a negative (market-level) inflation beta (for new perspectives on the pricing of inflation risk(s) and a discussion of the extant literature on inflation pricing, a subject which we do not explore in this article, we refer the reader to Fang et al., 2022).[4] Consistent with persistently lower inflation, we also show that positive shocks to TFP volatility lead to persistently lower consumption, R&D investment, capital investment, and output, among other real effects.

These observations lead to our second contribution. We illustrate how a model with (i) endogenous growth, (ii) Epstein-Zin preferences and (iii) nominal price rigidities reconciles the reported empirical evidence (cf. Section 3). Specifically, we show that the interaction between the above three features is important to yield both predictability and meaningful impacts on the real economy. First, differently from specifications implying a linear link between valuation ratios and economic uncertainty (and, therefore, no independent predictive role for the latter), the model delivers meaningful separation between the dividend price ratio and TFP volatility. The independent (of the dividend price ratio) component of TFP volatility is found to affect long-run risk premia through endogenous growth (which enhances the long-run real impact of TFP volatility shocks) and Epstein-Zin preferences (which price long-run risks). Second, due to nominal price rigidities and endogenous growth, the model jointly delivers persistently lower consumption, R&D and capital investment, output and inflation, as a response to increased TFP volatility, because of persistently higher mark-ups. The intuition is simple: shocks to TFP volatility lead to increases in precautionary savings (and decreases in consumption) as well as to increases in precautionary labor supply. In the presence of nominal price rigidities, downward wage pressure due to higher labor supply leads to increased mark-ups and, as a consequence, reductions in investment and further reductions in consumption. In equilibrium, reduced consumption and investment will lead to lower output, lower employment, and falling prices. Because of the role of nominal price rigidities in the model, we complement a recent macroeconomic literature on the impact of various notions of uncertainty shocks on the real economy through time-varying mark-ups (e.g., Basu and Bundick, 2017, and Fernández-Villaverde et al., 2015). Relative to this influential previous work, we discuss the importance of endogenous growth in generating meaningful real effects with empirically-warranted parameter values (cf. Subsection 3.2). Differently from this work, our main emphasis is on financial markets. We show how endogenous growth makes the real effects of uncertainty shocks persistent, as found in the data, thereby yielding the reported long-run impact on market risk premia.

In a third contribution, we document - in the data and in the model - that alternative measures of macroeconomic uncertainty, like consumption volatility and GDP volatility, are less successful in yielding predictable variation in risk premia than TFP volatility (cf. Section 4). Stock market volatility is different. Robust evidence points to the predictive ability for long-run risk premia of low-frequency notions of market variance/volatility (cf., Bandi and Perron, 2008, and Bandi et al., 2019). We begin by showing that, like in the case of TFP volatility, the predictive ability of low-frequency market volatility is not subsumed by the dividend price ratio (cf. Section 4). Specifically, orthogonalized low-frequency market volatility is found to display similar, if not stronger, predictive ability relative to TFP volatility. Why employ a low-frequency notion of market volatility, rather than the raw series itself, as in the case of TFP volatility? The answer resides in the persistence of TFP volatility. Model-based counterfactuals show that the long-run predictive ability of TFP volatility, as well as its slowly-decaying real implications, are an important by-product of its considerable persistence. Low persistence would result in TFP volatility shocks with transient impacts on both risk premia and real variables, thereby negating the lessons drawn from data. The extraction of a suitable low-frequency pricing signal from market volatility may, therefore, be viewed as a way to align the persistence of a traditional measure of uncertainty to the level of persistence of TFP volatility. Once its priced slow-moving signal is extracted, market volatility has similar implications as TFP volatility for risk premia as well as for the real economy. In essence, we provide a model-based justification for the predictive ability of a natural *uncertainty trend*, i.e. low-frequency market volatility, a justification which hinges on the persistence of TFP volatility.

The paper's fourth contribution focuses on cross-sectional asset prices explicitly. Because of the predictive ability of TFP volatility (cf. Section 2) - and its role as a key state variable in the model in Section 3 - *innovations* to TFP volatility are expected to contain cross-sectional pricing signal (Maio and Santa-Clara, 2012). Our results in Section 5 illustrate that this is, in fact, the case. We, however, emphasize that the theoretical sign of the price of risk associated with TFP volatility loadings is a function of the specification of the chosen empirical pricing model and may not be obvious, in general. We confirm, within the proposed endogenous-growth model, the *negative* sign obtained in the data for interesting cross-sections of risky assets, including the CRSP universe of individual stocks, when adding a TFP volatility factor to a market factor. Turning to bonds, we find that TFP volatility explains term premia - again, in the data and in the model - even when controlling for inflation and real growth uncertainty.

[4] A large body of work has documented a negative relation between stock returns and measures of *expected* or *unexpected* inflation (e.g., Lintner, 1975, Bodie, 1976, Nelson, 1976, Fama and Schwert, 1977, 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. We offer a novel economic justification for the negative relation (mediated by TFP volatility) between stock returns and inflation. We document that higher TFP volatility is associated with decreases in real activity coupled with prolonged lower inflation. At the same time, higher TFP volatility leads to a higher compensation for uncertainty risk and lower asset prices.

Table 1
Excess market returns and TFP volatility. The table reports results from linear predictive regressions (with an intercept) of excess market returns on the dividend price (DP) ratio (Panel A), on TFP volatility either raw (Panel B1) or orthogonalized with respect to the DP ratio (Panel B2), and on the DP ratio and orthogonalized TFP volatility jointly (Panel C). $R_{t,t+h}$ represents the excess return from time t to time $t+h$. For each regression, the table reports OLS estimates of the partial effects, p-values corresponding to the robust test of Kostakis et al. (2015) (in parentheses) and R^2 statistics over different horizons. TFP is utilization-adjusted Total Factor Productivity from Fernald (2012). TFP volatility is obtained by estimating an autoregressive TFP process with stochastic volatility, as in Eq. (1) and Eq. (2) in the main text. The sample is quarterly and spans the period 1947Q2-2020Q4.

	1y	2y	3y	4y	5y	6y	7y
Dependent Variable: Excess Returns, $R_{t,t+h}$							
A. DP Ratio							
β_{DP}	0.10	0.19	0.24	0.28	0.36	0.40	0.44
p-value	(0.05)	(0.08)	(0.13)	(0.18)	(0.18)	(0.20)	(0.22)
$R^2(\%)$	7.00	12.12	15.18	17.00	20.36	22.39	23.48
B1. TFP Volatility (raw)							
β_{TFPV}	0.52	0.97	1.46	1.75	2.11	2.38	2.58
p-value	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$R^2(\%)$	6.96	13.15	21.76	25.25	28.03	30.32	30.50
B2. TFP Volatility (orthogonalized w.r.t. the DP Ratio)							
β_{TFPV}	0.35	0.68	1.14	1.38	1.63	1.83	1.97
p-value	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$R^2(\%)$	2.46	5.04	10.38	12.47	13.28	14.35	14.33
C. DP Ratio & orthogonalized TFP Volatility							
joint p-value	(0.06)	(0.08)	(0.07)	(0.09)	(0.08)	(0.08)	(0.09)
$R^2(\%)$	9.46	17.16	25.56	29.47	33.64	36.74	37.81

Our use of the jargon *uncertainty trend* requires a clarification. As emphasized, our central notion of uncertainty, TFP volatility, is highly persistent. Low-frequency market volatility, whose impact on risk premia is connected logically with TFP volatility through model counterfactuals in Section 4, is also a (near) stochastic trend. High persistence, therefore, justifies our terminology from an econometric standpoint. We also note that a recent literature has been focusing on additional macro-finance *trends* from a variety of alternative vantage points (see, e.g., Lettau et al., 2008, Farhi and Gourio, 2018, Greenwald et al., 2019, Corhay et al., 2020b, and the references therein). We return to various trends and their impact, or lack thereof, on risk premia in Section 4.

We conclude this introduction by stressing that there is an emerging body of work in finance which employs general equilibrium settings with endogenous growth (as in, e.g., Comin and Gertler, 2006) in order to evaluate low-frequency implications for asset prices. Kung (2015) and Kung and Schmid (2015), in particular, study the term structure of interest rates and the equity premium, respectively, in model specifications with R&D-driven endogenous growth. In agreement with this line of work, we also exploit the potential of models with endogenous growth to generate meaningful impacts on asset prices. Our focus, however, is on the mapping between uncertainty and predictability. Our empirical work and model specification attribute a central role to *uncertainty trends* in the determination of risk premia over alternative horizons. In this sense, we address some of the dimensions of the call in Fernández-Villaverde and Guerrón-Quintana (2020) for more depth "[in the study of] the interaction between models of endogenous growth and uncertainty shocks".

2. Empirical evidence: risk premia and macro implications

This section builds a body of evidence regarding the link between risk premia and TFP volatility. We begin with reduced-form modeling, inclusive of economic restrictions from the real CS identity. We then discuss results from a structural VAR on financial and real variables. The findings in this section will progressively connect the reported predictability to real outcomes, thereby providing implications which will be evaluated by way of model-based factuals and counterfactuals in Section 3.

2.1. Reduced-form evidence

We start off by running regressions of excess market returns on TFP volatility over horizons between 1 and 7 years (cf. Table 1).[5] We focus on TFP volatility orthogonalized with respect to the dividend price ratio. Its predictive impact is apparent.[6] As we transition to longer horizons, TFP volatility captures more of the slow-moving adjustment in excess market returns failed to be captured by the dynamics of the dividend price ratio. At 1 year, the dividend price ratio explains 7% of the variability in excess returns, TFP volatility about 2.5%. At 4 years, the R^2 associated with the dividend price ratio reaches 17% and that associated with TFP volatility is about 12.5%. At 7 years, the former is 23.48% and the latter is 14.33%. Said differently, given the orthogonality between TFP volatility and the dividend price ratio, the joint R^2 from a regression of 7-year excess market returns on both variables is about 38%. In essence, TFP volatility serves as an effective long-run excess return predictor, but improves predictability at all horizons.

These numbers justify a thorough investigation. While several short-term return predictors have been put forward, the inability of these predictors to provide long-run signal beyond that offered by the dividend price ratio is well-established.[7] Not only is TFP volatility contributing to the predictive ability of the dividend price ratio over all horizons, the economic logic behind predictability driven by TFP volatility is particularly appealing, as we illustrate formally in Section 3.

The real CS identity provides a conceptual framework to rationalize the reported findings. Any variable that is orthogonal to the dividend price ratio, and predicts long-run excess returns, should also predict real dividend growth, real interest rates, or a combination of these variables. In Table 2, we document that, particularly over the long run, TFP volatility predicts real dividend growth (cf. Panel C) through inflation (cf. Panel A), the impact on real interest rates being more muted (cf. Panel B). In the absence of significant effects on nominal cash flows and real interest rates, the direction of predictability is constrained by the CS identity. Higher TFP volatility should lead to lower long-run inflation. This observation is consistent with empirical evidence: at 4 years and 7 years, the R^2s from regressions of inflation onto TFP volatility are 11.52% and 15.6%, respectively (Table 2, Panel A). The corresponding numbers for the same regressions with the dividend price ratio as the regressor are close to 1%. In conclusion, increases in TFP volatility predict long spells of low future inflation. Next, we turn to a formal evaluation of the real CS identity.

Table 2, Panel D, contains univariate regressions of k-period (weighted, by powers of ρ) log excess returns, k-period (weighted) log nominal dividend growth, k-period (weighted) log inflation, k-period

[5] We use the post-war 1947Q2-2020Q4 sample. A detailed description of the data and its sources is contained in Appendix A. The appendix also describes the filtering of TFP volatility. Such filtering is consistent with the assumed model specification in Section 3, cf. Eq. (1) and Eq. (2).

[6] The persistence of the predictor(s) and the use of an overlapping regressand are known to require robust inference in forecasting regressions. To address this issue, we rely on the methodology recently proposed by Kostakis et al. (2015). A previous draft of the paper used standard errors from reverse regressions in the spirit of Hodrick (1992). Specifically, we employed the Wei and Wright (2013) reverse regression delta method which extends Hodrick (1992) by allowing for near unit-root regressors. The use of this alternative method would not lead to material changes in our findings.

[7] The variance risk premium (VRP) is an important case in point. Bollerslev et al. (2009) show that VRP strongly predicts future stock returns at short horizons (i.e., approximately three months) but fail to do so over long horizons. The short-run return predictability of VRP has been justified through the volatility of the consumption volatility process (Bollerslev et al., 2009) and in a long-run risk economy with jump processes (Drechsler and Yaron, 2010).

Table 2
Inflation, real interest rates, real dividend growth and TFP volatility. The table reports results from linear predictive regressions (with an intercept) of macroeconomic variables on TFP volatility (orthogonalized with respect to the dividend price ratio). The dependent variables are cumulative inflation (Panel A), cumulative real interest rates (Panel B), and cumulative real dividend growth (Panel C). For each regression, the table reports the OLS estimates of the partial effects, p-values corresponding to the robust test of Kostakis et al. (2015) (in parentheses) and R^2 statistics over different horizons. TFP is utilization-adjusted Total Factor Productivity from Fernald (2012). TFP volatility is obtained by estimating an autoregressive TFP process with stochastic volatility, as in Eq. (1) and Eq. (2) in the main text. We also report Campbell and Shiller regressions (described in the main text) in Panel D. The sample is quarterly and spans the period 1947Q2-2020Q4.

	1y	2y	3y	4y	5y	6y	7y
A. Dependent Variable: Inflation							
β_{TFPV}	-0.13	-0.25	-0.34	-0.41	-0.50	-0.63	-0.78
p-value	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$R^2(\%)$	13.09	13.64	12.67	11.52	11.79	13.33	15.60
B. Dependent Variable: Real Interest Rates							
β_{TFPV}	-0.01	-0.01	-0.06	-0.11	-0.12	-0.11	-0.10
p-value	(0.20)	(0.19)	(0.17)	(0.14)	(0.14)	(0.13)	(0.15)
$R^2(\%)$	0.73	0.72	1.05	1.54	1.77	2.41	2.77
C. Dependent Variable: Real Dividend Growth							
β_{TFPV}	0.13	0.34	0.55	0.61	0.76	0.84	1.00
p-value	(0.16)	(0.08)	(0.06)	(0.07)	(0.03)	(0.02)	(0.02)
$R^2(\%)$	1.28	4.31	7.22	7.15	9.62	10.62	13.52
D. Campbell-Shiller Decomposition							
	(1)	(2)	(3)	(4)	(5)	(6)	
	$\beta^k_{r,x}$	$\beta^k_{\Delta d,x}$	$\beta^k_{\pi,x}$	$\beta^k_{rf,\text{real},x}$	$\beta^k_{dp,x}$	(1) - (2) + $\sum_{i=3}^{5}$ (i)	
$x = dp$	0.41	-0.09	0.04	0.08	0.38	1.00	
	(0.07)	(0.13)	(0.56)	(0.13)	(0.04)		
$R^2(\%)$	26.76	3.99	1.94	13.68	33.40		
x = TFP Volatility	1.64	0.24	-0.57	-0.08	-0.75	0.00	
	(0.01)	(0.31)	(0.01)	(0.71)	(0.07)		
$R^2(\%)$	15.90	1.17	12.80	3.20	4.87		

(weighted) log real risk-free rates and the k-period ahead (weighted) log dividend price ratio onto (i) the dividend price ratio and (ii) orthogonalized TFP volatility. The value of ρ in the CS identity is estimated to be equal to 0.9685[8] and k is chosen as our longest horizon of 7 years. The real CS identity implies that (i) the slope coefficients associated with the dividend price ratio should sum up to 1 whereas (ii) the slope coefficients related to TFP volatility should sum up to zero:

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

$$\beta^k_{r,x} - \beta^k_{\Delta d,x} + \beta^k_{\pi,x} + \beta^k_{rf,\text{real},x} + \beta^k_{dp,x} = 0 \quad if \quad x = \text{TFP volatility}.$$

Implication (i) follows directly from the work of, e.g., Cochrane (2008) after adding and subtracting inflation from the nominal CS identity. Implication (ii) follows from the same logic as in, e.g., Cochrane (2008), after - once more - adding and subtracting inflation and, importantly, after recognizing that TFP volatility has been orthogonalized with respect to the dividend price ratio.

Consistent with Table 1, the dividend price ratio has predictive ability for long-run (weighted) excess market returns. Over the reported 7-year horizon, the corresponding slope is close to 0.4 and much of the remaining predictive ability is associated with the future, i.e., 7-year ahead, (weighted) log dividend price ratio (with a slope of 0.38). TFP volatility also has predictive ability for long-run excess market returns. In this case, return predictability is coupled with the predictability of inflation.

In sum, when viewed through the lens of the real CS identity, the return predictability of TFP volatility is justifiable by its ability to predict future inflation. In light of the joint impact of TFP volatility shocks on the price dynamics of financial assets *and* goods, it is natural to investigate the broader implications of shocks to TFP volatility for the real economy. We do so in the next subsection.

2.2. Structural evidence

In order to explore the relation between TFP volatility, asset prices and the real economy (and derive implications to be tested within the model), we report findings from a structural vector autoregression (S-VAR). Studies which employ S-VARs to evaluate the response of economic activity to surprise changes in uncertainty include Bloom (2009), Bachmann et al. (2013), Bekaert et al. (2013), Jurado et al. (2015), Baker et al. (2016), Leduc and Liu (2016), Carriero et al. (2018), Bonciani and Oh (2020), Cesa-Bianchi et al. (2020) and Ludvigson et al. (2021).

We use a standard Cholesky decomposition to identify structural shocks. A similar approach has been adopted by Bloom (2009) and Leduc and Liu (2016), among others. The baseline S-VAR contains 9 variables, entering in the following order: (i) TFP volatility; (ii) the Standard and Poor's 500 index; (iii) GDP; (iv) personal consumption of nondurables and services; (v) private fixed investment in R&D; (vi) capital investment; (vii) the level of TFP; (viii) the price level and (ix) the nominal short rate. The S-VAR is estimated using two lags. Data are quarterly (Appendix A provides details).

Fig. 1 reports the responses of all variables to a one-standard-deviation TFP volatility shock (the shaded areas represent 90% confidence intervals). A well-known prediction of neoclassical models subject to uncertainty fluctuations is that investment, output and hours worked *increase* as a response to uncertainty shocks lowering consumption (cf., the discussion in Basu and Bundick, 2017). Consistent with a model with price rigidities, we document that a positive shock to TFP volatility is, instead, associated with a joint decline in consump-

[8] We recall the expression $\rho = \frac{\exp\{\mathbb{E}(p-d)\}}{1+\exp\{\mathbb{E}(p-d)\}}$, with $p-d$ denoting the log price dividend ratio.

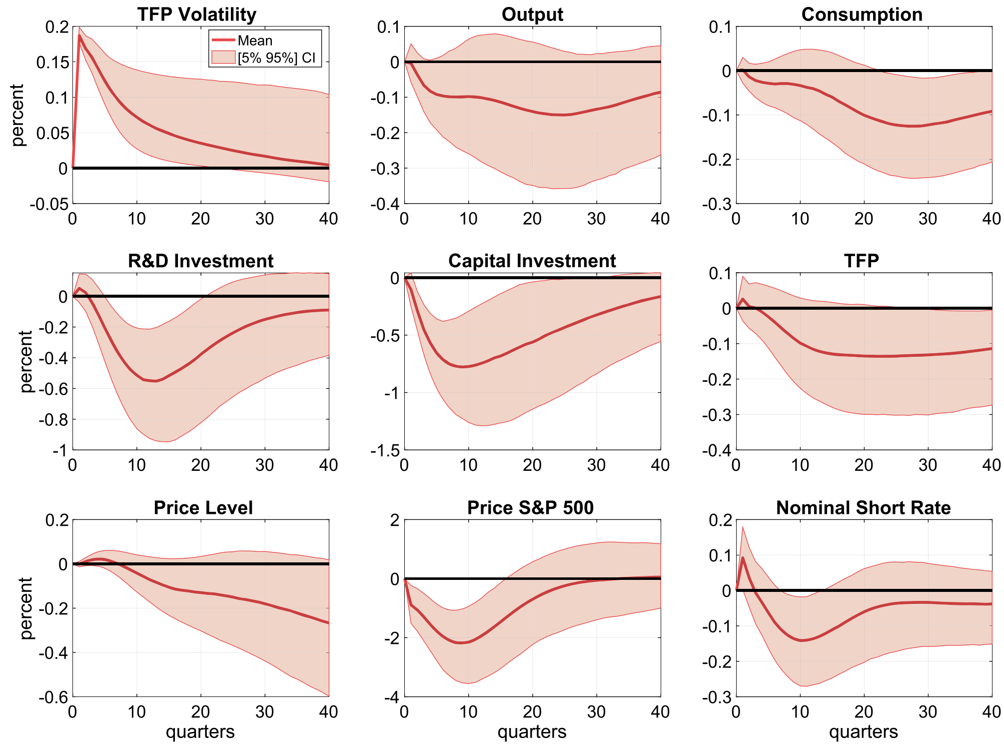

Fig. 1. The figure plots responses to a one-standard-deviation TFP volatility shock from an empirical structural VAR with TFP volatility, output, consumption, R&D investment, capital investment, TFP, the price level, the S&P 500 index, and the nominal short rate. TFP is utilization-adjusted Total Factor Productivity from Fernald (2012). TFP volatility is obtained by estimating an autoregressive TFP process with stochastic volatility, as in Eq. (1) and Eq. (2) in the main text. The sample is quarterly and spans the period 1947Q2-2020Q4.

tion, R&D investment, capital investment, output and price levels. The drop in R&D investment is further associated with reductions in the level of TFP. The decrease in the level of the S&P 500 index (and the corresponding increase in expected returns) is, of course, suggestive of the predictive ability of shocks to TFP volatility. Due to the persistence of TFP volatility (whose first-order quarterly autocorrelation is 0.98), these effects are long-lasting.

3. The model

We present and implement a dynamic model which will speak to our evidence. Consistent with our empirical analysis, we introduce macroeconomic uncertainty through the persistent stochastic volatility of an autoregressive TFP process. Three aspects are central to the adopted model specification. First, the model features an endogenous growth mechanism of vertical innovation (with intermediate-good firms) in the spirit of Romer (1990), Grossman and Helpman (1991) and Aghion and Howitt (1992). The endogenous growth channel is important for the propagation of shocks in the economy. Specifically, it allows TFP volatility shocks to have persistent effects. Second, households have Epstein and Zin (1989) preferences which make them averse to long-run risks, as in Bansal and Yaron (2004). A combination of both features will be shown to justify the (short-run and long-run) predictability shown in the data. Third, because our results relate higher uncertainty to lower consumption and output, we introduce New Keynesian price rigidities in order to generate meaningful co-movements between consumption and output as in, e.g., Basu and Bundick (2017). With the exception of added shocks to the dynamics of both capital and R&D investment and barring important, for our purposes, differences in the model parametrization which we discuss below, the model specification is broadly in line with that in Kung (2015). While Kung (2015) exploits the implications of the endogenous-growth channel to study term structure implications, our focus is on uncertainty-driven predictability and the real effects of slowly-propagating uncertainty shocks.

3.1. Demand, supply and monetary authority

On the demand side, the representative household has recursive utility over consumption, C_t, and leisure, $\overline{L} - L_t$:

$$U_t = \left\{ (1-\beta)(C_t(\overline{L}-L_t)^{\tau})^{\frac{1-\gamma}{\theta}} + \beta \left(\mathbb{E}_t \left[U_{t+1}^{1-\gamma} \right] \right)^{\frac{1}{\theta}} \right\}^{\frac{\theta}{1-\gamma}},$$

where β is the subjective discount rate, γ is the coefficient of risk aversion and the parameter θ is defined as $\theta = \frac{1-\gamma}{1-1/\psi}$, with ψ denoting the elasticity of inter-temporal substitution. The household supplies labor services, L_t, up to $\overline{L}$ and receives a real wage, W_t, and dividends from intermediate-good firms (described below).[9] The household's inter-temporal first-order condition is

$$1 = \mathbb{E}_t \left[\frac{M_{t,t+1}}{\Pi_{t+1}} R_{t,t+1} \right],$$

where $\Pi_{t+1} = \frac{P_{t+1}}{P_t}$ is the gross inflation rate (i.e., P_t is the time t price of the final good), $R_{t,t+1}$ is the gross (one-period) nominal short rate and

$$M_{t,t+1} = \beta \left(\frac{C_{t+1}(\overline{L}-L_{t+1})^{\tau}}{C_t(\overline{L}-L_t)^{\tau}} \right)^{\frac{1-\gamma}{\theta}} \left(\frac{C_{t+1}}{C_t} \right)^{-1} \left(\frac{U_{t+1}^{1-\gamma}}{\mathbb{E}_t[U_{t+1}^{1-\gamma}]} \right)^{1-\frac{1}{\theta}}$$

is the economy's stochastic discount factor (SDF). The household's within-period first-order condition is, instead,

$$W_t = \frac{\tau C_t}{\overline{L} - L_t}.$$

[9] The parameter τ is determined by the steady-state relation between hours worked and leisure. In the steady state, we set the fraction of time the representative household spends working equal to one third.

The supply side features the two-tier structure of a standard New Keynesian model. A representative firm produces the final consumption good, Y_t, in a perfectly competitive market. The firm's inputs are a continuum of intermediate goods, $X_{i,t}$, fed into a CES production technology:

$$Y_t = \left(\int_0^1 X_{i,t}^{\frac{\nu-1}{\nu}} di \right)^{\frac{\nu}{\nu-1}},$$

where ν is the elasticity of substitution between inputs. The intermediate-good firms are monopolistically competitive. These firms possess a Cobb-Douglas production function which combines capital, knowledge and labor. As in Kung (2015) and Kung and Schmid (2015), we assume spillovers in knowledge across firms. In particular, each intermediate-good firm produces $X_{i,t}$ with capital $K_{i,t}$, knowledge $N_{i,t}$ and labor $L_{i,t}$:

$$X_{i,t} = K_{i,t}^{\alpha} \left(A_t N_{i,t}^{\eta} N_t^{1-\eta} L_{i,t} \right)^{1-\alpha},$$

where $N_t = \int_0^1 N_{i,t} di$ is common knowledge across firms (and, therefore, public) and the parameter $\eta \in [0,1]$ captures the degree of technological appropriability. The inputs $K_{i,t}$ and $N_{i,t}$ are accumulated through capital investment, $I_{i,t}$, and R&D investment, $S_{i,t}$ (see below).

We note that, in the model, firm-specific total factor productivity is given by

$$\text{TFP}_{i,t} = A_t N_{i,t}^{\eta} N_t^{1-\eta}.$$

Thus, the exogenous portion of total factor productivity is A_t. The process A_t represents a stationary aggregate productivity process which is common across firms and evolves in logs as an AR(1) process:

$$a_t = (1-\rho_a)\bar{a} + \rho_a a_{t-1} + e^{\sigma_{a,t}} \epsilon_{a,t} \tag{1}$$

with $a_t = \log(A_t)$, $\epsilon_{a,t}$ i.i.d. $N(0,1)$ and $\bar{a} > 0$ denoting the unconditional mean of a_t. The process $\sigma_{a,t}$ is defined as

$$\sigma_{a,t} = (1-\rho_{\sigma_a})\bar{\sigma}_a + \rho_{\sigma_a}\sigma_{a,t-1} + \sigma_{\sigma_a}\epsilon_{\sigma_a,t} \tag{2}$$

with $\epsilon_{\sigma_a,t}$ i.i.d. $N(0,1)$ and independent of $\epsilon_{a,t}$. We emphasize that all of our empirical tests are conducted based on estimated values of $e^{\sigma_{a,t}}$ (i.e., TFP volatility).

The persistence parameter ρ_{σ_a} is important. We will vary ρ_{σ_a} to study the impact of a shock to TFP volatility relative to a counterfactual in which TFP volatility is less persistent than in the data. We note that we could have, instead, relied on a component specification for the evolution of $\sigma_{a,t}$. In a component specification, the model-based implications of TFP volatility persistence could be evaluated by focusing on individual components of the TFP volatility process rather than by running counterfactuals in which the overall process is driven by a lower level of persistence. We discuss this model extension in the Online Appendix.

The stocks of capital and knowledge are determined by capital investment, $I_{i,t}$, and R&D investment, $S_{i,t}$, and the corresponding depreciation rates:

$$K_{i,t+1} = (1-\delta_k)K_{i,t} + \Phi_k\left(\frac{I_{i,t}}{K_{i,t}}\right)K_{i,t},$$

$$N_{i,t+1} = (1-\delta_n)N_{i,t} + \Phi_n\left(\frac{S_{i,t}}{N_{i,t}}\right)N_{i,t},$$

where $\Phi_x(X)$, with $x \in \{k,n\}$, captures adjustment costs as follows:

$$\Phi_x(X) = \left(\frac{\alpha_{1,x}}{1-\frac{1}{\zeta_x}} (X)^{1-\frac{1}{\zeta_x}} + \alpha_{2,x} \right) e^{\epsilon_{x,t}}.$$

The parameters $\alpha_{1,x}$ and $\alpha_{2,x}$ are set in such a way as to dispense with adjustment costs in the deterministic steady state (cf. Kung, 2015, Footnote 4). The parameters ζ_x are elasticities of either new capital investment or R&D investment relative to existing stocks. As in Corhay et al. (2020a), the variables $\epsilon_{x,t}$ are i.i.d. $N(0,\sigma_x)$ shocks to capital/R&D adjustment costs, something which helps match the relative volatility of both forms of investment to consumption and output (cf. Table 4).

Table 3
Model parameters. The table reports our parameter choices. The model parameters are divided into four groups: demand (Panel A), supply (Panel B), monetary policy (Panel C), and TFP (Panel D).

A. Demand		C. Monetary Policy	
β	0.99	ρ_r	0.70
γ	15	ρ_π	1.5
ψ	2	ρ_y	0.10
$L_{ss}/\bar{L}$	0.33		
B. Supply		**D. TFP**	
α	0.33	ρ_a	0.99
η	0.10	$\bar{a}$	-1.279
ν	6	ρ_{σ_a}	0.98
δ_k	2.00%	$\bar{\sigma}_a$	log(1.05%)
ζ_k	2.35	σ_{σ_a}	0.1
σ_k	0.70%		
δ_n	3.75%		
ζ_n	2.35		
σ_n	0.30%		
ϕ_P	320		

When adjusting the nominal price (measured in units of the final good), the intermediate-good firms pay a Rotemberg cost (Rotemberg, 1982) defined as follows:

$$\frac{\phi_P}{2}\left(\frac{P_{i,t}}{\Pi_{ss}P_{i,t-1}} - 1\right)^2 Y_t,$$

where $\Pi_{ss} \geq 1$ is the steady-state (ss) inflation rate,[10] $P_{i,t}$ is the price set by firm i, and ϕ_P determines the magnitude of the cost. The parameter ϕ_P is hard to pin down but is central to match empirical evidence. Subsection 3.3 is devoted to its calibration.

Finally, the nominal dividend of a generic intermediate-good firm i is naturally expressed as follows:

$$D_{i,t} = P_{i,t}X_{i,t} - P_t W_{i,t} L_{i,t} - P_t I_{i,t} - P_t S_{i,t} - P_t \frac{\phi_P}{2}\left(\frac{P_{i,t}}{\Pi_{ss}P_{i,t-1}} - 1\right)^2 Y_t.$$

The monetary authority implements a Taylor rule which depends on output and inflation deviations from the steady state:

$$\ln\left(\frac{R_{t,t+1}}{R_{ss}}\right) = \rho_r \ln\left(\frac{R_{t-1,t}}{R_{ss}}\right) + (1-\rho_r)\left[\rho_\pi \ln\left(\frac{\Pi_t}{\Pi_{ss}}\right) + \rho_y \ln\left(\frac{\widehat{Y}_t}{\widehat{Y}_{ss}}\right)\right],$$

where $\widehat{Y}_t \equiv Y_t/N_t$ is de-trended output.[11]

In a symmetric equilibrium, the aggregate production function is

$$Y_t = K_t^{\alpha}\left(A_t N_t L_t\right)^{1-\alpha}$$

and similar to the neoclassical formulation with labor-augmenting technology. The difference is that total factor productivity, $A_t N_t$, is the endogenous outcome of R&D investment.

3.2. Model parameters and model fit

Table 3 reports the parameters used to simulate from the model.[12] The most consequential difference, for our purposes, between our values and those in Kung (2015) is the magnitude of the price-rigidity parameter, ϕ_P, which is chosen to match several empirical correlation

[10] Π_{ss} is set to 1.0775.

[11] $R_{ss} = 3.71\%$ (annualized) and $\widehat{Y}_{ss} = 0.838$.

[12] We employ perturbation methods to solve the model. Specifically, we use a third-order Taylor approximation of the policy functions characterizing the equilibrium dynamics (as in Fernández-Villaverde et al., 2011) and the pruned state space method of Andreasen et al. (2018).

Table 4

Empirical and model-implied moments. The table reports empirical moments as well as model-implied moments for our (baseline) model with endogenous growth, recursive utility and price rigidities, a model specification in which the representative household has CRRA preferences, and a model specification with exogenous growth. Panel A shows macroeconomic moments, Panel B displays asset pricing moments, and Panel C reports R^2s from predictive regressions of excess market returns over 1-, 3-, and 7-year horizons on (i) the dividend price ratio and (ii) the dividend price ratio and orthogonalized TFP volatility jointly. All moments are annualized. π is inflation. Δc, Δl, Δi, Δs and Δy are consumption growth, growth in hours worked, growth in physical capital investment, growth in R&D investment and output growth, respectively. y^x is the yield on the risk-less bond over x-quarters. Excess returns (r^{ex}) are defined as the log returns from holding the dividend claim on the model's firms minus the short rate. The excess returns are levered as in Croce (2014). Finally, pd denotes the natural log of the price dividend ratio.

	Data	Baseline	CRRA	Exog. Growth
A. Macroeconomic Moments				
$\mathbb{E}[\Delta y]$	2.00%	2.03%	0.23%	2.00%
$\sigma(\Delta c)$	1.42%	1.51%	3.52%	1.48%
$\sigma(\pi)$	1.64%	1.57%	1.12%	2.68%
$\sigma(\Delta c)/\sigma(\Delta y)$	0.68	0.78	1.04	1.04
$\sigma(\Delta l)/\sigma(\Delta y)$	0.92	0.89	1.51	0.91
$\sigma(\Delta i)/\sigma(\Delta y)$	2.84	2.75	1.17	2.32
$\sigma(\Delta s)/\sigma(\Delta y)$	1.62	1.58	0.61	-
$\mathbb{E}[y^1]$	4.65%	4.61%	6.55%	6.41%
$\sigma(y^1)$	3.12%	2.84%	1.64%	5.22%
B. Asset Pricing Moments				
$\mathbb{E}[y^{20}-y^1]$	1.02%	0.79%	0.22%	0.12%
$\sigma(y^{20}-y^1)$	1.00%	0.96%	0.37%	0.62%
$\mathbb{E}[r^{ex}]$	5.23%	3.38%	0.27%	0.05%
$\sigma(r^{ex})$	15.17%	10.61%	6.85%	1.22%
$\mathbb{E}[pd]$	3.49	3.69	3.38	4.01
$\sigma(pd)$	0.43	0.17	0.09	0.22
C. Predictive Regression R^2s (in %)				
Dividend price ratio only				
1-year	7.00	6.46	2.75	1.72
3-year	25.18	22.12	6.99	4.56
7-year	23.48	37.95	11.81	7.75
Dividend price ratio and TFP volatility				
1-year	9.46	10.02	4.44	3.21
3-year	25.56	31.69	9.79	9.34
7-year	37.81	50.03	16.71	17.65

coefficients and to which we devote - as emphasized above - a dedicated subsection (i.e., Subsection 3.3).

As a general observation, however, comparing our parameter values to analogous values used in the literature on the real impacts of uncertainty shocks reveals important differences. Our risk aversion coefficient, γ, of 15, for instance, is more than 5 times smaller than the value of 80 used in Basu and Bundick (2017). Similarly, our elasticity of substitution between intermediate goods, ν, of 6 is more than three times smaller than the corresponding value in Fernández-Villaverde et al. (2015). The differences speak to the role of endogenous growth in generating meaningful real effects without forcing individual parameters. As an example, we will show that dispensing with endogenous growth would generate muted real responses to an uncertainty shock given our chosen parameters (Fig. 5). An increase in γ to 80 (i.e., the chosen value in Basu and Bundick, 2017) would instead lead to more significant effects, which is consistent with the work of Basu and Bundick (2017).

The calibrated model matches well both macroeconomic and financial moments from data (cf. Table 4). On the macroeconomic side, the relative (to the volatility of output growth) variabilities of consumption, hours worked, physical capital investment, and R&D investment are in line with data (cf. Panel A). The level and the variability of the nominal short rate are also close to their empirical counterparts. In addition to matching macroeconomic moments, the model reproduces the level and the volatility of both the term structure slope and the levered equity risk premium (cf. Panel B). While the model replicates the level of the price dividend ratio, it downplays its volatility somewhat. Importantly, speaking now directly to the evidence on predictability reported in Section 2, the model captures the return predictability of the dividend price ratio as well as the incremental contribution to predictability of orthogonalized TFP volatility remarkably well (cf. Panel C).

Table 4 clarifies that dispensing either with the endogenous growth channel or with Epstein-Zin preferences leads to inferior performance. Specifically, a specification with exogenous growth cannot reproduce first and second moments of financial variables such as the level of the term structure, its slope and the excess return on levered equity. Similarly, preferences with constant relative risk aversion lead to counterfactual volatilities across macroeconomic variables, consumption being a clear example. In both cases, the extent of predictability induced by the dividend price ratio and TFP volatility would be considerably more muted than in the data.

In addition to matching unconditional moments as well as conditional means in predictive regressions, we note that the responses of the model's endogenous variables to TFP volatility shocks reported in Fig. 2 (red solid lines) are in line with their empirical counterparts in Fig. 1. In Fig. 2, we also plot model-implied responses for a counterfactually low level of TFP volatility persistence equal to 0.6 (blue dotted lines). These responses are very limited, thereby providing initial evidence regarding the role played by TFP volatility persistence in generating our findings.

3.3. *Calibrating price rigidities*

The presence of price rigidities is key to the model mechanism as stale prices are needed to induce time-varying mark-ups and sensible co-movements between output and consumption (Basu and Bundick, 2017). Unfortunately, there exists little guidance in the literature regarding how to choose the adjustment cost parameter, ϕ_P, in a model comparable to ours. Several papers use an equivalence approach between the price setting mechanism in Calvo (1983) and that in Rotemberg (1982). However, this equivalence only holds for a log-linearization around the zero steady-state inflation. This assumption is problematic in our setup as we are interested in higher-order approximations with non-zero trend inflation. Some articles have, in fact, shown that Calvo (1983) pricing works very differently from Rotemberg (1982) pricing in non-linear models with positive trend inflation (e.g., Lombardi and Vestin, 2008, and Ascari and Rossi, 2012). Thus, we calibrate ϕ_P by using empirical correlations (Fig. 3) and by evaluating the model-implied implications of time-varying mark-ups (Fig. 4).

Fig. 3 shows that varying ϕ_P is consequential for the correlations between the following variables: (i) price dividend ratio and TFP volatility, (ii) consumption growth and inflation, (iii) inflation and TFP volatility, and (iv) TFP and TFP volatility. Fig. 3 plots model-implied correlation coefficients. In light of our emphasis on risk premia, one correlation is particularly central to our goals: the one between the price dividend ratio and TFP volatility. For it to be negative, like in the data, prices have to be sufficiently rigid. Our choice of ϕ_P, which we set equal to 320, strikes a good balance between model-implied values and values in the data (black dots) across all four correlations.

Fig. 4 clarifies that, for values higher or lower than 320, the model-implied impulse responses to TFP volatility shocks might be counterfactual. Low values lead to quick recoveries in output driven by increased R&D investment associated with low consumption levels. High values yield excessive drops in R&D investment and TFP. Again, a value of 320 generates model-implied responses in line with the empirical evidence. Such value is well within the lower figure calibrated in, e.g., Kung (2015) and the considerably larger figures implied by the structural es-

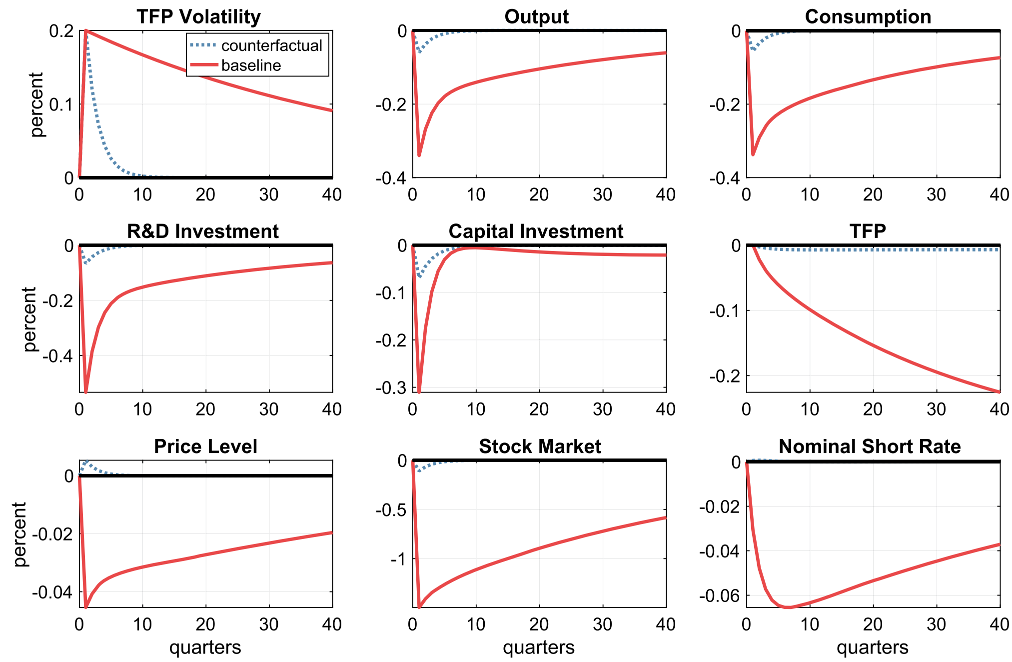

Fig. 2. The figure plots model-implied responses to a one-standard-deviation TFP volatility shock of output, consumption, R&D investment, capital investment, TFP, the price level, the stock market index, and the nominal short rate in the baseline model (red solid lines) and when setting the persistence of TFP volatility to a counterfactually low value (blue dotted lines), i.e., $\rho_{\sigma_a} = 0.6$.

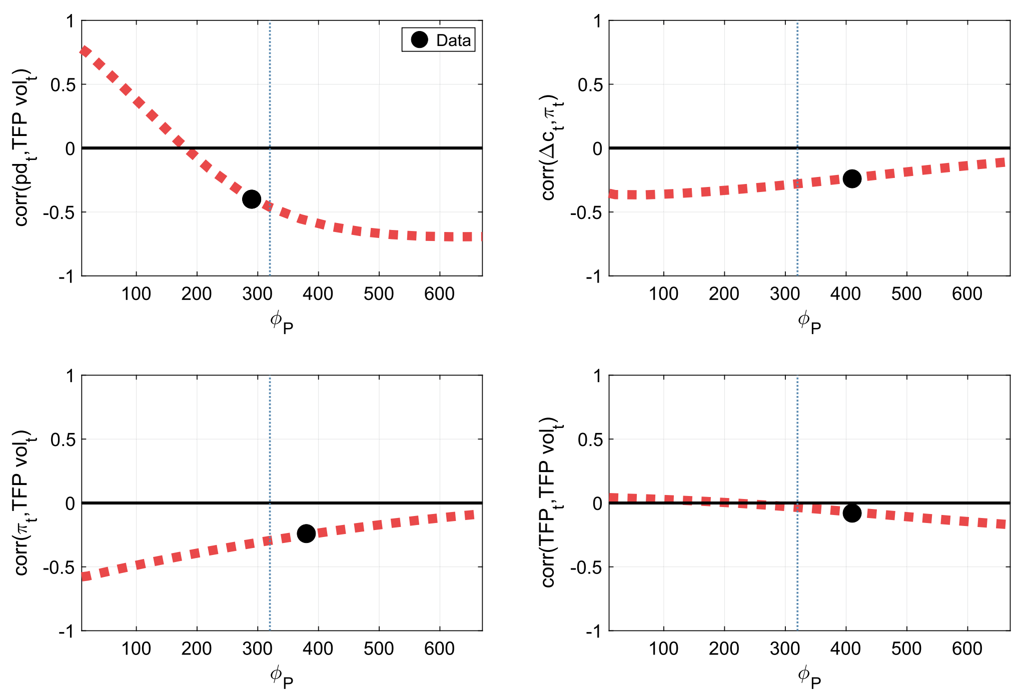

Fig. 3. The figure plots comparative statics for the adjustment cost parameter ϕ_P. The four panels show how the correlations between the price dividend ratio and TFP volatility, consumption growth and inflation, inflation and TFP volatility, and total factor productivity and TFP volatility vary with ϕ_P in the model (red dotted lines). The black dots correspond to the empirical estimates of each moment. The blue dotted (vertical) lines coincide with $\phi_P = 320$, which is our chosen value.

timates in, e.g., Bianchi et al. (2018) and Bianchi and Melosi (2019).[13] Moreover, our calibration implies a slope of the New Keynesian Phillips curve of 0.0156 (in the model the slope of the curve equals $\frac{\nu-1}{\phi_p}$), a value that is, also, well within the confidence bands estimated in Smets and Wouters (2007).

3.4. *The mechanism*

The three central features of the model are (i) an endogenous growth channel, (ii) Epstein-Zin preferences and (iii) price rigidities. The interaction between these three features leads to the long-run predictive ability of TFP volatility, the real economy counterparts of such pre-

[13] We note that our higher degree of price rigidity does not impact the findings in Kung (2015).

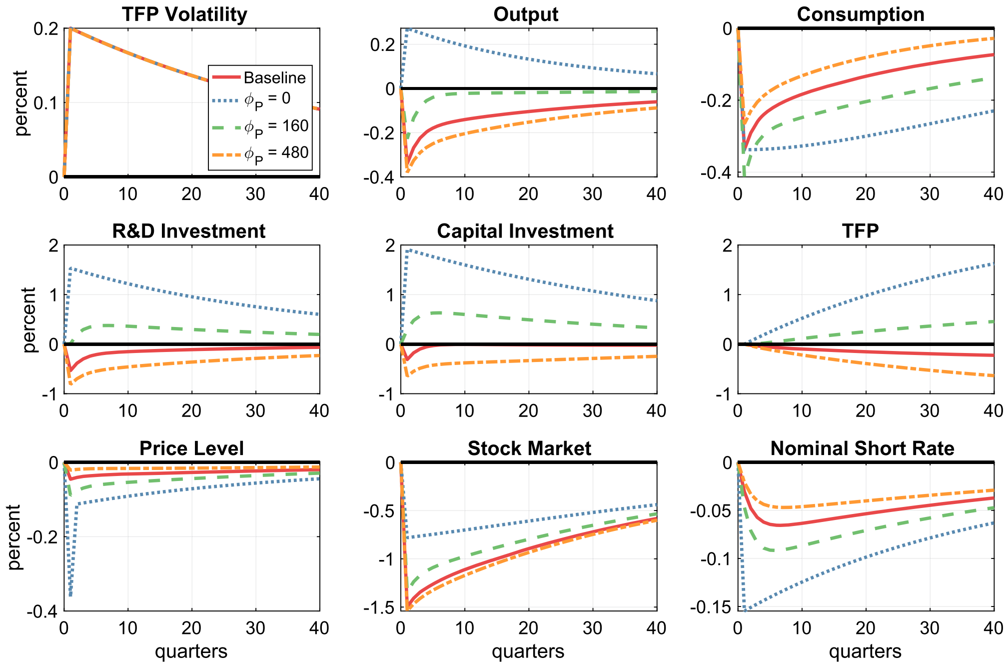

Fig. 4. The figure plots model-implied responses to a one-standard-deviation TFP volatility shock of output, consumption, R&D investment, capital investment, TFP, the price level, the stock market index, and the nominal short rate. For each outcome variable, the figure shows responses for the baseline model calibration (red solid lines) as well as for a model with $\phi_P = 0$ (blue dotted lines), $\phi_P = 160$ (green dashed lines) and $\phi_P = 480$ (orange dashed/dotted lines).

dictability as well as ubiquitous persistence in the responses of financial and macroeconomic variables to TFP volatility shocks.

We begin with price rigidities. An increase in TFP volatility leads to an increase in the representative household's savings due to precautionary motives and a simultaneous decrease in consumption. The magnitude of this effect depends on the degree of risk aversion. Given a relatively moderate risk aversion parameter of 15 (our choice), this effect contributes to dynamics but does not dominate our findings. Second, in addition to a decrease in consumption, a positive TFP volatility shock triggers an increase in the labor supply of the representative household, which results in lower wages and nominal marginal costs. Because physical capital and knowledge are predetermined, higher labor supply would lead to an increase in output with flexible prices. Thus, a model specification with flexible prices would not reproduce the co-movement between TFP volatility, consumption, investment and output in the data. Fig. 4 displays the model-implied impulse-responses for the case of flexible prices (cf. the blue dotted lines associated with $\phi_P = 0$). Capital/R&D investment, TFP and output counterfactually increase after a TFP volatility shock.

Increasing the adjustment cost parameter, however, allows the model to generate responses in line with data. With sticky prices, mark-ups are time-varying and output is demand-driven in the short term as discussed in Basu and Bundick (2017). Firms would demand less labor and decrease R&D investment, as well as investment in physical capital, as a response to a positive TFP volatility shock. Hence, time-varying mark-ups are important for the workings of the proposed economic mechanism. Extending the S-VAR in Section 2.2, Panel A of Fig. 6 displays an increase in mark-ups following a positive shock to TFP volatility.[14] The model-implied impulse-response in Panel B replicates the empirical evidence.[15]

Endogenous growth leads to the amplification/propagation of shocks. As R&D investment and, hence, the stock of knowledge fall upon an increase in TFP volatility, TFP and long-run growth are also negatively affected. As a result, TFP volatility shocks have long-lived impacts on macroeconomic quantities, as documented in the data. Fig. 5 plots impulse-responses for the baseline model along with those from an otherwise identical model with exogenous growth (i.e., without R&D investment). Since the model without R&D investment does not feature the endogenous growth channel, TFP volatility shocks have responses that are rather transient and small.[16] On the contrary, the fact that - in our model specification - TFP volatility shocks affect long-run growth via the stock of knowledge gives rise to endogenous long-run risks, thereby attributing a key role to the third model feature, i.e., Epstein-Zin preferences.

These preferences, along with an elasticity of inter-temporal substitution larger than one, make the representative household averse to long-run risks (Bansal and Yaron, 2004). This, in turn, exacerbates the household's precautionary saving motive and leads to an amplification of the endogenous responses to TFP volatility shocks. The importance of Epstein-Zin preferences is, again, evidenced by Fig. 5. Comparing the responses in the constant relative risk-aversion (CRRA) case[17] to those in our baseline case illustrates the amplification effect due to endogenous long-run risks. In the CRRA case, consumption drops less, even though the risk aversion parameter is left unchanged. Also, R&D investment counterfactually increases, which leads to an increase in TFP and a positive correlation between uncertainty shocks and productivity levels (accompanied by a positive response of the stock market). Among other

[14] Consistent with Fernández-Villaverde et al. (2015), we add to our benchmark S-VAR the inverse of the labor share as a measure of mark-ups. The mark-up proxy is placed below TFP volatility, thereby implying that mark-up shocks do not affect TFP volatility.

[15] Panel B shows that a counterfactually low level of persistence in the transmission of TFP volatility shocks would translate into a smaller and less persistent increase in mark-ups. Lowering the persistence of TFP volatility in the S-VAR would yield an analogous result in the data. While suggestive, we do not report explicitly the corresponding counterfactual in the data because of the lack of response on impact in this case.

[16] Basu and Bundick (2017) obtain sizable effects with a risk aversion coefficient more than four times larger than in our article.

[17] In order to construct model-implied impulse-responses for the CRRA case, we set $\psi = 1/\gamma$.

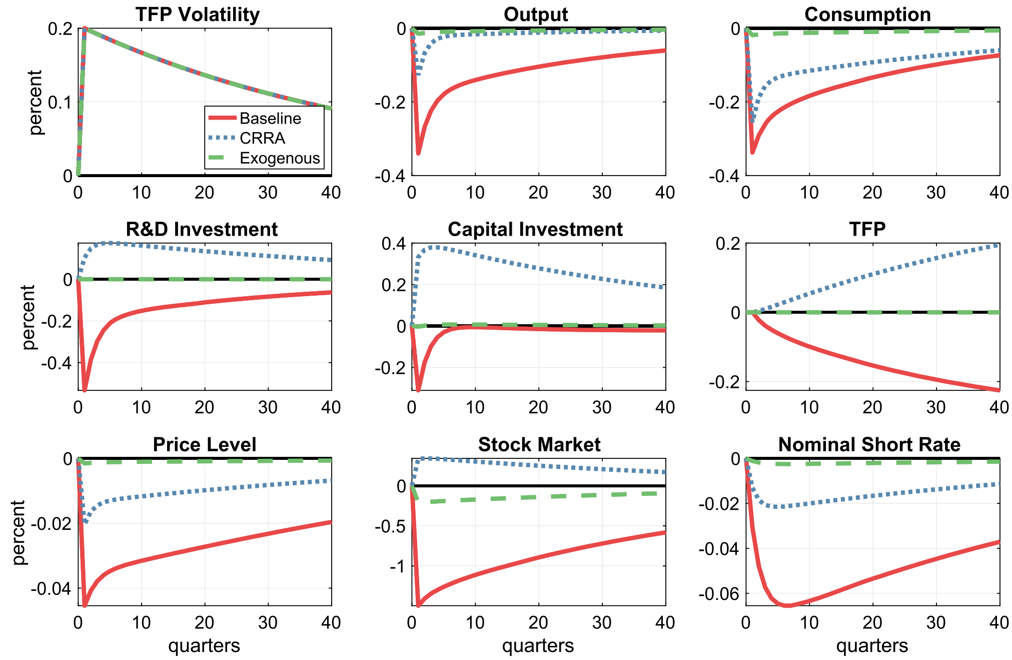

Fig. 5. The figure plots model-implied responses to a one-standard-deviation TFP volatility shock of output, consumption, R&D investment, capital investment, TFP, the price level, the stock market index, and the nominal short rate. For each outcome variable, the figure shows responses for the baseline model (red solid lines), a model in which the representative household has CRRA preferences (blue dotted lines), and a model with exogenous growth (green dashed lines).

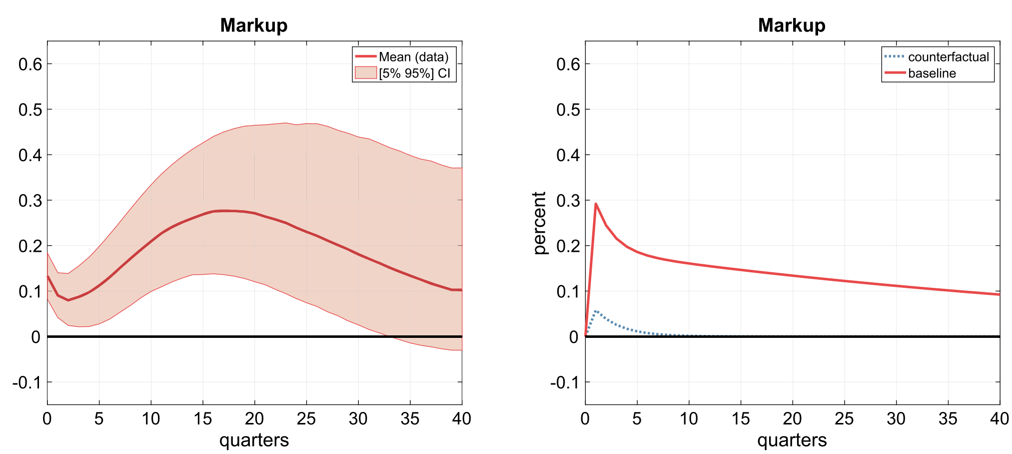

Fig. 6. The left panel (Panel A) reports the empirical response of mark-ups to a one-standard-deviation TFP volatility shock (we extend the structural VAR in Section 2.2). The right panel (Panel B) reports the model-implied response in the baseline model (red solid line) and in a model in which the persistence of TFP volatility is set to a counterfactually low value (blue dotted line), i.e., $\rho_{\sigma_a} = 0.6$.

effects, CRRA preferences would not be able to yield the predictability in the data. We now return to predictability.

3.5. Model-implied predictive regressions

After examining model-implied impulse-responses and their coherence with their empirical counterparts from the S-VAR in Section 2.2, we add details to the model-implied predictive regressions in Panel C of Table 4. Table 5 is the model-implied analogue of Table 1, i.e., it provides model-based evidence on the predictability of excess market returns over different horizons using the dividend price ratio (Panel A), raw TFP volatility (Panel B1) and orthogonalized TFP volatility, individually (Panel B2) and jointly (Panel C). TFP volatility enhances the predictive ability of the dividend price ratio over all horizons. Analogously to the results in the data, the R^2 increases due to the addition of TFP volatility are large.[18]

[18] Dating back to, at least, Ding and Granger (1996) and Engle and Lee (1999), several papers have investigated the role of short-run and long-run components of volatility using reduced-form econometric models (see, e.g., Engle and Rangel, 2008, and Engle et al., 2013, for more recent developments). The bulk of the literature has focused on stock market volatility. There is, however, recent work on firm-level short-run and long-run uncertainty captured through option-implied volatility (Barrero et al., 2017). Barrero et al. (2017) find that R&D investment is particularly sensitive to long-run uncertainty. We have shown that the sensitivity of R&D investment to shocks to TFP volatility - a persistent notion of uncertainty or, using our jargon, an *uncertainty trend* - is essential to generate long-lasting impacts on asset prices.

Table 5
Model-implied predictive regressions: excess market returns and TFP volatility. The table reports results from model-implied linear predictive regressions (with an intercept) of excess market returns on the dividend price (DP) ratio (Panel A), on TFP volatility either raw (Panel B1) or orthogonalized with respect to the DP ratio (Panel B2), and on the DP ratio and orthogonalized TFP volatility jointly (Panel C). $R_{t,t+h}$ represents the excess return from time t to time $t+h$. For each regression, the table reports OLS estimates of the partial effects, p-values corresponding to the robust test of Kostakis et al. (2015) (in parentheses) and R^2 statistics over different horizons. The model is simulated 100 times.

	1y	2y	3y	4y	5y	6y	7y
Dependent Variable: Excess Returns, $R_{t,t+h}$							
A. DP Ratio							
β_{DP}	0.08	0.17	0.25	0.32	0.38	0.45	0.52
p-value	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
$R^2(\%)$	6.46	15.16	22.12	27.53	31.70	35.15	37.95
B1. TFP Volatility (raw)							
β_{TFPV}	0.10	0.20	0.30	0.38	0.47	0.54	0.61
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R^2(\%)$	9.06	20.38	29.01	35.28	39.69	42.81	45.02
B2. TFP Volatility (orthogonalized w.r.t. the DP Ratio)							
β_{TFPV}	0.08	0.16	0.24	0.29	0.35	0.38	0.41
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R^2(\%)$	3.56	7.17	9.66	11.23	12.11	12.34	12.33
C. DP Ratio & orthogonalized TFP Volatility							
joint p-value	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
$R^2(\%)$	10.02	22.33	31.78	38.76	43.81	47.49	50.28

We emphasize that, because of the absence of debt in the model, model-implied returns are *unlevered*. As a consequence, while the regressions in Table 5 are using *unlevered* quantities (e.g., Panel A regresses *unlevered* returns on the *unlevered* dividend price ratio), the slope coefficients associated with TFP volatility (in Panels B1 and B2) are not directly comparable to those in the same panel of Table 1. A direct comparison is, instead, provided in the Online Appendix, where we re-lever returns. There, we show that the model is able to reproduce the magnitudes of the predictive slope coefficients on TFP volatility when using model-implied *levered* returns, as in the data.

As discussed, price rigidities are central to the real impacts of TFP volatility shocks in endogenous growth models. Turning to financial markets, while the predictive power of TFP volatility would remain qualitatively unchanged in their absence (cf. Fig. 4), the same is not true for the predictive ability of the dividend price ratio (as reported in Table 5, Panel A). With flexible prices, the dividend price ratio would still predict (with a lower R^2) risk premia. However, it would do so with the wrong sign, i.e., it would *negatively* predict excess returns. This effect is due to the behavior of aggregate dividends under flexible prices. We recall the definition of aggregate real dividend paid out to the representative household:

$$D_t = Y_t - W_t L_t - S_t - I_t - \frac{\phi_P}{2}\left(\frac{\Pi_t}{\Pi_{ss}} - 1\right)^2 Y_t. \tag{3}$$

With flexible prices, output, labor, R&D investment and capital investment jointly increase (while wages decrease) following a positive TFP volatility shock. The increase in capital/R&D investment - along with the combined effect of labor and wages - outweigh the increase in output and reduce aggregate dividends. Aggregate dividends decrease at a time during which asset prices are lower, i.e., in association with a positive TFP volatility shock, an effect which makes the dividend price ratio predict risk premia with a negative slope. We conclude that price rigidities are also central to the financial implications of endogenous growth models.

Next, we run model-implied regressions of inflation, the real interest rate, and real dividend growth on TFP volatility (Table 6). Consistent - once more - with empirical evidence, TFP volatility predicts inflation (with a negative sign) and, through inflation, real dividend growth (with a positive sign). The impact on real rates is negative, again, as in the data.

Table 6
Model-implied predictive regressions: inflation, real interest rates, real dividend growth and TFP volatility. The table reports results from model-implied linear predictive regressions (with an intercept) of macroeconomic variables on TFP volatility (orthogonalized with respect to the dividend price ratio). The dependent variables are cumulative inflation (Panel A), cumulative real interest rates (Panel B), and cumulative real dividend growth (Panel C). For each regression, the table reports the OLS estimates of the partial effects, p-values corresponding to the robust test of Kostakis et al. (2015) (in parentheses) and R^2 statistics for the different horizons. The model is simulated 100 times.

	1y	2y	3y	4y	5y	6y	7y
A. Dependent Variable: Inflation							
β_{TFPV}	-0.23	-0.43	-0.60	-0.76	-0.89	-1.01	-1.09
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R^2(\%)$	45.04	42.02	39.28	36.85	34.52	32.31	30.26
B. Dependent Variable: Real Interest Rates							
β_{TFPV}	-0.02	-0.03	-0.05	-0.06	-0.07	-0.08	-0.08
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R^2(\%)$	3.31	4.16	4.38	4.44	4.51	4.61	4.75
C. Dependent Variable: Real Dividend Growth							
β_{TFPV}	0.01	0.02	0.04	0.08	0.09	0.11	0.13
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R^2(\%)$	0.43	1.03	1.67	2.28	2.83	3.33	3.83

We note that the reaction of inflation to uncertainty shocks is not homogenous across model specifications in the literature. In, e.g., Fernández-Villaverde et al. (2015) and in Basu and Bundick (2017) fiscal volatility shocks and discount rate volatility shocks lead to inflation increases and decreases, respectively.[19] It is therefore revealing to zoom into the relation between TFP volatility and inflation (as well as into the relation between TFP volatility and real dividend growth) in our assumed model specification.

Because the model belongs to the New Keynesian class, inflation dynamics depend on current real marginal costs and discounted expected future real marginal costs. To see this, let us first consider real marginal costs, i.e., the ratio between wages and the marginal product of labor:

$$MC_t = \frac{W_t}{MPL_t} = \frac{W_t L_t}{(1-\alpha)Y_t}.$$

Equipped with this expression, it is standard to rewrite the price-setting equation of the firm in the following form (e.g., Kung, 2015):

$$\nu MC_t - (\nu - 1) = \phi_P\left(\frac{\Pi_t}{\Pi_{ss}} - 1\right)\frac{\Pi_t}{\Pi_{ss}} - \mathbb{E}_t\left[M_{t+1}\phi_P\left(\frac{\Pi_{t+1}}{\Pi_{ss}} - 1\right)\frac{\Delta Y_{t+1}\Pi_{t+1}}{\Pi_{ss}}\right].$$

A classical log-linearization of the equation above around the steady state now yields the New Keynesian Phillips Curve:

$$\widetilde{\pi}_t = \frac{\nu - 1}{\phi_P}\widetilde{mc}_t + \beta\Delta Y_{ss}^{1-1/\psi}\mathbb{E}_t\left[\widetilde{\pi}_{t+1}\right],$$

where the variables with tildes define (logarithmic) deviations from the steady state. Recursively substituting out future inflation terms implies that current real marginal costs and discounted expected future real marginal costs drive inflation dynamics.

To understand the negative relation between TFP volatility and inflation, Fig. 7 reports the model-implied impulse-responses of real marginal costs, expected inflation, wages, labor, and output to a TFP volatility shock. When TFP volatility increases, real marginal costs decrease and remain at a lower level for a prolonged period of time. As

[19] The increase in inflation following a fiscal uncertainty shock is a feature of the baseline model in Fernández-Villaverde et al. (2015), one which is modified by Fernández-Villaverde et al. (2015) (in order to determine price decreases, as in most of their evidence) using an alternative Taylor rule. Our own unreported S-VAR results, obtained by replacing TFP volatility with tax uncertainty, yield price increases even steeper than those in Fig. 5 of Fernández-Villaverde et al. (2015). The response of inflation to fiscal uncertainty shocks requires more work, both empirically and in terms of modeling.

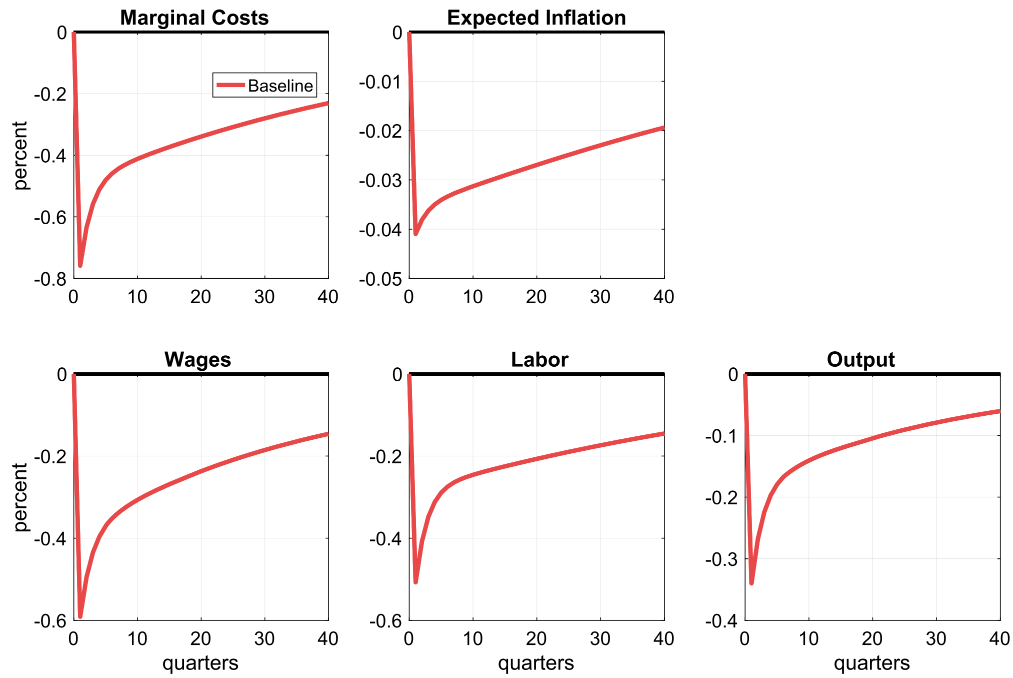

Fig. 7. The figure plots model-implied responses of real marginal costs, expected inflation, wages, labor, and output to a one-standard-deviation TFP volatility shock.

a consequence, inflation is negatively related to TFP volatility. The second row of Fig. 7 shows why real marginal costs drop when TFP volatility shocks occur. In times of high TFP volatility, firms reduce their investment and production activities. Thus, the demand for labor drops, which results in a decrease in real wages. Importantly, the contemporaneous reduction in output is not large enough to offset the decrease in labor demand and real wages, which leads real marginal costs (and prices) to decrease.

We conclude with the apparent disconnect between output (which is *negatively* affected by increases in TFP volatility) and real dividends (which are affected *positively*). Fig. 1 and Fig. 2 show that consumption and output diminish upon arrival of a positive shock to TFP volatility in the data and in the model, respectively. Results from predictive regressions reported in Panel C of Table 2 and Table 6 illustrate that TFP volatility is *positively* related to real dividends, again, in the data and in the model, respectively.

In order to shed light on this disconnect, let us return to the definition of aggregate real dividends paid out to the representative household in Eq. (3). The positive response of real dividends to a TFP volatility shock reflects the fact that the decreases in wages, labor, R&D investment and capital investment jointly outweigh decreases in output. Inflation decreases too, thereby increasing real dividends, all else equal. Intuitively, in times of high TFP volatility, firms cut back investment (both in capital as well as in R&D) and employment. Absent paybacks to investors, firms would accumulate excess cash. The model, however, does not allow firms to keep idle cash within the firm.

4. TFP volatility vs. alternative volatility measures

An established literature has investigated the link between specific forms of uncertainty (the volatility of consumption growth and market volatility, in particular) and asset prices. Consumption growth volatility is the measure of (macroeconomic) uncertainty, in, e.g., Kandel and Stambaugh (1990), Bansal et al. (2005), Duffee (2005), Lettau et al. (2008) and the references therein. Market volatility is, instead, the adopted measure of (financial) uncertainty in, e.g., Engle et al. (1987), French et al. (1987), Baillie and DeGennaro (1990), Campbell and Hentschel (1992), Glosten et al. (1993), Brandt and Kang (2004), Ghysels et al. (2005), Ludvigson and Ng (2007) and the references therein. In this section, we relate TFP volatility to consumption growth volatility, arguably the most widely-employed notion of macroeconomic volatility in the literature. We then turn to market volatility.

4.1. Predictability with consumption growth volatility

First, we investigate the predictive ability of consumption growth volatility extracted from an autoregressive model with stochastic volatility, the same model specification estimated for TFP volatility (cf. Eqs. (1) and (2)). Contrary to TFP volatility, we do not find any evidence that consumption growth volatility has predictive power for excess market returns.[20]

We turn to the measure of consumption growth volatility proposed by Bansal et al. (2005). This measure is obtained by first running an autoregressive model on consumption growth and by then summing up the absolute value of the estimated residuals over a specific horizon J: $\sigma_{t-1,J} = \log\left(\sum_{i=1}^{J} |\hat{\varepsilon}_{t-i}|\right)$. We restrict our attention to it because (i) it is obtained in a univariate setting (as in our autoregressive specification with stochastic volatility) and (ii) it can be readily recomputed within the model. The comparison with other measures is, in general, more subtle and less direct. For instance, Bansal et al. (2014) obtain an estimate of ex-ante consumption growth volatility from a vector autoregressive model that employs both macroeconomic and financial variables (like the dividend price ratio). Suffice it to say that our analysis does not exclude that alternative notions of macroeconomic volatility might yield different findings.

Returning to the consumption growth volatility estimates proposed by Bansal et al. (2005), Panel A1 in Table 7 suggests that this macroeconomic volatility mildly forecasts excess market returns over medium/long horizons. For instance, the R^2 at 5 years is close to 13% and the coefficient estimate is statistically significant at the 10% level.

[20] For brevity, we do not report the corresponding results, but they are available upon request. In unreported work, we have also conducted the same analysis on output growth volatility, a less utilized notion of macroeconomic volatility than consumption growth volatility. The predictive ability of output growth volatility is even more muted than that associated with consumption growth volatility.

Table 7
Excess market returns, consumption volatility, and low-frequency market volatility. The table reports linear predictive regressions (with an intercept) of excess market returns on consumption volatility (left panels), low-frequency market volatility (right panels), and a combination of each volatility measure and the dividend price (DP) ratio. $R_{t,t+h}$ represents the excess return from time t to time $t+h$. For all regressions, the table reports the OLS estimates of the partial effects, p-values corresponding to the robust test of Kostakis et al. (2015) (in parentheses) and R^2 statistics over different horizons. Consumption volatility is constructed as in Bansal et al. (2005). The measure is orthogonalized with respect to the DP ratio in Panel A2. Low-frequency market volatility is the logarithm of market variance aggregated over 7-years. The measure is orthogonalized with respect to the DP ratio in Panel B2. For the results on the left (resp. right) panel, the sample is quarterly and spans the period 1950Q1-2020Q4 (resp. 1947Q2-2020Q4).

	1y	2y	3y	4y	5y	6y	7y
Dependent Variable: Excess Returns, $R_{t,t+h}$							
A1. Consumption Volatility (raw)							
β_{CV}	0.01	0.06	0.14	0.22	0.28	0.30	0.26
p-value	(0.40)	(0.23)	(0.22)	(0.14)	(0.08)	(0.07)	(0.10)
$R^2(\%)$	0.09	1.40	5.53	10.01	12.90	13.10	9.26
A2. Consumption Volatility (orthogonalized w.r.t the DP Ratio)							
β_{CV}	-0.07	-0.05	0.03	0.10	0.14	0.14	0.07
p-value	(0.40)	(0.45)	(0.22)	(0.14)	(0.08)	(0.07)	(0.13)
$R^2(\%)$	2.21	0.73	0.17	1.62	2.24	1.98	0.45
A3. DP Ratio & Consumption Volatility							
joint p-value	(0.30)	(0.44)	(0.43)	(0.36)	(0.26)	(0.26)	(0.39)
$R^2(\%)$	9.36	12.05	13.31	16.25	20.55	21.63	20.29

	1y	2y	3y	4y	5y	6y	7y
Dependent Variable: Excess Returns, $R_{t,t+h}$							
B1. Low-Frequency Market Volatility (raw)							
β_{MKTV}	0.07	0.16	0.31	0.47	0.62	0.74	0.85
p-value	(0.05)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.00)
$R^2(\%)$	2.52	3.00	17.25	31.74	32.52	41.05	46.81
B2. Low-Frequency Market Volatility (orthogonalized w.r.t. the DP Ratio)							
β_{MKTV}	0.06	0.13	0.20	0.29	0.38	0.45	0.52
p-value	(0.12)	(0.11)	(0.08)	(0.06)	(0.05)	(0.04)	(0.04)
$R^2(\%)$	3.09	7.00	13.57	22.19	29.46	35.53	39.91
B3. DP Ratio & Low-Frequency Market Volatility							
joint p-value	(0.06)	(0.08)	(0.11)	(0.11)	(0.09)	(0.08)	(0.09)
$R^2(\%)$	10.09	19.12	28.75	39.19	49.82	57.92	63.39

Table 8
Excess market returns on TFP volatility controlling for other volatility notions. The table reports linear predictive regressions (with an intercept) of excess market returns on TFP volatility controlling for either consumption volatility (Panel A) or market volatility (Panel B). $R_{t,t+h}$ represents the excess return from time t to time $t+h$. For each regression, the table reports the OLS estimates of the partial effects, p-values corresponding to the robust test of Kostakis et al. (2015) (in parentheses) and R^2 statistics over different horizons. Consumption volatility is constructed as in Bansal et al. (2005). Low-frequency market volatility is the logarithm of market variance aggregated over 7-years. TFP is utilization-adjusted Total Factor Productivity from Fernald (2012). TFP volatility is obtained by estimating an autoregressive TFP process with stochastic volatility, as in Eq. (1) and Eq. (2) in the main text. The sample is quarterly and spans the period 1950Q1-2020Q4 in Panel A and 1947Q2-2020Q4 in Panel B.

	1y	2y	3y	4y	5y	6y	7y
Dependent Variable: Excess Returns, $R_{t,t+h}$							
A. TFP Volatility and Consumption Volatility (raw)							
β_{TFPV}	0.60	1.01	1.33	1.48	1.82	2.02	2.17
p-value	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
β_{CV}	-0.03	-0.01	0.05	0.12	0.16	0.17	0.12
p-value	(0.42)	(0.69)	(0.99)	(0.72)	(0.59)	(0.78)	(0.60)
$R^2(\%)$	7.35	12.72	20.75	25.55	30.65	32.05	29.26
B. TFP Volatility and Market Volatility (raw)							
β_{TFPV}	0.53	1.04	1.55	1.85	2.23	2.47	2.60
p-value	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
β_{MKTV}	0.06	0.12	0.24	0.40	0.52	0.62	0.72
p-value	(0.35)	(0.24)	(0.08)	(0.02)	(0.03)	(0.03)	(0.03)
$R^2(\%)$	7.74	16.48	28.76	37.25	44.18	49.47	51.46

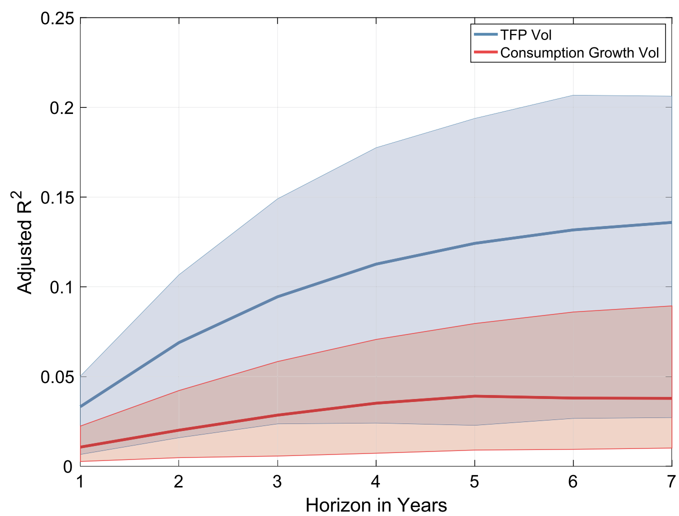

Fig. 8. The figure plots the distribution of the model-implied adjusted R^2s of univariate predictive regressions for excess market returns over horizons between 1 and 7 years. The predictors are either TFP volatility or consumption growth volatility. The model is simulated 100 times. The solid lines correspond to the median adjusted R^2s. The shaded areas are 90% confidence bands.

However, Panel A2 indicates that the somewhat limited predictive power of consumption growth volatility disappears when we orthogonalize the measure with respect to the dividend price ratio. Table 7, Panel A3, documents that in a multiple regression of excess market returns on the dividend price ratio and consumption growth volatility, the two variables are jointly insignificant. As expected, in a multiple regression of excess market returns on consumption growth volatility and TFP volatility, only the latter has statistically significant explanatory power (cf. Table 8, Panel A).

Next, we show that in an endogenous growth model with recursive utility and price rigidities, TFP volatility captures the long-run volatility of the SDF better than consumption growth volatility. The result provides a model-based justification for the limited predictive ability of consumption growth volatility relative to TFP volatility.

We begin by showing that, in the model, TFP volatility contains more information about risk premia as compared to consumption growth volatility. To this end, Fig. 8 plots the dispersion of the adjusted R^2s across horizons for univariate predictive regressions on model simulated data. The predictors are either TFP volatility or consumption growth volatility. Both predictors are orthogonalized with respect to the dividend price ratio. We simulate the model 100 times in order to obtain distributions of model-implied adjusted R^2s. TFP volatility leads to consistently higher adjusted R^2s as compared to consumption growth volatility. The model yields a wedge between the predictive power of TFP volatility and that of consumption growth volatility, a finding which is consistent with the empirical evidence in Tables 1 and 7. We now detail - and quantify - the role of both recursive preferences and endogenous growth in generating the reported wedge.

4.1.1. Recursive preferences

As discussed, recursive preferences play a key role in the model as endogenous growth gives rise to endogenous long-run risks. Whenever

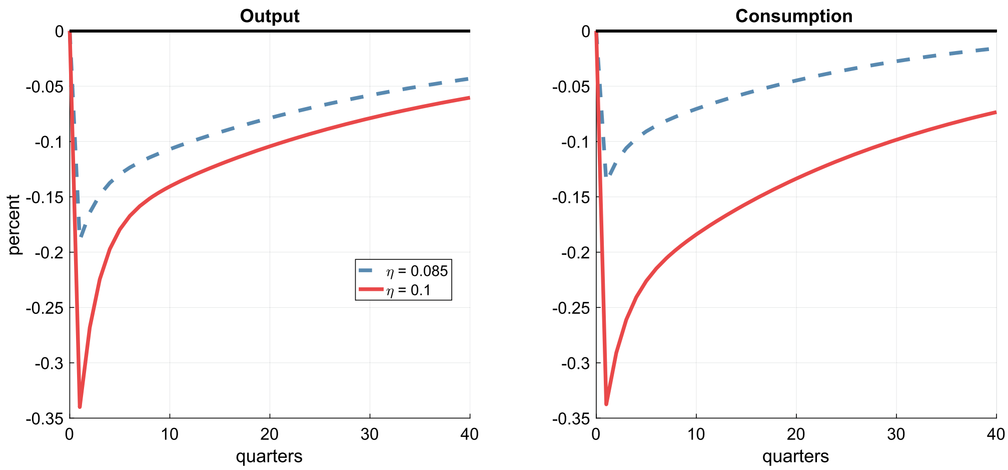

Fig. 9. The figure plots model-implied responses to a one-standard-deviation TFP volatility shock for output and consumption given different values of the knowledge spillover parameter, η. All else equal, a higher η value corresponds to lower knowledge spillover.

economic agents have a preference for early resolution of uncertainty, endogenous long-run risks are critical in determining risk premia and, consequently, asset prices.

In order to quantify the role of recursive preferences for predictability, as well as for explaining the short-run vs. long-run volatility of the SDF, we cannot simply set the inter-temporal elasticity of substitution, IES, equal to the inverse of risk aversion, which would reduce the assumed preferences to CRRA preferences. In this case, in fact, the model implications would be drastic since risk premia would virtually vanish and so would, of course, predictability.

We, instead, study recursive preferences in a neighborhood of CRRA preferences by lowering the IES towards the inverse of risk aversion. Importantly, however, even lowering the IES has an impact on the real effects of TFP volatility as the endogenous growth channel becomes more muted: R&D investment reacts less negatively to an increase in TFP volatility, which ultimately results in a less pronounced drop in TFP, output, and consumption. In essence, evaluating the model by assuming a lower IES helps us shed light on the *combined* effect of recursive preferences and endogenous growth. To address this issue, we turn to a procedure that allows us to better separate the effect of the endogenous growth channel.

4.1.2. Endogenous growth

In order to alleviate the concern of a combined effect, we single out the impact of the endogenous growth channel without changing preferences. To this end, we vary the degree of knowledge spillover in the model by modifying the parameter η. All else equal, a high η value (close to 1) corresponds to low knowledge spillover, which implies that knowledge created by firms is mostly proprietary. Conversely, a low value of η (close to 0) corresponds to large spillover effects. In this case, knowledge created by the firms can be seen more as a common good. As a result, the higher the value of η, the stronger the incentive for firms to innovate and create knowledge capital. Thus, a higher value of η yields a higher steady-state value of R&D investment and a more pronounced divestment from/investment in R&D as a response to TFP volatility shocks, which translates into larger real effects of these shocks. Fig. 9 shows that both output and consumption drop less in response to TFP volatility shocks when η is low. In sum, lowering the value of η weakens the endogenous growth channel without changing preferences.

Having made these observations, we turn to the evaluation of the relation between SDF volatility (in the short run and in the long run), TFP volatility and consumption growth volatility. We add output growth volatility to this analysis in order to study, within the model, an alternative notion of macroeconomic volatility (one which, in the data, has similar - if not inferior - predictive ability relative to consumption growth volatility). Table 9 displays the results. The table reports the correlations between the SDF (conditional) volatility and the volatility of consumption growth (first row), the volatility of output growth (second row), TFP volatility (third row) and market volatility (fourth row). We will turn to market volatility in the next subsection. Panels A and B refer to short-run volatility and long-run volatility, respectively. The conditional volatility of the SDF is obtained by fitting an AR(1)-GARCH(1,1) model to the SDF.

Table 9
Short- and long-run volatility of the SDF. The table reports model-based correlations (in percent) between the conditional volatility of the one- and five-year SDF and the conditional volatility of consumption growth, output growth, TFP and market returns. In the model, we define market volatility as the conditional volatility of the return on the firm equity, $\sqrt{Var_t(R^E_{t,t+1})}$, where $Var_t(R^E_{t,t+1})$ is the quarterly conditional variance of the return on equity $R^E_{t,t+1}$. Our baseline calibration is based on $\psi = 2$ and $\eta = 0.1$.

	baseline	$\psi = 1.10$	$\eta = 0.085$	$\psi = 1.10$ $\eta = 0.085$
	A. 1-year horizon			
$\sigma_{\Delta c,t}$	54.67	72.22	51.51	74.47
$\sigma_{\Delta y,t}$	55.49	59.93	70.02	77.71
$\sigma_{\mathrm{TFP},t}$	63.97	76.22	75.98	77.73
$\sigma_{\mathrm{MKT},t}$	59.15	66.92	69.46	68.45
	B. 5-year horizon			
$\sigma_{\Delta c,t}$	57.47	66.79	48.73	71.76
$\sigma_{\Delta y,t}$	58.39	54.76	65.29	74.65
$\sigma_{\mathrm{TFP},t}$	69.46	78.79	78.67	79.78
$\sigma_{\mathrm{MKT},t}$	64.87	69.59	72.38	70.67

We begin with Panel A. The first column corresponds to our benchmark calibration, which is based on $\psi = 2$ and $\eta = 0.1$. The second column lowers the IES ($\psi = 1.1$), the third column weakens endogenous growth ($\eta = 0.08$), the last column combines the two. TFP volatility is more correlated with SDF volatility than consumption growth volatility and output growth volatility. As we move from the benchmark case (column 1) to the case of low IES *and* weaker endogenous growth (last column), the correlation between consumption (resp. output) growth volatility and SDF volatility increases by 36% (40%) which compares to an increase of 21% in the case of TFP volatility. In other words, reducing the importance of key model ingredients, i.e., endogenous growth and recursive preferences, increases the correlation between the SDF volatility and both macroeconomic volatilities while narrowing the relative wedge between TFP volatility and the macroeconomic volatilities. For reference, lowering η from the baseline value of 0.1 to the value of

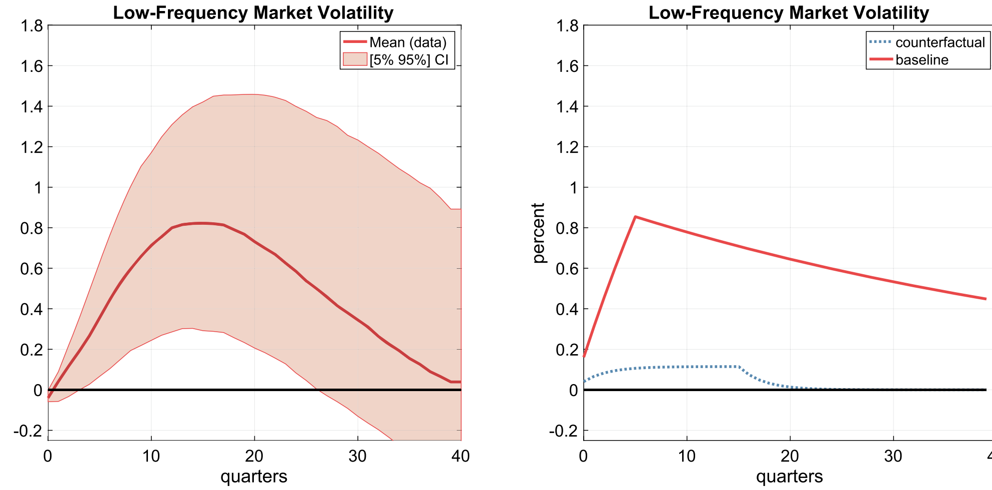

Fig. 10. The left panel (Panel A) reports the empirical response of low-frequency market volatility to a one-standard-deviation TFP volatility shock (we extend the structural VAR in Section 2.2). The right panel (Panel B) reports the model-implied response in the baseline model (red solid line) and in a model in which the persistence of TFP volatility is set to a counterfactually low value (blue dotted line), i.e., $\rho_{\sigma_a} = 0.6$.

0.085 (in the last column) reduces the steady-state R&D investment rate by 20%. Hence, the documented change in η is quantitatively meaningful.

Panel B, which focuses on the 5-year SDF, paints a similar picture. Lowering the IES *and* weakening the endogenous growth channel leads to an increase in the correlation between the macroeconomic volatilities and the SDF volatility. In particular, the correlation between consumption growth volatility and the SDF volatility raises from 57.47% (in the benchmark case) to 71.76% (a 24% increase). In comparison, the correlation between TFP volatility and the SDF volatility increases by 14% from 69.46% (again, in the benchmark case) to 79.78%.

Independently of the horizon, lowering the IES has a larger effect on the correlation of the SDF volatility with consumption growth volatility as compared to output growth volatility. This can be seen by comparing the results across columns 1 and 2. Intuitively, the lower the IES, the more weight is placed on the portion of the SDF which corresponds to CRRA preferences which, in logarithmic terms, is equal to the product of risk aversion and consumption growth. In addition, comparing columns 1 and 3 reveals that the opposite conclusion is true when we lower η. This is consistent with the idea that, in an exogenous growth model, current output is an almost sufficient statistics for state prices. Said differently, the output level is an effective proxy for how good, or bad, the state of the economy is. In contrast, in an endogenous growth model, current output levels are not fully informative about growth cycles determining long-run risks and, hence, asset prices.

In sum, even though endogenous growth is a first-order driver of the relative predictability of TFP volatility as compared to consumption growth volatility and output growth volatility, recursive preferences are also important (in particular, for the predictability of TFP volatility relative to that of consumption growth volatility).

Before turning to market volatility, we emphasize that, while the *relative* comparison between numbers in Table 9 is consistent with economic logic and informative, the *absolute* magnitude of the same numbers should be interpreted with caution. First, the dynamics of the SDF, a rather complex object given the structure of the model, are represented by a simple AR(1)-GARCH(1,1) reduced-form specification which is, in turn, used to filter the SDF (conditional) volatility. Second, even if the conditional volatility of the SDF were observed, hard-to assess but likely nonlinear dependences and lagged effects (as induced by model frictions, such as adjustment costs to physical and R&D investment) between the SDF volatility and alternative volatility notions are bound to render the correlation between *contemporaneous* SDF volatility and alternative *contemporaneous* notions of volatility (i.e., what we report in Table 9) an imperfect proxy of true dependence. In light of the role of TFP volatility as the model's key state variable, the latter observation is important to justify, e.g., the wedge from one in the correlation between SDF volatility and TFP volatility.

4.2. Predictability with low-frequency market volatility

Panels B1, B2 and B3 of Table 7 contain predictive regressions using the logarithm of market variance aggregated over a 7-year horizon as the predictor. We call this measure *low-frequency market volatility*.[21] Its predictive ability for long-run excess market returns has been discussed extensively (Bandi and Perron, 2008). We confirm it here in Panel B1. Panel B2 and B3 document that its independent (of the dividend price ratio) explanatory power is, also, striking. In Table 8, Panel B, we further document that low-frequency market volatility has residual predictive ability after controlling for TFP volatility.

We now show, using counterfactuals, that the explanatory power of low-frequency market volatility may be viewed as a by-product of the persistence of TFP volatility and, hence, of its inherent low-frequency nature. Fig. 10 reports impulse-responses for market volatility following a shock to TFP volatility, in the data and in the model. We focus on the model. When the level of persistence of TFP volatility is as high as in the data, market volatility, which inherits the persistence of TFP volatility in the model, increases significantly (along with evident increases in expected returns - cf. Fig. 1). Should the level of persistence of TFP volatility be, instead, counterfactually low, the impacts on market volatility and expected returns would be considerably more muted. Milder predictive ability of TFP volatility in the counterfactual translates into milder predictive ability of (the endogenous) market volatility.

An admittedly more direct way to illustrate the same finding is to run model-implied predictive regressions on market volatility when TFP volatility is highly persistent (as in the data) and when the persistence of TFP volatility is counterfactually low. Table 10, Panel A and B, show that, in the former case, orthogonalized market volatility has strong predictive ability for market risk premia whereas in the latter case its predictive power is drastically diminished.

The last row in Table 9, Panels A and B, reports the short-run correlation and the long-run correlation between the SDF volatility and market volatility. Short-run volatility is, as earlier in Section 4, volatility computed over a 1-year horizon whereas long-run volatility is volatil-

[21] Almost identical results are obtained by taking the square root of market variance, rather than the logarithm.

Table 10
Model-implied predictive regressions: excess market returns and market volatility. The table reports results from model-implied linear regressions (with an intercept) of excess market returns on market volatility (Panel A) and on the same quantity, but in a counterfactual model specification in which the persistence of TFP volatility has been lowered from 0.98 to 0.6 (Panel B). $R_{t,t+h}$ represents the excess return from time t to time $t+h$. For each regression, the table reports OLS estimates of the partial effects, p-values corresponding to the robust test of Kostakis et al. (2015) (in parentheses) and R^2 statistics over different horizons. The model is simulated 100 times.

	1y	2y	3y	4y	5y	6y	7y
Dependent Variable: Excess Returns, $R_{t,t+h}$							
A. Market Volatility							
β_{MKTV}	0.07	0.15	0.22	0.28	0.36	0.42	0.49
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$R^2(\%)$	1.66	3.43	7.48	8.66	8.29	8.72	9.96
B. Counterfactual: Market Volatility, $\rho_{\sigma_a}=0.6$							
β_{MKTV}	-0.00	-0.01	-0.00	-0.00	0.01	0.02	0.03
p-value	(0.38)	(0.43)	(0.45)	(0.44)	(0.46)	(0.45)	(0.44)
$R^2(\%)$	0.49	1.08	1.46	1.86	1.87	2.02	2.70

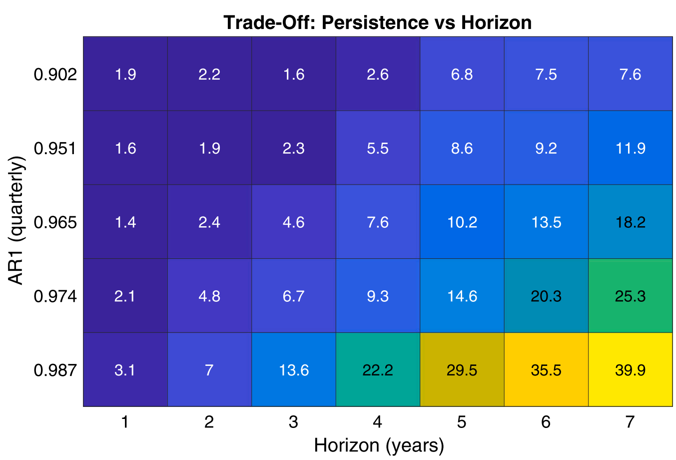

Fig. 11. The figure reports the adjusted R^2s from regressions of h-year excess market returns on a notion of low-frequency market volatility (i.e., the logarithm of backward aggregated market variance). The vertical axis gives the autoregressive coefficient of the quarterly-sampled volatility series. These time series correspond to backward aggregates of the original monthly time series over 1, 2, 3, 4 and 7 years. The horizontal axis denotes the holding period (in years) of the excess returns.

ity computed over a 5-year horizon. Across horizons, model-implied market volatility is generally more closely related to the SDF volatility than both consumption and output growth volatility. In fact, market volatility behaves fairly similarly to TFP volatility, which is not surprising given the high model-implied correlation between the two series (0.95).

We emphasize that computing - in the data - a *low-frequency* notion of market volatility aligns - consistent with the model - the persistence of market volatility to that of TFP volatility. In order to investigate the role of aggregation in leading to the persistence of market volatility and its predictability for excess market returns, we employ equally-weighted averages of past observations to compute slow-moving measures of market volatility and relate them to risk premia. Fig. 11 shows the results. The y-axis reports, from top to bottom, the persistence of market volatility aggregated over 1, 2, 3, 4 and 7 years. As expected, persistence increases with the level of aggregation. Importantly, the persistence of TFP volatility (in the data and in the model) is matched for an horizon corresponding to a level of aggregation equal to 7 years. Each row reports the R^2 from a predictive regression of h-period excess market returns, with $h=1,\ldots,7$ years, on (logarithmic) market variance (for

Table 11
Excess market returns and trends. Panel A reports linear predictive regressions (with an intercept) of excess market returns on the logarithm of long-run bond volatility. Long-run bond volatility is computed as the rolling 20-year bond return volatility (as in Asness, 2000). Panel B reports linear predictive regressions (with an intercept) of excess market returns on a weighted average of past inflation (as in Cieslak and Povala, 2015). Panel C reports linear predictive regressions (with an intercept) of excess market returns on a 20-year moving average of the growth in earnings per share (Ferreira and Santa-Clara, 2011). Panel D reports linear predictive regressions (with an intercept) of excess market returns on long-run productivity growth (Antolin-Diaz et al., 2017). $R_{t,t+h}$ represents the excess return from time t to time $t+h$. For each regression, the table reports OLS estimates of the partial effects, p-values corresponding to the robust test of Kostakis et al. (2015) (in parentheses) and R^2 statistics over different horizons. The sample is quarterly and spans the period 1947Q2-2020Q4 (except for Panel D, where the sample ends in 2015Q1).

	1y	2y	3y	4y	5y	6y	7y
Dependent Variable: Excess Returns, $R_{t,t+h}$							
A. Long-Run Bond Volatility							
β_{BV}	0.06	0.09	0.11	0.13	0.19	0.23	0.26
	(0.20)	(0.30)	(0.40)	(0.44)	(0.39)	(0.39)	(0.39)
$R^2(\%)$	1.96	2.72	3.03	3.55	5.42	6.83	7.94
B. Weighted Average of Past Inflation							
β_{IN}	-0.13	-0.24	-0.30	-0.32	-0.35	-0.35	-0.31
	(0.20)	(0.23)	(0.33)	(0.43)	(0.50)	(0.56)	(0.65)
$R^2(\%)$	1.95	3.66	4.12	3.96	3.53	3.12	2.19
C. Long-Run Earnings Growth							
β_{EG}	0.63	0.34	0.15	-0.50	-0.81	-0.63	-0.34
	(0.42)	(0.62)	(0.66)	(0.79)	(0.84)	(0.82)	(0.76)
$R^2(\%)$	0.35	0.05	0.01	0.07	0.15	0.08	0.02
D. Long-Run Productivity Growth							
β_{PG}	-0.02	-0.06	-0.09	-0.11	-0.15	-0.17	-0.18
	(0.48)	(0.36)	(0.32)	(0.31)	(0.27)	(0.27)	(0.28)
$R^2(\%)$	0.69	2.23	3.86	4.73	5.65	5.93	5.88

which persistence is given by the y-axis). As always, market volatility has been orthogonalized with respect to the dividend price ratio. We observe small R^2 values for most horizons whenever the level of persistence is low. For instance, the predictive power for 3-year ahead returns is uniformly below 7% but raises to 13.6% when the persistence of market volatility in the data matches the model-implied persistence. This is on par with (and even higher than) the contribution (equal to 10.38%) of TFP volatility (cf. Table 1, Panel B). Importantly, when the compounding horizon for returns is longer than 3 years, market volatility - aggregated to the level of persistence of TFP volatility - virtually doubles the R^2 relative to a regression that only exploits the dividend price ratio. In sum, our framework justifies a significant risk-return trade-off in the long run.

We conclude with two observations. First, persistence - and the potential for spurious dependence (cf. Granger and Newbold, 1974, and Phillips, 1986) - cannot be the mechanical reason for the reported impact of low-frequency notions of uncertainty on risk premia. In order to justify this statement, we othogonalize several recently-proposed trends and show that they are considerably less effective than either TFP volatility or low-frequency market volatility in driving predictability. In Table 11, we employ long-run bond volatility (Asness, 2000), a weighted-average of past inflation (Cieslak and Povala, 2015), long-run earnings growth (Ferreira and Santa-Clara, 2011) and long-run productivity growth (Antolin-Diaz et al., 2017). None comes close to replicating the long-run predictive ability of our reported *uncertainty trends*.[22]

Second, there is a vibrant, recent literature on whether uncertainty (as defined in a variety of ways) is an exogenous driver of economic cycles or an endogenous response (see, e.g., Bachmann et al., 2013, Baker and Bloom, 2013, Cesa-Bianchi et al., 2020, and Berger et al., 2020).

[22] Alternative uncertainty trends are evaluated in the Online Appendix.

There is also work on the role of macroeconomic uncertainty relative to financial uncertainty and whether one, or the other, should be viewed as being endogenously determined (e.g., Carriero et al., 2018, and Ludvigson et al., 2021). As emphasized, our central result is the reduced-form link between two alternative notions of uncertainty and risk premia. In this sense, this article is not about the relative role of uncertainty, in general, and of different uncertainty measures, in particular, as an impulse or a response. Having made this point, because we work with a formal model with implications for both financial markets and the real economy, structure necessarily has to be imposed. While our main notion of uncertainty, i.e., TFP volatility, is exogenous in the structure we propose, market volatility is an endogenous response. Such endogeneity is helpful to link the persistence of low-frequency market volatility to that of a key exogenous impulse, i.e., TFP volatility.

5. TFP volatility and cross-sectional asset risk premia

Because of the predictive ability of TFP volatility (cf. Section 2) - and its role as the central state variable driving investment opportunities in the model specification in Section 3 - we expect *innovations* to TFP volatility to yield cross-sectional pricing signal (Maio and Santa-Clara, 2012). To this extent, we now provide evidence on the pricing of innovations to TFP volatility for interesting cross sections of assets.

We begin with stocks. We add innovations to TFP volatility to a market factor, a two-factor specification which will be shown to price very accurately a cross section of dividend strips in the model. When doing so, we note that the theoretical sign of the price of risk associated with innovations to TFP volatility is, a priori, not obvious. In a dynamic model with stochastic volatility, like the one in Section 3, risk premia are a function of loadings with respect to cash-flow news, discount-rate news and news about "risk", i.e., the conditional variance of the SDF plus market returns (cf. Bansal et al., 2014, and Campbell et al., 2018). The market factor loading captures, of course, the loading with respect to cash-flow news. Innovations to TFP volatility proxy for *both* discount-rate news, given our predictability results in Section 2, and for news about "risk", given our results in Section 4. When innovations to TFP volatility proxy for discount-rate news, the price of risk would, in general, be positive.[23] It would be negative when innovations to TFP volatility proxy for "risk" news. By letting the data and the model speak jointly, we document that - in our assumed two-factor model - the price of risk associated with innovations to TFP volatility is, in fact, negative. As a result, we provide support for the emphasis placed by Bansal et al. (2014) and Campbell et al. (2018) on the cross-sectional pricing role of "risk" (proxied in this article by innovations to TFP volatility) from an alternative vantage point.

We then turn to bonds and show that TFP volatility explains term premia - in the data and in the model - even when controlling for inflation and real growth uncertainty.

5.1. Stocks

In Table 12, we investigate the pricing of (TFP) volatility risk both in portfolios and in individual stocks. In Panel A, the cross section consists of excess returns on 25 portfolios sorted by size and value. This cross section is of course traditional, in general, and widely used in the literature on volatility pricing (e.g., Campbell et al., 2018).[24] We observe that the price of volatility risk is negative at 1% (annualized). The first-stage betas are all negative. The spread in betas between high and low book-to-market portfolios (averaged across size quintiles) is $-8.03-(-6.52)=-1.5$. Once multiplied by a negative price of risk of 1%, such spread accounts for 34% of the value premium (4.3% in our data). Similarly, the spread in betas between small- and large-firm portfolios is $-7.93-(-6.66)=-1.3$, which accounts for 54% of the size premium (2.32% in our data). Overall, a simple two-factor empirical pricing model justifies satisfactorily the cross-sectional spread in premia across the 25 size and book-to-market portfolios.

Table 12
Cross-sections of equity returns and TFP volatility. Panel A and B report risk premia estimates from cross-sectional regressions of portfolio-level average excess returns on estimated factor loadings with respect to innovations in TFP volatility and the market. We focus on two sets of portfolios: 25 size and book-to-market portfolios (Panel A) and duration-sorted portfolios (Panel B). Panel D reports second-stage cross-sectional regressions of quarterly excess returns on individual stocks on lagged estimated factor loadings with respect to TFP volatility and the market. In Panel A and B, the factor loadings are estimated in a first-stage time-series regression. In Panel D, the factor loadings are first-stage Fama-MacBeth betas estimated using a ten-year rolling-window time-series regression. We report the second-stage coefficients (in percent per year) with t-statistics in parentheses (GMM in Panels A and B, Fama-MacBeth in Panel D) as well as the cross-sectional R^2. The exposures are normalized so that the point estimates can be interpreted as the risk premium per unit of cross-sectional standard deviation. Panel C reports on the cross-sectional pricing of dividend strips in the model. TFP is utilization-adjusted Total Factor Productivity from Fernald (2012). TFP volatility is obtained by estimating an autoregressive TFP process with stochastic volatility, as in Eq. (1) and Eq. (2) in the main text.

A. 25 Size & Book-to-Market Portfolios				
	λ_0	$\lambda_{\Delta TFPV}$	λ_{MKT}	R^2 (%)
	4.96	-1.02	-0.29	17.78
t-stat	(1.34)	(-2.71)	(-0.45)	
B. 10 Duration-Sorted Portfolios				
	λ_0	$\lambda_{\Delta TFPV}$	λ_{MKT}	R^2 (%)
	-3.06	-1.11	0.48	35.03
t-stat	(-0.47)	(-1.84)	(0.75)	
C. Model - Dividend Strips				
	λ_0	$\lambda_{\Delta TFPV}$	λ_{MKT}	R^2 (%)
	-0.31	-0.15	2.26	99.66
t-stat	(-9.00)	(-33.89)	(19.91)	
D. Individual Stocks				
	λ_0	$\lambda_{\Delta TFPV}$	λ_{MKT}	R^2 (%)
	8.89	-0.72	1.08	2.48
t-stat	(4.69)	(-1.66)	(1.06)	

In Panel B, we study a cross section of ten duration-sorted portfolios. We do so for two reasons. First, duration is now at the heart of several anomaly portfolios (cf. Gormsen and Lazarus, 2021). Second, the model has implications for equity claims with different durations. Hence, importantly, model-based implications may be evaluated (cf. Panel C). In the data (cf. Panel B), volatility risk is negatively priced in the cross section of duration portfolios. The price of risk is similar in magnitude to that of Panel A. In the model (cf. Panel C), we obtain qualitatively similar results. The price of TFP volatility risk is, again, negative and equal to 0.15% (annualized), which is slightly below the empirical estimate. Importantly, a two-factor specification with the market and innovations to TFP volatility explains 99.7% of the cross-sectional variability in the pricing of dividend strips, a model-based finding which justifies our attention to an empirical two-factor model.

We conclude by reporting the price of volatility risk in the universe of CRSP individual stocks (Panel D). We continue to find a negative price of volatility risk with a magnitude consistent with that of the set of anomaly-sorted portfolios in Panels A and B.

[23] It could be negative if the state variable, TFP volatility in our case, predicts the conditional variance of excess market returns, possibly in addition to the conditional mean (cf. Maio and Santa-Clara, 2012).

[24] Bansal et al. (2014) use a similar, albeit, smaller cross section of assets which includes five size- and five value-sorted portfolios.

Table 13
Bond term premia and TFP volatility. We report regressions of term premia on alternative variables. The slopes β_{TFPV}, β_{INV}, and β_{RGV} correspond to term premia regression coefficients on TFP volatility, inflation volatility and real growth volatility. TFP is utilization-adjusted Total Factor Productivity from Fernald (2012). TFP volatility is obtained by estimating an autoregressive TFP process with stochastic volatility, as in Eq. (1) and Eq. (2) in the main text. Following Bansal and Shaliastovich (2013), we construct the variances of expected real growth and expected inflation using survey data. Panel A reports the empirical regression results and Panel B reports coefficients from regressions on model-simulated data. Inflation volatility is calculated in the model using a 5-year moving window.

A. Data				
	β_{TFPV}	β_{INV}	β_{RGV}	R^2 (%)
Term Premium 5y	1.08			13.14
p-value	(0.00)			
Term Premium 10y	1.41			12.61
p-value	(0.00)			
Term Premium 5y		0.24		11.67
p-value		(0.03)		
Term Premium 10y		0.35		14.41
p-value		(0.01)		
Term Premium 5y	0.93	0.22		22.21
p-value	(0.00)	(0.02)		
Term Premium 10y	1.18	0.33		24.24
p-value	(0.01)	(0.01)		
Term Premium 5y	0.63	0.95	-0.01	51.39
p-value	(0.01)	(0.00)	(0.00)	
Term Premium 10y	0.80	1.26	-0.01	50.40
p-value	(0.02)	(0.00)	(0.00)	
B. Model				
	β_{TFPV}	β_{INV}		R^2 (%)
Term Premium 5y	0.25			94.79
Term Premium 5y		0.75		25.91
Term Premium 5y	0.25	0.04		94.84

5.2. Bonds

Table 13 reports on the relation between bond term premia and TFP volatility. We consider regressions of realized term premia (long-term yields minus expected short-term rates over the corresponding horizon) on TFP volatility.[25] The first two rows show a positive and statistically significant slope coefficient associated with TFP volatility.

Bansal and Shaliastovich (2013) and Wright (2011) offer evidence on the role of inflation uncertainty in determining bond risk premia. Rows 3 and 4 confirm this evidence in our data. Importantly, in rows 5 and 6, we show that TFP volatility conveys information which is not contained in inflation uncertainty. The correlation between the two measures is a mere 7%. As a consequence, the partial effects in the univariate regressions in rows 1 to 4 are very similar to those in the multivariate regressions reported in rows 5 and 6. Also, the multivariate regression R^2s are close to the sum of the R^2s from the univariate regressions.

The findings in Bansal and Shaliastovich (2013) also provide a role for real growth uncertainty. Rows 7 and 8 report results from a multivariate regression of term premia on all three uncertainty measures, inclusive of real growth uncertainty. As in Bansal and Shaliastovich (2013), we report a negative coefficient associated with this additional uncertainty measure. The coefficient on TFP volatility continues to be positive and statistically significant at all levels.[26]

Finally, in Panel B, we replicate our empirical results using model-implied regressions. We confirm that TFP volatility is determining term premia in the model with a positive coefficient (and an R^2 close to 100%). Inflation uncertainty is an important driver of term premia when considered in isolation. As shown in Bansal and Shaliastovich (2013), when agents prefer early resolution of uncertainty, an increase in inflation uncertainty raises nominal bond risk premia, consistent with empirical evidence. Different from empirical evidence, however, inflation uncertainty is no longer related to term premia after controlling for TFP volatility. This finding should not come as a surprise since TFP volatility is the model's central state variable. A positive TFP volatility shock increases uncertainty in real marginal costs. Because equilibrium inflation depends on real marginal costs, a positive TFP volatility shock also increases inflation uncertainty.

6. Conclusions

TFP volatility has forecasting ability for future (short-term and long-term) risk premia above and beyond that of the dividend price ratio. When viewed through the lens of the CS identity, this fact implies that TFP volatility ought to predict - in the long run - at least one between nominal cash flows, real interest rates, and inflation. We find support for the latter result: TFP volatility is associated with a persistent decline in future inflation.

We rationalize the relation between TFP volatility, risk premia and the real economy within an endogenous-growth model with price rigidities and Epstein-Zin preferences: in the model, positive shocks to TFP volatility reduce the long-run demand for consumption goods and, through mark-ups, hours worked, employment, output and inflation. Price rigidities (leading to joint persistent declines in consumption, investment and output), endogenous growth (generating slow-moving propagation of shocks) and Epstein-Zin preferences (assigning meaningful prices to low-frequency risk(s)) combine in the model to yield the uncertainty-driven predictability found in the data.

Low-frequency notions of market volatility also have predictive power separate from that of the dividend price ratio. This outcome is intimately related to the persistence of the TFP volatility dynamics. We conclude that suitable *uncertainty trends* appear to be revealing drivers of risk premia.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The code and data package for this article can be found at https://doi.org/10.17632/5939yh85bh.5 (Mendeley Data).

Appendix A. Data

Our TFP measure is the quarterly series in Fernald (2012), a series which is adjusted for capacity utilization. Consistent with the model, our estimate of TFP volatility is based on Eqs. (1) and (2) in the main text. We estimate the equations by using a particle filter as in, e.g., Fernández-Villaverde et al. (2011), on HP-filtered TFP. We choose Beta priors for the autoregressive coefficients ρ_a and ρ_{σ_a} with mean 0.7 and

[25] Bansal and Shaliastovich (2013) use a realized measure of term premia, i.e., they subtract from long-term yield the average of the realized short-term rates. We use the term premia estimates constructed by Adrian et al. (2013). Results are generally stronger if we use realized term premia as in Bansal and Shaliastovich (2013).

[26] We follow Bansal and Shaliastovich (2013) and construct variances of expected real growth and expected inflation using survey data. We find these two measures to be highly correlated (83% correlation).

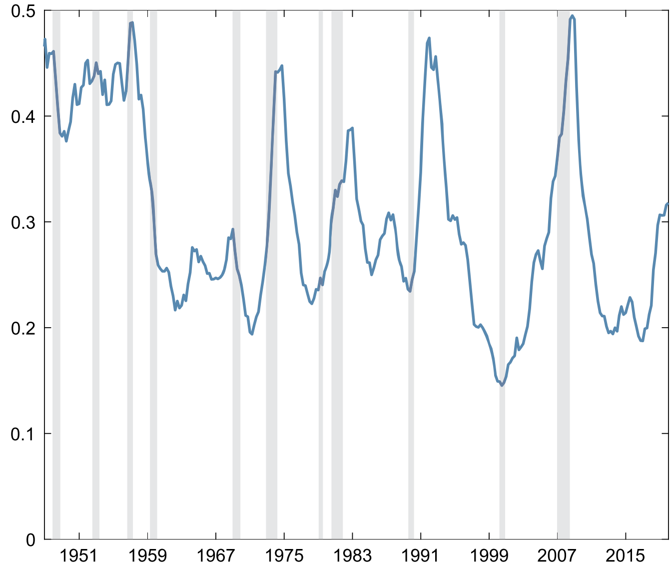

Fig. 12. Estimated time series of TFP volatility (blue solid line) along with NBER recessions (shaded areas). The series is computed using 5,000 draws and 1,000 particles.

standard deviation 0.2. The Inverse-Gamma distribution is used for the standard deviation of the second-moment shocks. We set the mean of σ_{σ_a} equal to 0.4 and the variance equal to 2. We select a Uniform distribution between −6 and −4 for the mean of (log) TFP volatility, $\bar{\sigma}_a$. Our measure of uncertainty, $e^{\sigma_{a,t}}$, is the median estimate from the particle filter. We plot the series in Fig. 12.

A.1. *Predictive and cross-sectional regressions*

Inflation is calculated from the Consumer Price Index (CPI) for all urban consumers, a series which is available from the Goyal and Welch (2008) dataset.[27]

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. We start with monthly cum-dividend and ex-dividend returns. Their difference, multiplied by the lagged ex-dividend price, is the monthly dividend:

$$D_t = \left(R^{\text{cum}}_{t-1,t} - R^{\text{ex}}_{t-1,t} \right) P_{t-1}.$$

The quarterly series is obtained by aggregating the dividends paid out over the quarter. One important question, raised, e.g., by Chen (2009) and van Binsbergen and Koijen (2010), is what to assume regarding the re-investment of these monthly dividends received within the year. Throughout the paper we assume that the dividends are re-invested at a zero rate. This amounts to adding up the dividends in the current month and the past 3 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 quarterly return series under the stock market re-investment assumption. We verified that using directly CRSP annual data on total returns and returns without dividends does not alter our results. In short, the quarterly nominal dividend and return series are obtained by summing the monthly observations within the quarter. To obtain real returns and dividends, we deflate these series by the CPI.

The risk-free rate is the 3-month Treasury yield from the FRED database at the Federal Reserve Bank of St. Louis. We take the nominal log yield on a three-month Treasury bill $y_t^{(3)}$ in month t and subtract three-month log inflation $\pi_{t,t+3}$ from period t to $t+3$ to form a measure of the ex-post real three-month interest rate.

We obtain the 25 portfolios formed on size and book-to-market from Kenneth French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) and the 10 portfolios formed on duration from the q library of Hou et al. (2020) (http://global-q.org/testingportfolios.html). The term premia are from Adrian et al. (2013) and can be downloaded from the New York Fed's website (https://www.newyorkfed.org/research/data_indicators/term-premia-tabs#/interactive). Portfolio returns are aggregated from the monthly to the quarterly frequency whereas the term premia are sampled at the end of each quarter.

A.2. *The S-VAR*

We retrieve the following variables from the FRED database (FRED series IDs are in parentheses): Gross Domestic Product (GDP), Services Consumption (PCES), Nondurables Consumption (PCEND), Private Fixed Investment in R&D (Y006RC1Q027SBEA), Durables Expenditures (PCEDG), Private Fixed Nonresidential Investment (PNFIC1), Private Fixed Residential Investment (PRFIC1), GDP Implicit Deflator (GDPDEF). The S&P 500 Index is from Yahoo Finance (Ticker GSPC). Investment is Durables plus Private Fixed Investment. We take the logarithm of the uncertainty measure in order to interpret the impulse responses in percentage terms. Output, consumption, R&D and capital investment are expressed in logarithmic, real and per capita terms. In Fig. 6 we use the inverse of the Labor Share (PRS85006173) as the mark-up proxy.

Appendix B. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2023.103724.

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