Temperature Volatility Risk

M. DONADELLI[∓], M. JÜPPNER, A. PARADISO, C. SCHLAG[*]

Abstract

We produce novel empirical evidence on the relevance of temperature volatility shocks for the dynamics of macro aggregates and asset prices. Using two centuries of UK temperature data, we document that the relationship between temperature volatility and the macroeconomy varies over time. First, the sign of the causality from temperature volatility to TFP growth is negative in the post-war period (i.e., 1950-2015) and positive before (i.e., 1800-1950). Second, over the pre-1950 (post-1950) period temperature volatility shocks positively (negatively) affect TFP growth. In the post-1950 period, temperature volatility shocks are also found to undermine equity valuations and other main macro aggregates. More importantly, temperature volatility shocks are priced in the cross section of returns and command a positive premium. We rationalize these findings within a production economy featuring long-run productivity and temperature volatility risk. In the model temperature volatility shocks generate non-negligible welfare costs. Such costs decrease (increase) when associated with immediate technology adaptation (capital depreciation).

JEL classification: E30, G12, Q0

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[*]Michael Donadelli (e-mail: michael.donadelli@unibs.it) is at the University of Brescia. Antonio Paradiso (email: antonio.paradiso@unive.it, phone: +39 041 234 916) is affiliated with the Department of Economics of Ca' Foscari University. Marcus Jüppner (e-mail: marcus.jueppner@bundesbank.de) is affiliated with Deutsche Bundesbank and the Faculty of Economics and Business Administration, Goethe University Frankfurt. Christian Schlag (e-mail: schlag@finance.uni-frankfurt.de) is affiliated with the Faculty of Economics and Business Administration and Research Center SAFE, Goethe University Frankfurt. The authors acknowledge helpful discussions with Monica Billio, Fulvio Corsi, Patrick Grüning and Kai Lessmann. We also thank conference/seminar participants at the 8th IAERE Annual Conference, 1st RCEA Warsaw Money-Macro-Finance Conference, 1st Paris Environmental Economics Workshop,13th Dynare Conference, Aix-Marseille University, LUISS, Portsmouth Business School, University College of Dublin, Ca'Foscari University, and University of Bologna, We gratefully acknowledge research and financial support from the Research Center SAFE, funded by the State of Hessen initiative for research LOEWE. The contents of this article are the sole responsibility of the authors and can in no way be taken to reflect the views of the Deutsche Bundesbank or the Eurosystem or any other institution providing funding for this study. All remaining errors are our own. [∓] Corresponding author.

1 Introduction

There is near unanimous scientific consensus that climate change affects human health, behaviour, and activity (Patz et al., 2005; Deschênes and Moretti, 2009; Zivin and Neidell, 2014; Cattaneo and Peri, 2016) and has a negative impact on economic development (Stern, 2007; Hsiang and Meng, 2015). Over the past decades, the economic risk of climate change has been quantified by means of so-called Integrated Assessment Models (IAMs) in which the effects of climate change are captured in terms of their cost and benefits via damage functions. IAMs easily allow to relate climate variables (e.g., temperature, sea-level rise, rainfall, CO_2 concentration) to economic welfare. However, these models have been widely criticized, since they suffer from several limitations. In particular, it has been questioned that IAMs have weak empirical supports (Pindyck, 2013; Diaz and Moore, 2017). To address some of the issues associated with the use of IAMs to study the economic costs of climate change, more recent analyses have incorporated empirical evidence suggesting that rising temperatures negatively affect real economic activity (Dell et al., 2012; Colacito et al., 2016; Du et al., 2017) into Dynamic Stochastic General Equilibrium (DSGE) models (Bansal et al., 2016; Donadelli et al., 2017). Empirical findings and quantitative model-based results confirm that a rise in average temperature has a negative impact on key macroeconomic aggregates (e.g., productivity and consumption growth) and equity prices.

However, as also pointed out by Diaz and Moore (2017), both standard IAMs and recently developed temperature-related DSGE models typically estimate the effects of equilibrium changes in mean temperature (or rainfall or sea-level), but not necessarily the effects of extremes (persistent heatwaves) or stochastic variability (storm surges). The impact of climate change may be actually the result of variations in both the mean and the standard deviation of climate drivers (Rind et al., 1989; Mearns et al., 1996). By focusing exclusively on changes in the mean, the overall and true impact of climate change on human activity could be seriously underestimated (Katz and Brown, 1992; Schär et al., 2004). For example, modifications of climate variability at the inter-annual time scale are key to capturing extreme weather events such as multi-year droughts (Peel et al., 2005) and water scarcity (Veldkamp et al., 2015). In this respect, Elagib (2010) and Ito et al. (2013) show that intra-annual temperature variability is associated with extreme air temperature. Moreover, changes in the intensity of extreme weather events, such as heatwaves, are highly sensitive to shifts in intra-annual temperature variability (Fischer and Schär, 2010). Thus, other than mean values, the dynamics of volatility in climate drivers may be relevant for the understanding of extreme events, and, consequently, for the impact of climate change on real economic activity (Brown and Lall, 2006).[1]

Supporting the view that volatile climate conditions matter, some studies have examined the relationship between weather dynamics and fluctuations in consumer spending. Heavy rain, snow, and other extreme events are factors that tend to force people to stay home. This in turn would lower sales (Parsons, 2001). Broadly, the idea is that highly volatile weather conditions may impact consumption decisions (Starr-McCluear, 2000; Lazo et al., 2011). Another stream of research argues that the effect of weather on consumer spending is mediated by mood. High variability in weather conditions has a negative impact on mood. For instance, Spies et al. (1997) and Murray et al. (2010) empirically observe that people in good mood tend to be more willing to buy consumer goods than those in bad moods. In a similar spirit, another branch of literature finds instead that stock market anomalies may be the consequence of relevant weather factors (Saunders, 1993; Kamstra et al., 2003; Cao and Wei, 2005). For example, Kamstra et al. (2003) and Garrett et al. (2005) find that seasonal weather effects (such as the number of daylight hours in a day) tend to influence investors' risk-aversion (i.e., market returns).

Taken together, existing evidence suggests the presence of two channels through which an adverse shock in climate conditions may affect economic factors. The first one operates via the destruction of capital through adverse weather events dampening innovations, output, and productivity (Fankhauser and S.J. Tol, 2005; Stern, 2013). The second one operates via the influence that weather has on mood translating into consumption spending (Spies et al., 1997; Murray et al., 2010) and investment decisions in equity markets (Kamstra et al., 2003; Cao and Wei, 2005). Loosely speaking, more volatile weather conditions lead to a higher probability of extreme events, which in turn implies stronger effects on capital accumulation and consumers' mood.

Motivated by this evidence, we examine the effects of volatility in weather conditions on macro-variables and asset prices. Specifically, we investigate both empirically and theoretically whether shifts in the volatility of temperature affect aggregate productivity, economic growth, welfare, and equity prices. While the majority of climate change studies examine the effect of rising temperatures on real economic activity, to the best of our knowledge there is no study focusing on temperature volatility and its macroeconomic effects. With this paper we aim to fill this gap.

Monthly data on UK temperature for the period 1659-2015 are employed to build an intra-

[1] In this respect, Cater and Lew (2018) using data of North American grocery prices from the 1920s show that temperature dispersion is able to explain deviations of goods prices from the law of one price.

annual temperature volatility index. Since both relatively low and relatively high temperature volatility may be harmful, our temperature volatility index is represented by the absolute deviation from an annual benchmark volatility value (i.e., historical average intra-annual volatility observed in the pre-industrial revolution era).[2] We then employ data on TFP (macro-aggregates, stock market, risk-free rate) for the period 1800-2015 (1900-2015). Empirically, we study the effect of changes in temperature volatility via Granger causality and standard VAR analyses over different historical periods (i.e., 1800-1900, 1900-1950, and 1950-2015). We find that the sign of the causality going from temperature volatility to TFP growth changes across time. For the sample 1800-1900, no causality is present between temperature volatility and productivity growth. Over the period 1900-1950, the causality is unidirectional, going from temperature volatility to TFP growth, with a positive sign. In the post-war period, the direction of the causal effect remains unchanged but temperature volatility now affects TFP growth negatively. On one hand, this change in direction could be due to the different sectoral structures characterizing the UK economy during those periods. On the other, it can be driven by the increasing number of extreme weather events observed over the period 1950-2015. The VAR analysis confirms that the way in which temperature volatility affects TFP growth varies over the three subsamples. During the period 1800-1900 no effect is present, while it seems to be positive for the period 1900-1950 and negative for the period 1950-2015. These results are robust to the inclusion of macroeconomic and financial variables. Over the period 1950-2015, temperature volatility is also found to significantly undermine equity valuations. In our cross-sectional asset pricing tests using UK stock market portfolios, we then find that temperature volatility risk carries a significant and positive risk premium. Similar results are obtained after controlling for market and macroeconomic risk and for EU portfolios.

This set of novel empirical facts is rationalized by means of a production economy featuring long-run macro and temperature volatility risk. More precisely, we calibrate the model to match the drop in TFP growth generated by a temperature volatility shock as well as to the main temperature statistics observed in the UK over the past 60 years. We choose the post-war sample, since we find the strongest adverse climate effects in this period. This is in line with existing evidence documenting negative temperature effects in the post-war period (see e.g., Dell et al., 2012; Colacito et al., 2016). In our production economy a temperature volatility shock gives rise to a negative response of productivity, macroeconomic quantities, and equity valuations, consistent

[2] In a robustness test we study the effect on the TFP using a different temperature volatility index (i.e., inter-annual volatility). The results from this test are reported in Appendix B and discussed in Section 3.4.

with our novel empirical evidence. In addition, in the model temperature volatility risk commands a positive risk premium. Welfare costs of this type of risk are substantial and amount to 9% of the agent's consumption bundle in our benchmark scenario. Moreover a rise in temperature volatility is found to have long-lasting negative effects on output and labor productivity growth. Over a 50-year horizon, a single one-standard deviation shock reduces both cumulative output and labor productivity by about 1.0 percentage points (pp). In an economy featuring capital depreciation risk, welfare costs of temperature volatility risk increase when depreciation shocks are positively correlated with temperature volatility shocks, meaning that higher climate variability results in an increasing occurrence of natural disasters, which destroys capital faster. If we allow for adaptation to climate uncertainty by assuming a positive correlation between temperature volatility shocks and long-run productivity shocks (i.e., the economy immediately responds to temperature volatility shocks in terms of technology, which increases productivity), temperature volatility risk produces welfare gains and a drop in the equity risk premium. This evidence suggests that "adaptation" is important to reduce the economic costs associated to temperature volatility risk.

Our benchmark production economy features capital and labor dynamics. For reasons of robustness, we also study the macro and welfare effects of temperature volatility shocks in an endowment economy. By calibrating the model to match the main consumption dynamics and the empirically observed impact of temperature volatility shocks on consumption growth, we find qualitatively and quantitatively similar results.

The rest of this paper is organized as follows. In Section 2, we review the related literature. Section 3 presents the main empirical findings concerning the effects of temperature volatility shocks on macro and financial aggregates. In Section 4, we describe our production economy featuring temperature volatility risk. Section 5 presents the quantitative results. To shed light on the robustness of the quantitative implications of temperature volatility shocks, we analyse an endowment economy in Section 6. Section 7 concludes.

2 Related Literature

Our study is primarily related to the most recent empirical and theoretical literature examining the effects of climate change on macroeconomic and financial aggregates. Most papers in this field investigate this issue by looking at the impact of changes in mean temperatures. For example, Dell et al. (2012), Colacito et al. (2016), and Du et al. (2017) find that rising temperatures negatively affect economic growth. Moreover, Bansal et al. (2016) and Donadelli et al. (2017) show that temperature shocks have a significant negative effect on equity valuations and carry a positive premium in equity markets. Unlike these studies, we do not examine the effects of a rising temperature level but examine the implications of temperature volatility shocks on aggregate productivity, consumption, and equity prices. In this respect, we support Katz and Brown (1992) and Schär et al. (2004) who argue that focusing exclusively on the change in the mean of climate variables may underestimate the overall economic costs of climate change.

Our paper is also connected to the literature on the economics of climate change quantifying the macroeconomic and financial effects of global warming. A popular approach to quantifying the economic costs of climate change and carbon emissions is the use of IAMs (Stern, 2007; Nordhaus, 2008). Recent contributions in this class of models are provided by Golosov et al. (2014) and Cai et al. (2015) who study climate change within a DSGE framework. Bansal and Ochoa (2011a) and Bansal et al. (2016) account for temperature dynamics in long-run consumption risk models to quantify the effects of temperature shocks on consumption and asset prices. We differ from IAMs as we do not model temperature effects on economic activity as a damage function on the level of GDP, but rather on the growth rate of TFP. We therefore allow temperature to permanently affect economic activity as in the long-run consumption risk models (see also Pindyck, 2012). Unlike the latter, we model temperature effects in a production economy framework, which allows us to analyze the effects of temperature on investment and labor quantities. Moreover, as opposed to IAMs, we do not compute economic costs as losses in GDP but follow Bansal and Ochoa (2011b) who define welfare costs of temperature risk as in Lucas (1987).

Finally, our theoretical analysis builds on the recent production-based asset pricing literature dealing with the long-run effects of aggregate productivity shocks (Croce, 2014) or oil shocks (Hitzemann, 2016; Hitzemann and Yaron, 2016; Ready, 2016) on macroeconomic aggregates and asset prices. Most of the elements of our production economy are therefore as in Croce (2014). What is new in our model is that aggregate productivity is influenced by temperature volatility shocks, as suggested by the empirical evidence. In this respect, we are more closely related to Hitzemann et al. (2016) who develop a two-sector production model to study the effects of oil volatility risk on macroeconomic variables and asset prices.

3 The Facts

This section empirically examines the implications of temperature volatility shocks. First, in Section 3.1, we describe the data employed in our analysis and presents some preliminary facts. In Section 3.2, we analyze the effects of temperature volatility shocks on aggregate macro quantities such as productivity, output, consumption, and investment. For robustness purposes, Section 3.3 compare temperature level and temperature volatility shocks. A battery of robustness tests on the macroeconomic implications of temperature volatility shocks are discussed in Section 3.4. The effect of temperature volatility shocks on asset prices are then presented in Section 3.5. We finally examine whether temperature volatility shocks are priced in the cross-section of equity returns in Section 3.6.[3]

3.1 *Data description and some preliminary facts*

Our empirical analysis on the effects of temperature volatility (hereinafter $TVOL$) on macroeconomic and financial aggregates is based on UK annual data. Data on real TFP, output, consumption, investment, and labor force have been retrieved from the "Bank of England's Three Centuries Macroeconomic Dataset". All macroeconomic series run from 1900 to 2015, except for TFP which starts in 1800. The equity market return and the risk-free rate have been obtained from the "Barclays Equity Gilt Study 2016" Data are annual for the period from 1900 to 2015. Monthly temperatures have been retrieved from MET Office for the period 1659-2015 (`http://www.metoffice.gov.uk/hadobs/hadcet/`). This dataset represents one of the longest continuous temperature records available. We acknowledge that MET temperatures are observed only for central England. However, for the purpose of our analysis this does not represent an issue. In fact, as suggested by Croxton et al. (2006), temperature in the central UK represents a good proxy for the average temperature in the UK.

In the spirit of Katz and Brown (1992) and Schär et al. (2004), we capture changes in climate conditions by means of shifts in $TVOL$. Precisely, we rely on a temperature anomaly volatility index, defined as the difference between the intra-annual volatility and a benchmark volatility level. The latter is represented by the average intra-annual volatility calculated over the pre-industrial revolution era in the UK (i.e., 1659-1759). Note that both positive and negative deviations with respect to the benchmark may adversely affect the economy. It has been shown that a relatively high

[3] A brief explanation of the methods used to study the effects of temperature volatility on real and financial aggregates is reported in Appendix A.

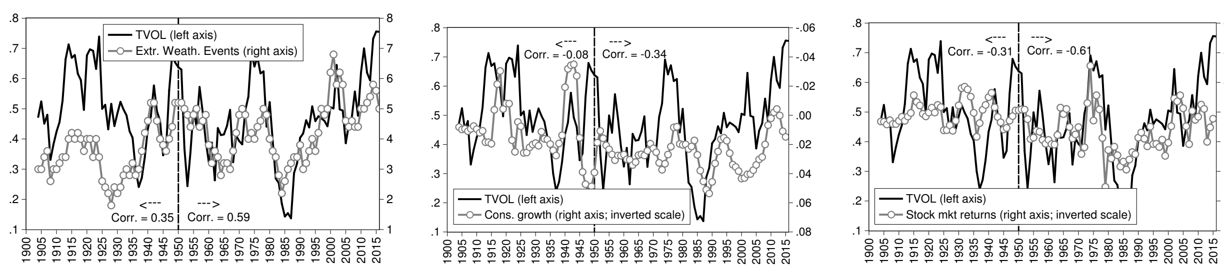
level of $TVOL$ tends to be associated with more frequent extreme weather events (see, for example, Elagib, 2010; Ito et al., 2013; Brown and Lall, 2006). On the other hand, a year with relative low variation across monthly temperatures – caused, for instance, by a persistent summertime heatwave – could results in severe droughts and flow of surface waters. As a consequence, crop and hydroelectricity production drop and irrigation is largely reduced. In addition, substantial weather fluctuations (positive or negative) may affect people's mood leading to changes in consumption dynamics (Spies et al., 1997; Murray et al., 2010) and portfolio investment decisions (Kamstra et al., 2003; Cao and Wei, 2005). Our $TVOL$ measure is thus defined as follows:

$$TVOL_t = \mid \sigma_{(JAN-DEC)_t} - \bar{\sigma}_{(JAN-DEC)_{1659-1759}} \mid, \quad \text{for } t = 1760, ..., 2015, \tag{1}$$

where $\sigma_{(JAN-DEC)_t}$ indicates intra-annual volatility in year t (i.e., the standard deviation measured from January to December of each post-industrial revolution era), and $\bar{\sigma}_{(JAN-DEC)_{1659-1759}}$ represents the average intra-annual volatility observed over the industrial revolution era (i.e., 1659-1759).

Figure 1: Temperature dynamics and extreme weather events

Panel A: $TVOL$ vs. Extreme Weather Events | Panel B: $TVOL$ vs. Δc | Panel C: $TVOL$ vs. Rm



Notes: Panel A depicts the dynamics of the UK intra-annual temperature volatility (black line, 5Y average) and the annual average number of weather extreme events (dotted gray line, 5y average). Annual number of extreme events := number of extreme rainfalls, floods, frosts, hot temperature anomaly, and droughts occurred within a year in the UK for the period 1900-2015. The number of extreme events is constructed using the chronological listing of events reported in the website http://www.trevorharley.com/weather_web_pages/britweather_years.html. Panel B plots the dynamics of the UK intra-annual temperature volatility (black line, 5Y average) and consumption growth (dotted gray line, 5y average). Panel C presents the dynamics of the UK intra-annual temperature volatility (black line, 5Y average) and the stock market returns (dotted gray line, 5y average). In all graphs the dotted vertical line indicates the year 1950. "Corr":= correlation between the two time series plotted in the graphs.

Climate change is expected to increase the frequency of extreme weather events. Of course, linking any single weather event to global warming can be complicated. However, volatility in main climate drivers (especially in temperature and rainfall) seems to be more strongly connected with the frequency of severe weather events. This is confirmed by Figure 1 (Panel A) which shows (historically) a positive correlation between $TVOL$ and the number of extreme weather events.

Importantly, this positive relationship has intensified over the post-war period. In addition, $TVOL$ is found to be negatively correlated with consumption growth (Figure 1, Panel B) and aggregate equity market returns (Figure 1, Panel C). In both cases, the negative relationship is stronger for the period 1950-2015. These dynamics confirm an increasing link between climate-change related uncertainty and economic quantities, and could be responsible for increasing adaptation costs (or slower adaptation).

3.2 *Temperature Volatility Shocks and the UK Macroeconomy*

To test for the sign and direction of effects between $TVOL$ and macroeconomic dynamics over time, we perform a Granger causality test (GC) between TFP growth (Δa) and $TVOL$ for three sub-samples: (i) 1800-1900; (ii) 1900-1950; (iii) 1950-2015. This allows us to account for the fact that both climate change-related phenomena and the structure of the UK economy have changed substantially over the last two centuries. In order to improve the size and power of the test, a residual-based bootstrap technique is employed. Entries in Table 1 suggest the presence of a time-varying component in the sign of the causality between TFP growth and $TVOL$.

Table 1: Granger causality: Productivity growth vs. temperature volatility.

Period	1800-1900	1900-1950	1950-2015
Panel A: LAG 1			
$TVOL \rightarrow \Delta a$	0.366 (+)	0.051* (+)	0.074* (–)
$\Delta a \rightarrow TVOL$	0.386 (+)	0.522 (–)	0.665 (+)
Panel B: LAG 2			
$TVOL \rightarrow \Delta a$	0.544 (+)	0.099* (+)	0.039** (–)
$\Delta a \rightarrow TVOL$	0.193 (+)	0.439 (–)	0.411 (–)

Notes: p-values for the bootstrap test statistics are reported. ** and * denote significance, respectively at the 1% and 5% significance level. The sign of the causality is reported in parentheses. "LAG" indicates the number of lags used in the test regressions.

Across all samples, the causality goes in one direction, i.e., from $TVOL$ to TFP growth. However, the sign of the observed causality changes over time. During the period 1900-1950, the sign of causality is positive and statistically significant while in the past 60 years it is negative and also statistically significant. Over the period 1800-1900 there is no evidence of a statistical significant causality between $TVOL$ and productivity. This finding may seem surprising as one would expect negative effects from $TVOL$ on TFP growth during periods in which production relied largely on the agricultural sector which is well known to be more influenced by climate change, and in particular by rising temperatures (Dell et al., 2012).[4] We suspect that during the period 1900-1950, work-

[4] As highlighted by Roses and Wolf (2018), the agricultural sector's average share in total employment across

ers in the agricultural sector were forced to adapt and invest in technology in order to reduce the economy's vulnerability to extreme weather events, which may explain the positive and statistically significant sign in the causality running from $TVOL$ to TFP growth. In contrast, the past 60 years show negative temperature volatility effects on TFP growth. During that time it is widely accepted that the services-related sectors have contributed most to economic growth in developed countries. As discussed in Tol et al. (2000), these sectors tend to be less influenced by climate change-related phenomena. It is thus plausible that they used to invest in technologies for the purpose of increasing productivity and not adapting to climate change. However, when extreme whether-related events such as flood and storms – induced by drastic changes in temperature dynamics – occur, the economy as a whole is affected.[5] In other words, it is most likely that natural disasters will generate more sizeable adverse effects in an economy characterized by highly-productive sectors than in agricultural-based economies. Note also that the period 1950-2015 is characterized by a higher number of extreme weather events compared to the pre-war period (see Figure 1, Panel A). Even in the presence of a relatively high level of technology, a stronger variation in temperature levels (within and across years) and an increasing number of extreme weather events could seriously harm investments in adaptation to climate change. In particular, more volatile weather conditions make (i) firms less willing to invest in adaptation due to higher cost and (ii) existing adaption mechanisms weaker and slower.

To quantify the impact of time-varying temperature uncertainty, we compute the impulse response of future TFP growth to a one-standard deviation shock in $TVOL$.[6] The analysis follows the same strategy as the GC analysis and is thus carried out for the following sub-periods: 1800-1900, 1900-1950, and 1950-2015. Impulse responses (dashed grey lines) – obtained from a bi-variate VAR of $TVOL$ and TFP growth – are depicted in Figure 2. It is worth noting that the impact

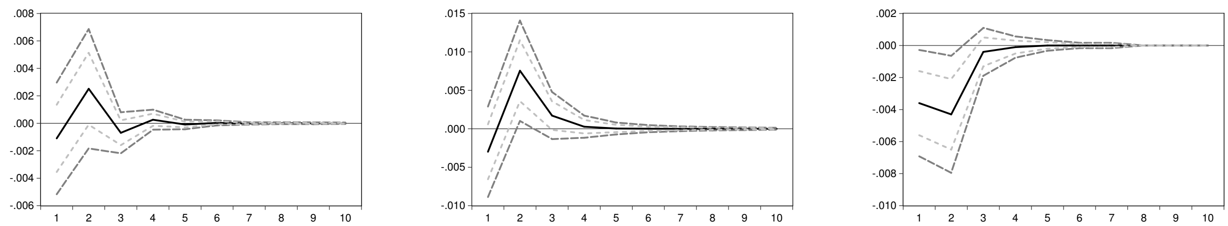
European regions was about 45% in at the beginning of the 20th century while during the period 1950-2010 it quickly fell to less than 10%. This suggests that adverse effects of temperature volatility on TFP are found in the productive sectors and not in the agricultural one which nowadays only marginally contributes to total output.

[5] Using U.S. data at the industry-level for two different sub-periods (i.e., 1993-1997 and 1997-2011), Colacito et al. (2016) find that over the last 20 years there is a stronger and more statistically significant negative effect of rising temperatures on the two largest sectors of the U.S. economy: (i) services and (ii) finance, insurance, real estate. This confirms the increasing inattention of these sectors to climate change as well as their lack in efficiency in fighting against the occurrence of an increasing number of extreme weather events.

[6] Even if the direction of the causality between $TVOL$ and TFP growth (Δa) results clear from entries in Table 1, we decide to use the generalized impulse response function (GIRF) approach to detect the impact of $TVOL$ shocks on Δa. We do so in order to be consistent with a multivariate VAR analysis (see Figures 3 and 4) that cannot rely on a pre-determined variables' ordering supported by an economic theory. In the presence of uncertainty around the mechanisms driving the economy following $TVOL$ shocks, a GIRF approach seems to be more appropriate. Anyway, the patterns depicted in Figure 2 do not differ from the dynamics obtained using a Cholesky decomposition where $TVOL$ is ordered first. Results, not reported for the sake of brevity, are available upon request.

Figure 2: Impulse-responses of TFP growth to $TVOL$ shocks

Panel A: $TVOL \Rightarrow \Delta a$ (1800-1900) Panel B: $TVOL \Rightarrow \Delta a$ (1900-1950) Panel C: $TVOL \Rightarrow \Delta a$ (1950-2015)

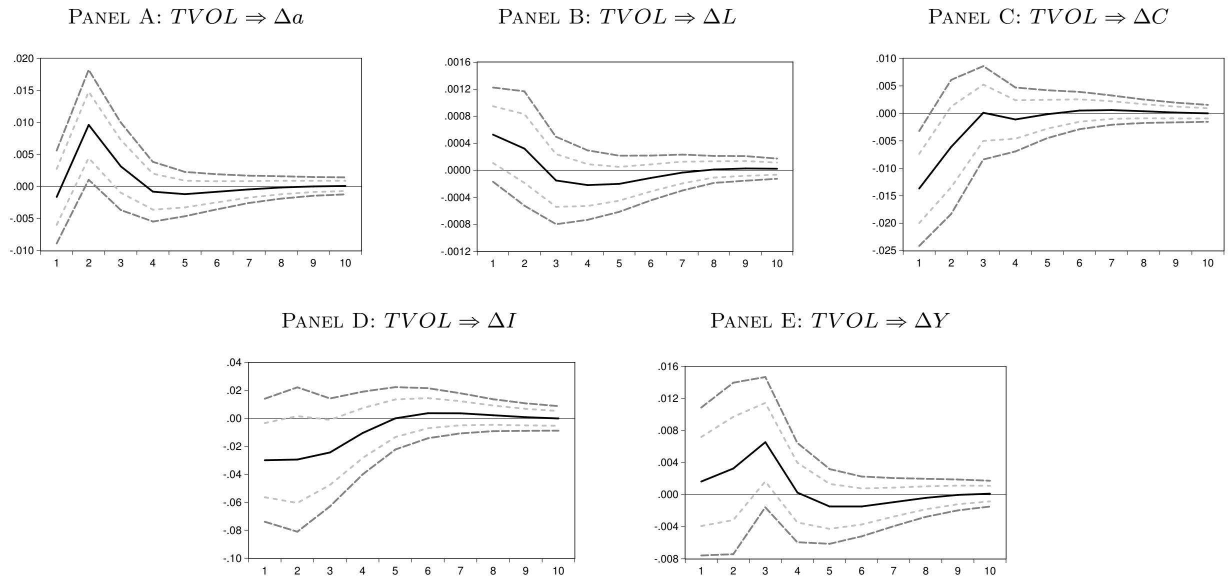


Notes: This figure depicts the generalized impulse response of TFP growth (Δa) to a one-standard-deviation shock in temperature volatility ($TVOL$). The impulse-response functions (IRFs) are obtained by estimating a bi-variate VAR(1) using data for three different periods: (i) 1800-1900 (PANEL A); (ii) 1900-1950 (PANEL B); and (iii) 1950-2015 (PANEL C). VAR estimations include a constant. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

of a temperature volatility shock on TFP is not constant over time. Over the period 1800-1900, the effect of a positive shock in $TVOL$ on productivity growth oscillates around zero, ranging from negative to positive responses, but is not statistically significant. The period 1900-1950 is instead characterized by a positive impact of TFP growth following a $TVOL$ shock: in the beginning the response of productivity is slightly negative, but it becomes positive and statistically significant after two periods. In line with the evidence provided by our preliminary GC analysis, the impact of a $TVOL$ shock on TFP growth has changed in the post-war era. In particular, a rise in $TVOL$ now dampens TFP growth. Importantly, this negative effect is statistically significant and lasts for almost five years (Figure 2, Panel C).

For robustness purposes and to getter a better understanding of the effects of an increase in our TVOL index on real economic activity, we also compute impulse responses of consumption, output, investment, employment, and TFP growth to a $TVOL$ shock. Given the absence of theories linking temperature volatility and macroeconomic aggregates, we do not rely on any specific identification scheme and compute generalized impulse responses that do not depend on the ordering of variables in the system. Impulse responses of main macro-aggregates obtained from our augmented VAR are reported in Figure 3 for the sub-period 1900-1950 and in Figure 4 for the post-war period. First, and most importantly, we find that the inclusion of additional macroeconomic variables does not affect the impact of the $TVOL$ shock on TFP growth. As in Figure 2 (Panel B), over the period 1900-1950, TFP growth displays a small and statistically insignificant drop, with a fast subsequent recovery and rebound from two years after the shock. Differently, for the period 1950-2015, a $TVOL$ shock produces a statistically significant drop in the TFP of around 0.4pp. In line with

Figure 3: Impulse response of macro-variables to $TVOL$ shocks (1900-1950)



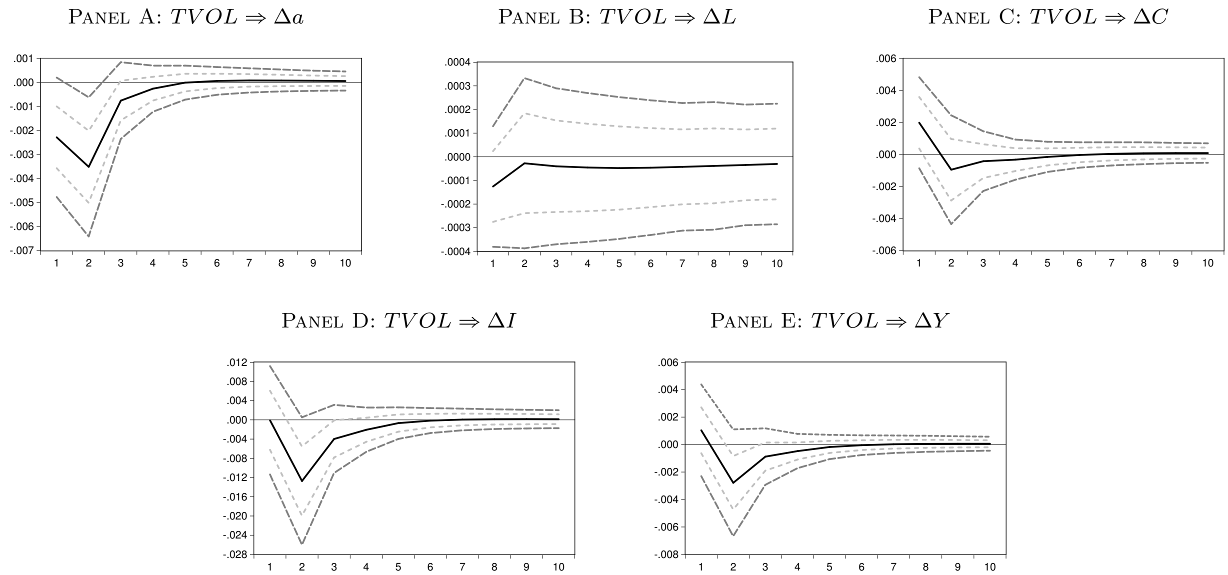
Notes: This figure depicts generalized impulse responses of TFP growth (Δa), labor growth (ΔL), consumption growth (ΔC), investment growth (ΔI), and output growth (ΔY) to a one-standard-deviation shock in temperature volatility ($TVOL$). The impulse-response functions (IRFs) are obtained by estimating a six-variate VAR(1). A constant is included. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

our preliminary bi-variate estimations (see Figure 2, Panel C), this adverse effect lasts for (approx) five years. Impulse responses on the other macroeconomic aggregates also differ across sub-periods. For the period 1900-1950, we observe a drop in consumption and investment (Figure 3, Panels C and D). Instead, labor and output increase on impact (Figure 3, Panels B and E). However, most of these effects are not statistically significant. Over the post-war period, labor, consumption and output react differently to a $TVOL$ shock. The impact on labor growth is negative and lasts for several years, but statistically insignificant (Figure 4, Panel B). Output increases on impact and displays a significant drop from two years after the shock (Figure 4, Panel E). Consumption displays a similar (but less significant) response.

Overall, our empirical findings suggests that in the post-war era $TVOL$ shocks tend to have non-negligible adverse effects on real economic activity.[7]

[7] To quantify the relative importance of temperature volatility shocks to macroeconomic fluctuations we have also computed the variance decomposition of consumption, output, investment, and labor. In particular, in line with our IRF analysis, we compute a generalized forecast error variance decomposition in the spirit of Lanne and Nyberg (2016). Results suggest that $TVOL$ shocks account for around 5% of the fluctuation in output and consumption over a horizon of 3-5 years.

Figure 4: Impulse response of macro-variables to $TVOL$ shocks (1950-2015)



Notes: This figure depicts generalized impulse responses of TFP growth (Δa), labor growth (ΔL), consumption growth (ΔC), investment growth (ΔI), and output growth (ΔY) to a one-standard-deviation shock in temperature volatility ($TVOL$). The impulse-response functions (IRFs) are obtained by estimating a six-variate VAR(1) including a constant. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

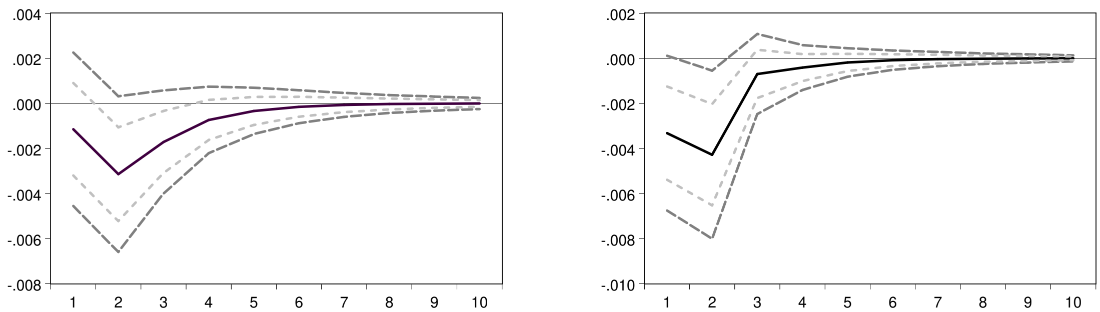
3.3 *Temperature Volatility and Temperature Level Shocks*

Results presented so far have focused exclusively on the role of $TVOL$ shocks. What about temperature level shocks? Are results still valid once accounting for temperature level dynamics? To address these issues, we need to investigate whether the negative effect of a $TVOL$ shock on TFP growth observed over the period 1950-2015 is driven by shifts in the UK temperature level. We therefore estimate a VAR(1) including TFP growth, average temperature level and temperature volatility. Impulse responses from this test are depicted in Figure 5 and suggest that the adverse effect of a $TVOL$ shock on the TFP growth is not absorbed by temperature level shifts. Surprisingly, the $TVOL$-induced negative effect on TFP growth (Panel B) is more statistically significant than the one induced by a temperature level shock. Note also that our robustness check corroborates recent empirical findings – based mainly on U.S. data – showing that shifts in temperature levels undermine real economic activity (Dell et al., 2012; Colacito et al., 2016; Bansal et al., 2016; Du et al., 2017; Donadelli et al., 2017).

Figure 5: Impulse-responses of TFP growth to temperature (T) and temperature volatility ($TVOL$)

Panel A: $T \Rightarrow \Delta a$ (1950-2015)

Panel B: $TVOL \Rightarrow \Delta a$ (1950-2015)



Notes: This figure depicts the generalized impulse response functions of TFP growth (Δa) to a shock in the temperature anomaly index (Panel A) and in temperature volatility (Panel B). Impulse responses are obtained by estimating a tri-variate VAR(1). A constant is included. In line with climate change studies, temperature anomaly index is calculated as deviation of yearly average temperature respect to pre-industrial revolution temperature mean (1659-1759). Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

3.4 *Robustness Tests*

We consider various robustness checks regarding the effect of $TVOL$ shocks on TFP growth and other macroeconomic aggregates. First, we compute impulse responses using a different identification scheme. By relying on a simple Cholesky decomposition where $TVOL$ is ordered first, we show that a $TVOL$ shock produces qualitatively and quantitatively similar impulse responses (see Figure B.1). In a second check, we ask whether different VAR models provide similar responses of TFP growth and other macroeconomic variables to a TVOL shock. In practice, we compute impulse responses using a different lag order (i.e., VAR(2)), the local-projection methodology suggested by Jordà (2005), and a Bayesian VAR (BVAR). The impulse responses estimated from these different VAR models and for the periods 1900-1950 and 1950-2015 are reported in Appendix B. The pattern of the response of TFP growth to a $TVOL$ shock seems to be quite robust with respect to the choice of the VAR model. Actually, the dynamics depicted in Figure B.2 are similar to those obtained from our benchmark bi-variate VAR (see Figure 2). Similar conclusions can be drawn by comparing Figures B.3 and B.4 to Figures 3 and 4. Third, in order to further investigate the time-varying nature of the impact of TFP growth to $TVOL$ shocks, we compute the dynamics of the impulse response of TFP growth to a shock in $TVOL$ by estimating a Bayesian VAR in a rolling-window fashion. Using a window length of 50 years, we confirm that $TVOL$ began to undermine productivity only around the middle of the 20th century (see Figure B.6). Importantly, our time-varying estimates show that the magnitude of the negative impact of $TVOL$ shocks on the TFP is increasing over time. Similar conclusions can be drawn by looking at the responses of $TVOL$ shocks estimated from a time-varying parameter VAR a là Primiceri (2005).

Fourth, we consider a different proxy for temperature volatility. Specifically, we rely on an inter-annual measure of temperature volatility. This is captured by computing the standard deviation of annual average temperatures using a rolling window of 10 (or 15) years. Bi-variate VAR estimates suggest that an inter-annual volatility shock has a negative effect on productivity, as observed in Figure 2 (Panel C) where $TVOL$ is defined as in Eq. (1). The effect is weaker in statistical terms but more long-lasting (see Figure B.7). Finally, in attempting to further capture the effect of climate change variability on real economic activity, we estimate a bi-variate VAR using a different climate variable. Specifically, we build a Rainfall Volatility Index for the UK and estimate its impact on TFP growth. Similarly to the volatility of temperature, rainfalls volatility is found to undermine aggregate productivity growth only in the post-war era. However, the impact is less statistically significant and (slightly) less persistent (see Figure B.8).

Taken together, our empirical findings suggest that the nature of the effects of $TVOL$ on TFP growth in not constant over time. In particular, $TVOL$ is found to positively (negatively) affect TFP growth over the pre-war (post-war) period. Data for the period 1950-2015 also suggest that $TVOL$ shocks adversely affect the growth rate of output, investments, and consumption. This evidence might be the result of firms' inattention to the potential effects of climate change on the technology stock in the manufacturing and services sectors. To examine whether these climate change-related effects are also reflected in the dynamics of financial variables, we move to study the relationship between $TVOL$ and asset prices in the next section.

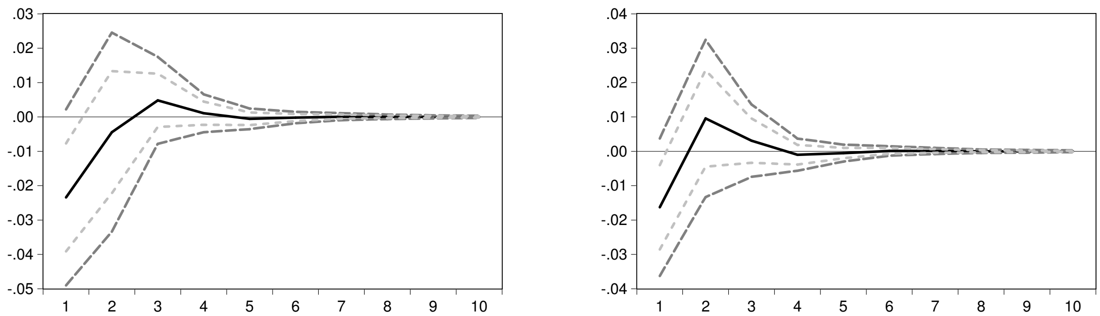
3.5 *Temperature Volatility Shocks and Financial Variables*

In the spirit of the most recent macro-finance literature focusing on the effects of climate change, we also examine whether shocks in temperature volatility affect asset prices (Bansal and Ochoa, 2011a,b; Bansal et al., 2016). To this end we run a VAR with three variables including $TVOL$, the equity market return (R), and the risk-free rate (R_f). In doing so, we also check whether the previously obtained response of TFP growth to $TVOL$ is robust to the inclusion of these additional variables which also might affect productivity growth (see Bansal et al., 2016; Croce, 2014).

Based on data availability, impulse responses are presented for two sub-samples: (i) 1900-1950 (Figure 6) and (ii) 1950-2015 (Figure 7). For the period 1900-1950, we find that the response of both the risk-free rate (Figure 6 Panel A) and the equity return (Figure 6 Panel B) to a $TVOL$

Figure 6: Impulse response of financial-variables to $TVOL$ shocks (1900-1950)

Panel A: $TVOL \Rightarrow R_f$ Panel B: $TVOL \Rightarrow R$



Notes: This figure depicts generalized impulse responses of the risk-free rate (R_f) and the equity market return (R) to a one-standard-deviation shock in temperature volatility ($TVOL$). The impulse-response functions (IRFs) are obtained by estimating a three-variate VAR(1) including a constant. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

shock is negative. However, these two effects are not statistically significant. Similar effects are found for the period 1950-2015, but differently from the results of the pre-war period, we find that the effect of a $TVOL$ shock on the equity return is immediate and highly statistically significant (Figure 7 Panel B). In Appendix B we also show that this pattern is robust with respect to different VAR model specifications (Figure B.5, Panel B).

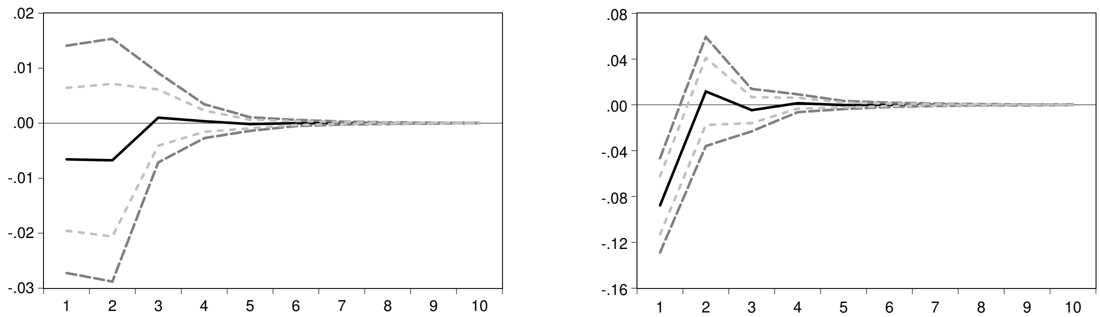
Finally, for the sake of robustness, we compute IRFs also from a tri-variate VAR with $TVOL$, Δa, and R. The idea here is to investigate whether the two main transmission channels through which $TVOL$ shocks affect the economy do not vanish, when they are jointly considered. Figure B.9 shows that the effect of a $TVOL$ shock is negative and statistically significant for productivity (Panel A) and equity return (Panel B) over the post-war period, so it confirms that TFP and equity represent the two main direct transmission channels of temperature volatility shock on the UK economy.

3.6 *Temperature Volatility Shocks and the Cross-Section of Returns*

In this paper we are not only interested in the implications of $TVOL$ shocks for macroeconomic variables but also in their effect on asset prices, in particular the cross-section of stock returns. Our interest in the asset pricing implications of $TVOL$ risk is also motivated by recent evidence on the effects of temperature shifts on asset prices. Using US data, for instance, Balvers et al. (2017) find that temperature shocks have a negative impact on equity market returns. Temperature shocks are also found to have a positive impact on the cost of capital. The magnitude of this

Figure 7: Impulse response of financial-variables to $TVOL$ shocks (1950-2015)

Panel A: $TVOL \Rightarrow R_f$ Panel B: $TVOL \Rightarrow R$



Notes: This figure depicts generalized impulse responses of risk-free rate (R_f) and equity market return (R) to a one-standard-deviation in temperature volatility ($TVOL$) shock. The impulse-response functions (IRFs) are obtained by estimating a tri-variate VAR(1) including a constant. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

impact is increasing over time. Using panel data from 39 countries, Bansal et al. (2016) also show that temperature risks have a significant negative impact on equity valuations. Bansal and Ochoa (2011a) find that temperature risk is priced in the cross-section of portfolio equity returns. In particular, their cross-sectional tests suggest temperature-related risks carry a positive risk premium. Moreover, the risk premium arising from temperature-related risks tends to be larger in countries closer to the equator than in those further away from it.

We contribute to this literature by examining the implications of temperature volatility shocks for the cross-section of UK (and EU) stock returns. To the best of our knowledge, ours is the first study to investigate whether $TVOL$ shocks carry a risk premium and if so, of which sign. We fill this gap by means of standard cross-sectional regressions of stock returns. In our framework average returns are a function of the newly introduced climate driver, namely $TVOL$ innovation. In the spirit of Bansal et al. (2016) and Garlappi and Song (2016), when estimating temperature volatility risk premia, we control for market and productivity risks. In this respect, we let portfolio returns be a function also of the excess return of the market portfolio, R_M^e, and the two-year moving-average of aggregate productivity growth, Δa.[8] The following factor model is thus estimated:

$$\mathbb{E}[R_i] = \lambda \beta_i', \tag{2}$$

[8] To make our cross-sectional analysis comparable to existing studies focusing on effects of temperature shifts on asset prices (Bansal and Ochoa, 2011a; Bansal et al., 2016; Balvers et al., 2017), in a robustness test, changes in temperature level are considered as additional risk factor. The results remain unaffected and are available upon request.

where R^i is the return of asset i, $\beta_i = [\beta_{mkt,i}, \beta_{\Delta a,i}, \beta_{\Delta TVOL,i}]$ is the vector of risk exposures of asset i containing the exposures of stock returns to the market, variations in macro-economic growth and innovations to temperature volatility. Finally, $\lambda = [\lambda_{MKT}, \lambda_{\Delta a}, \lambda_{\Delta TVOL}]$ are the implied factor risk premia which encompass both the vector of the underlying prices of risks and the quantity of risks. The classical two-stage regression approach is followed. Therefore, in the first stage, we estimate the exposure to the above risk factors (i.e., the betas) from full-sample time series regressions:

$$R_{t,i} = \alpha_i + \beta_{MKT,i} R^e_M + \beta_{\Delta a,i} \Delta a_t + \beta_{\Delta TVOL,i} \Delta TVOL_t + \varepsilon_{t,i}, \quad \forall i. \tag{3}$$

The vector of risk premia is estimated from the cross-sectional second stage regression:

$$\mathbb{E}[R^i] = \alpha + \hat{\beta}_{MKT,i} \lambda_{MKT} + \hat{\beta}_{\Delta a,i} \lambda_{\Delta a} + \hat{\beta}_{\Delta TVOL,i} \lambda_{\Delta TVOL} + \nu_i, \tag{4}$$

where $\mathbb{E}[R^i]$ is the average return of each asset over time and the vector of estimated betas $\hat{\beta}_i = [\hat{\beta}_{MKT,i}, \hat{\beta}_{\Delta a,i}, \hat{\beta}_{\Delta TVOL,i}]$ for each portfolio is taken from the first stage regression (3).[9] We refer to this approach as "Avg Returns".

An alternative second stage regression is suggested by Fama and MacBeth (1973). Here, the second step consists of computing T cross-sectional regressions of the returns on the betas estimated from the first step. Formally,

$$R_{t,i} = \alpha + \hat{\beta}_{MKT,i} \lambda_{MKT,t} + \hat{\beta}_{\Delta a,i} \lambda_{\Delta a,t} + \hat{\beta}_{\Delta TVOL,i} \lambda_{\Delta TVOL,t} + \nu_{t,i}. \tag{5}$$

The estimated λ is then computed by averaging the λs over T. This alternative "Fama-McBeth" procedures gives exactly the same values for λ, but different standard errors.

In our benchmark tests, we use UK portfolios formed on different characteristics provided in Stefano Marmi's Data Library following the methodology outlined in Fama and French (1993).[10] We first use six portfolios formed on size and book-to-market and six portfolios formed on size and momentum, a total of twelve portfolios. We then use 40 portfolios formed on the following characteristics: price-earnings, price to book, price to cash flow and gross profit margin. All these portfolios are available for the period 1989-2011.

Table 2 reports the risk premium estimates from the second stage for the twelve UK benchmark

[9] Note that we obtain similar results when we use excess returns and impose a zero-beta restriction in the estimation by running the second stage regression without an intercept.

[10] Data are freely available at http://homepage.sns.it/marmi/Data_Library.html.

Table 2: TEMPERATURE RISK AND 12 UK PORTFOLIO RETURNS (1989-2011)

Panel A:		Risk Premia (λ)		
Avg Returns	Intercept	λ_{MKT}	$\lambda_{\Delta a}$	$\lambda_{\Delta TVOL}$
"1"	15.121			0.535
	[9.481]			[3.972]
"2"	11.901	-0.545	-0.155	0.652
	[3.992]	[-0.216]	[-0.742]	[6.255]
Panel B:		**Risk Premia (λ)**		
Fama-MacBeth	**Intercept**	**λ_{MKT}**	**$\lambda_{\Delta a}$**	**$\lambda_{\Delta TVOL}$**
"1"	15.121			0.535
	[2.934]			[2.369]
"2"	11.901	-0.545	-0.155	0.652
	[1.661]	[-0.066]	[-0.578]	[2.588]

Notes: This table reports the estimates of the temp-vol risk premium. Test assets are twelve UK portfolios: six portfolios formed on size and book-to-market and six portfolios formed on size and momentum (Source: Stefano Marmi's Data Library). All portfolio returns are value-weighted returns expressed in local currency (GBP). We use annual data for the period 1989-2011. The t-statistics in square brackets for the risk premium are adjusted for autocorrelation and heteroskedasticity following Newey and West (1987).

portfolios. Results are reported for both the univariate model where only temperature volatility risk is considered (specification "1") and the multivariate model accounting for market and macroeconomic risk (specification "2"). The risk premium estimates from $TVOL$ shocks are positive and statistically significant. Results are similar after controlling for market and macroeconomic (TFP) risk. Similar conclusions can be drawn by looking at Table 3 which reports risk premia estimated by employing the 40 UK portfolios. In this larger set of portfolios, the temperature volatility related risk premium is still found to be positive but smaller. Moreover, results are less statistically significant when the "Fama-McBeth" approach is used (Table 3, Panel B).[11]

To get additional insights on the effect of temperature volatility shocks on the cross-section of stock returns, in an alternative test we use also a larger number of portfolios. Precisely, we use 100 EU portfolios: 25 portfolios formed on size and book-to-market; 25 portfolios formed on size and operating profitability; 25 portfolios formed on size and investment; and 25 portfolios formed on size and momentum. Data on these EU portfolios are freely available from Kenneth R. French's Data Library for the period 1990-2015. Results from this alternative test are reported in Table 4. The result with respect to temperature volatility shocks are qualitatively similar to those reported in Tables 2 and 3.

Finally, for the sake of robustness, we perform our cross-sectional tests by controlling for the 2008-2009 Great Recession. We first run our one factor regression by focusing on the pre-2008 period. Second, in order to control for the crisis years we run a four factors regression where a

[11] We have repeated the test by using each set of 10 single factor sorted portfolios and other portfolios formed on alternative characteristics (e.g., price to sales, dividend yield, and 1 year EPS growth). The results – not reported for the sake of brevity – are qualitatively similar.

Table 3: Temperature risk and 40 UK portfolio returns (1989-2011)

Panel A:		Risk Premia (λ)		
Avg Returns	Intercept	λ_{MKT}	$\lambda_{\Delta a}$	$\lambda_{\Delta TVOL}$
"1"	12.247			0.146
	[31.645]			[2.770]
"2"	10.530	0.854	0.151	0.161
	[7.388]	[0.549]	[1.038]	[2.370]
Panel B:		Risk Premia (λ)		
Fama-MacBeth	Intercept	λ_{MKT}	$\lambda_{\Delta a}$	$\lambda_{\Delta TVOL}$
"1"	12.247			0.146
	[3.293]			[0.873]
"2"	10.530	0.854	0.151	0.161
	[3.071]	[0.152]	[0.497]	[1.209]

Notes: This table reports the estimates of the temp-vol risk premium. Test asset are 40 UK portfolios: 10 portfolios formed on price-earnings, 10 portfolios formed on price to book, 10 Portfolios formed on price to cash flow, 10 portfolios formed on gross profit margin (Source: Stefano Marmi's Data Library). All portfolio returns are value-weighted returns expressed in local currency (GBP). We use annual data for the period 1989-2011. The t-statistics in square brackets for the risk premium are adjusted for autocorrelation and heteroskedasticity following Newey and West (1987).

dummy capturing the 2008 and 2009 is added. Results are qualitatively similar and are reported in Appendix C (see Tables C.1 and C.2).

Table 4: Temperature risk and 100 EU portfolios (1991-2016)

Panel A:		Risk Premia (λ)		
Avg Returns	Intercept	λ_{MKT}	$\lambda_{\Delta a}$	$\lambda_{\Delta TVOL}$
"1"	11.625			0.270
	[31.366]			[5.561]
"2"	3.774	6.330	0.738	0.368
	[0.831]	[1.512]	[2.359]	[3.093]
Panel B:		Risk Premia (λ)		
Fama-MacBeth	Intercept	λ_{MKT}	$\lambda_{\Delta a}$	$\lambda_{\Delta TVOL}$
"1"	11.625			0.270
	[2.756]			[1.637]
"2"	3.774	6.330	0.738	0.368
	[0.821]	[1.031]	[2.640]	[2.406]

Notes: This table reports the estimates of the temp-vol risk premium. Test assets: 100 European portfolios, i.e., 25 European portfolios formed on size and book-to-market, 25 European portfolios formed on size and operating profitability, 25 European portfolios formed on size and investment, 25 European portfolios formed on size and momentum (Source: Kenneth R. French's Data Library). We use annual data for the period 1991-2015. The t-statistics in square brackets for the risk premium are adjusted for autocorrelation and heteroskedasticity following Newey and West (1987).

Note that the evidence that $TVOL$ risk demands a positive risk premium in the cross-section of stock market returns – even after controlling for market and macroeconomic risk – corroborates the findings in Section 3.5. In Section 3.5 we find that $TVOL$ shocks significantly affect financial variables. Given that our empirical analysis predicts significant adverse effects of temperature volatility on asset prices and macroeconomic variables for the post-war period, we will rationalize these findings in a production economy featuring $TVOL$ shocks. This will allow us to assess the economic costs of this type of risk.

4 A Framework to Examine the Macro-Effects of TVOL Shocks

We rationalize our empirical findings within a production economy featuring long-run macro risk à la Croce (2014) and temperature risk along the lines of Bansal and Ochoa (2011a) and Donadelli et al. (2017). As a main novel ingredient, we introduce stochastic uncertainty of temperature into the model (i.e., $TVOL$ risk). Specifically, temperature dynamics are coupled with the evolution of TFP in a way that innovations in temperature volatility adversely affect long-run productivity, consistent with evidence in UK post-war data. In a robustness test, we also introduce a stochastic depreciation rate of capital to provide new insights on the interplay of capital accumulation and climate change. Note that our main goal here is to maximize the intuition and insight into the relationships between $TVOL$ risk and the macroeconomy and asset prices, and avoid tangential complications. We therefore strive to keep the model as simple as possible while still matching main macro-quantities and asset prices. For this reason, we deliberately introduce real rigidities into the model only in the form of capital adjustment costs and abstract from any other type of frictions (e.g., financial and labor market frictions).

Temperature and productivity. We capture the economic effects of temperature volatility shocks by using the following specification for productivity and temperature dynamics:

$$\begin{aligned}
\Delta a_{t+1} &= \mu_a + x_t + x^z_{t+1} + \sigma_a \epsilon_{a,t+1} \\
x_t &= \rho_x x_{t-1} + \sigma_x \epsilon_{x,t} \\
x^z_{t+1} &= \rho^z_x x^z_t + \tau_z \sigma_z \epsilon_{z,t+1} + \tau_\theta \sigma_\theta \epsilon_{\theta,t+1} \\
z_{t+1} &= \mu_z + \rho_z (z_t - \mu_z) + e^{\theta_{t+1}} \sigma_z \epsilon_{z,t+1} \\
\theta_{t+1} &= \rho_\theta \theta_t + \sigma_\theta \epsilon_{\theta,t+1},
\end{aligned} \tag{6}$$

where the shocks $\epsilon_{a,t+1}$, $\epsilon_{x,t}$, $\epsilon_{\theta,t+1}$ and $\epsilon_{z,t+1}$ are independent of each other and are each distributed i.i.d. standard normally. In addition to temperature level shocks $\epsilon_{z,t}$, we introduce shocks to the volatility of temperature $\epsilon_{\theta,t}$.[12] The unconditional expected growth rate of productivity is μ_a. The parameter μ_z captures the long-run average temperature level. In this economy, short-run productivity shocks are induced by $\epsilon_{a,t}$, whereas $\epsilon_{x,t}$, $\epsilon_{\theta,t}$, and $\epsilon_{z,t}$ indicate long-run shocks affecting the persistent stochastic components in productivity growth x_t and x^z_t. The persistence of long-run macro and temperature-related productivity shocks is measured by ρ_x and ρ^z_x, respectively. We

[12] We specify stochastic volatility in the temperature process, depicted in the last two equations of the System 6, as Hitzemann et al. (2016) model oil volatility risk to quantify the macroeconomic and financial effects of oil-specific uncertainty shocks.

specify two distinct long-run components for macro and temperature shocks in order to disentangle the timing of those innovations. In contrast to long-run macro shocks, temperature-related shocks contemporaneously impact TFP growth, as observed in the data.

The shock terms $\tau_z\sigma_z\epsilon_{z,t+1}$ and $\tau_\theta\sigma_\theta\epsilon_{\theta,t+1}$ represent the impact of changes in the temperature level and temperature volatility, respectively, both on TFP growth, as suggested by our novel empirical analysis on UK data (see Figure 5).[13] $\sigma_z\epsilon_{z,t+1}$ is the unpredictable part of the change in temperature level, while the term $e^{\theta_{t+1}}$ represents time-varying volatility of temperature. In this setup, θ represents a proxy for the volatility of key climate variables (in our case temperature volatility as defined in Eq. (1)). The parameters τ_z and τ_θ in the dynamics for x^z in the system (6) capture the direction and the intensity with which unpredictable temperature level and temperature volatility shocks impact long-run productivity growth. Based on the empirical analysis in Section 3.2, we assume $\tau_\theta < 0$ when we study the quantitative implications of the model, i.e., $TVOL$ shocks have a negative impact on long-run expected productivity growth. For completeness and to be consistent with our UK-based empirical evidence, we also let the model replicate the negative effect on productivity of a shock in the level of temperature (i.e., $\tau_z < 0$). This is also in line with recent studies showing that temperature level shocks harm real economic activity (see, among others, Bansal and Ochoa, 2011b; Colacito et al., 2016; Du et al., 2017). Our goal here is to study exclusively the quantitative implications of $TVOL$ risk. We therefore abstract from studying the effects of temperature level shocks on the UK macroeconomy.[14]

Households. The representative household is equipped with recursive preferences, as in Epstein and Zin (1989):

$$U_t = \left[(1-\beta)\tilde{C}_t^{1-\frac{1}{\psi}} + \beta\left(\mathbb{E}_t[U_{t+1}^{1-\gamma}]\right)^{\frac{1-1/\psi}{1-\gamma}}\right]^{\frac{1}{1-1/\psi}}. \tag{7}$$

$\tilde{C}_t$ is a Cobb-Douglas aggregator for consumption C_t and leisure $1 - L_t$ (the remainder of a total time budget of 1, when the amount of labor is L_t):

$$\tilde{C}_t \equiv \tilde{C}(C_t, L_t) = C_t^{\nu}(A_t(1-L_t))^{1-\nu},$$

where A_t denotes aggregate productivity (i.e., TFP).

[13]Note that we slightly differ from Croce (2014) and Hitzemann et al. (2016) who introduce time-varying economic uncertainty directly in the TFP. Said differently, we do not include uncertainty shocks to macro productivity. Consistently with our empirical analysis, here we are exclusively interested on capturing the long-run effects of a shock to the volatility of temperature (i.e., $\sigma_\theta > 0$).

[14]Note that imposing $\tau_z = 0$ would not affect our results on the implications of $TVOL$ shocks.

The stochastic discount factor (SDF) reads:

$$M_{t,t+1} = \beta \left(\frac{\tilde{C}_{t+1}}{\tilde{C}_t}\right)^{1-\frac{1}{\psi}} \left(\frac{C_{t+1}}{C_t}\right)^{-1} \left(\frac{U_{t+1}^{1-\gamma}}{\mathbb{E}_t[U_{t+1}^{1-\gamma}]}\right)^{\frac{1/\psi-\gamma}{1-\gamma}}. \tag{8}$$

Firms. The production sector admits a representative, perfectly competitive firm utilyzing capital and labor to produce the output. The production technology is given by

$$Y_t = K_t^{\alpha}(A_t L_t)^{1-\alpha},$$

where α is the capital share and labor L_t is supplied by the household. The aggregate productivity growth rate, $\Delta a_t = \log(A_t/A_{t-1})$, has a standard long-run macro risk component and is subject to temperature and temperature volatility risk, as described in Eq. (6).

The capital stock evolves according to

$$K_{t+1} = (1-\delta_K)K_t + G\Big(\frac{I_t}{K_t}\Big)K_t,$$

where δ_K is the depreciation rate of capital. $G(\cdot)$, the function transforming investment into new capital, features convex adjustment costs as in Jermann (1998):

$$G := G\Big(\frac{I_t}{K_t}\Big) = \frac{\alpha_1}{1-\frac{1}{\tau}}\Big(\frac{I_t}{K_t}\Big)^{1-\frac{1}{\tau}} + \alpha_2.$$

Asset prices. The intertemporal Euler conditions defining the risk-free rate R_t^f and the return on capital R_t are as follows:

$$\frac{1}{R_t^f} = \mathbb{E}_t[M_{t,t+1}], \quad 1 = \mathbb{E}_t[M_{t,t+1}R_{t+1}],$$

where

$$R_{t+1} = \frac{\frac{\alpha Y_{t+1} - I_{t+1}}{K_{t+1}} + q_{t+1}(G_{t+1} + 1 - \delta_K)}{q_t}.$$

The price of capital q_t is equal to the marginal rate of transformation between new capital and consumption:

$$q_t = \frac{1}{G'\left(\frac{I_t}{K_t}\right)}$$

Given the risk-free rate $R_t^f = \frac{1}{\mathbb{E}_t[M_{t,t+1}]}$ we calculate the unlevered equity risk premium as

$$R_{ex,t} = R_t - R_{t-1}^f.$$

Labor market. In the absence of labor market frictions, optimal labor allocation implies that the marginal rate of substitution between consumption and leisure equals the marginal product of labor:

$$\frac{1-\nu}{\nu}\Big(\frac{C_t}{1-L_t}\Big) = (1-\alpha)\frac{Y_t}{L_t}.$$

Market clearing. Goods market clearing implies that

$$Y_t = C_t + I_t.$$

The model is solved numerically by a second-order approximation using perturbation methods as provided by the `dynare++` package.

5 Quantitative Analysis

5.1 *Calibration*

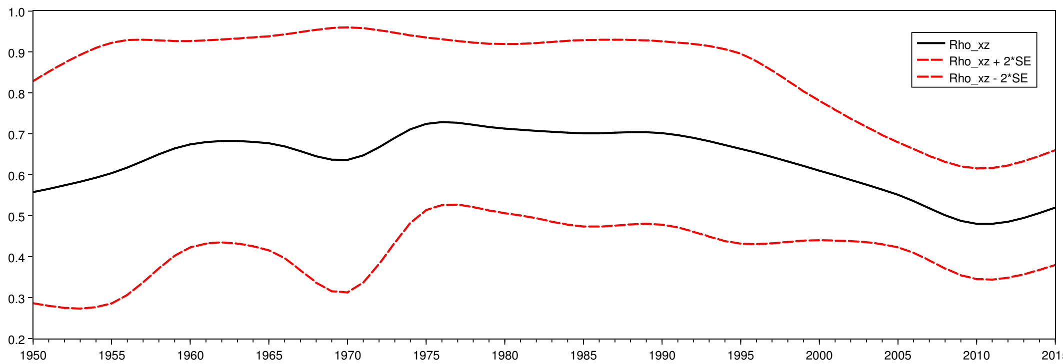
Our benchmark model is calibrated to an annual frequency and requires us to specify nineteen parameters: four for preferences, three relating to the final goods production technology and labor market, four describing the TFP process, and eight for the dynamics of the UK temperature.[15] The model is calibrated to match the adverse climate effects on TFP growth for the period 1950-2015 as they are found to be the strongest among all periods.

Let us first discuss the "less standard", i.e., UK temperature-related parameters. The persistence of the innovations in the long-run temperature risk component is chosen to let the model reproduce the relative persistent effect of $TVOL$ shocks on productivity growth observed in postwar-UK data (Figure 2, Panel C). To this end, we set $\rho_z^x = 0.6$. Note that this value is in line with the average empirical estimates reported in Figure 8 where we compute a series of ρ_z^x using a rolling window of 50 years for the period 1900-2015.[16]

[15] Note that the calibration presented here is meant as a benchmark. We have found that our main results are robust to reasonable variations around this benchmark.

[16] In the literature on adaptation to climate change, the parameter ρ_z^x can be interpreted as the speed of adaptation (see e.g. Tol, 2002). A value of 0 refers to the case of an immediate adaptation to temperature-related shocks while a value of 1 would imply no adaptation. According to figure 8, the speed of adaptation has increased during the last

Figure 8: Speed of adaptation



Notes: This figure shows the time series of the parameter ρ_x^z representing the persistence of temperature-related TFP shocks. ρ_x^z is estimated from the system in Eq. (6) – in a state space framework – using a rolling window of 50 years for the period 1900-2015. Covariance is estimated using Huber-White standard errors.

The two parameters measuring the sensitivity of TFP growth to temperature-related shocks are jointly calibrated using the empirical evidence provided in Section 3.3. Therefore, the parameter τ_θ, measuring the impact of $TVOL$ shocks on TFP growth, is calibrated to a value of -0.0285. This implies that in the model productivity growth falls by 0.4pp following a one-standard deviation temperature volatility shock (see Figure 5, Panel B). The parameter τ_z, measuring the impact of temperature level shocks on TFP growth, is then calibrated to a value of -0.0054, which implies in our model that productivity growth declines by around 0.3pp after an unexpected one-standard deviation increase in temperature (see Figure 5, Panel A). Regarding the stochastic volatility parameters in the temperature process, we set the persistence of $TVOL$ shocks equal to 0.85, as suggested by empirical estimates. The standard deviation of time-varying temperature uncertainty, σ_θ, is assumed to be a small fraction of the volatility of temperature level shocks. Precisely, we impose $0.25 \cdot \sigma_z$.[17] The other parameters regarding temperature dynamics are set to match the UK temperature statistics observed in the data over the period 1950-2015. In particular, we set $\mu_z = 9.74$ (degrees Celsius), $\rho_z = 0.4$, and $\sigma_z = 0.56$ to match the long-term mean, persistence and volatility of UK temperature, respectively.

We next turn to the standard parameters. Most of the parameters are set in accordance with the long-run risk literature and are chosen to match the main dynamics of UK macroeconomic quantities and prices. More precisely, as in Croce (2014), we set the coefficient of relative risk aversion, γ, and

three decades, which may be due to technological improvements.

[17] Note that both temperature uncertainty-related parameter values (i.e., $\rho_\theta = 0.85$ and $\sigma_\theta = 0.25\sigma_z$) are in line with GARCH(1,1) estimations which confirm that the conditional variance of UK temperature is time-varying.

Table 5: BENCHMARK CALIBRATION

Parameter	Description	Source	Value
PREFERENCES			
β	Subjective time discount factor	2	0.988
ψ	Elasticity of intertemporal substitution	1	2
γ	Relative risk aversion	1	10
ν	Consumption share in utility bundle	5	0.3407
PRODUCTION AND INVESTMENT PARAMETERS			
α	Capital share in final good production	1	0.345
δ_K	Depreciation rate of physical capital	1	0.06
τ	Capital adjustment costs elasticity	3/4	0.7
TFP			
μ_a	Long-run mean of TFP	5	0.0142
σ_a	Volatility of short-run shocks to TFP	5	0.0205
ρ_x	Long-run TFP shock persistence	5	0.97
σ_x	Volatility of long-run shocks to TFP	5	$0.12^*\sigma_a$
TEMPERATURE			
μ_z	Long-run mean of UK temperature	5	9.74°C
τ_z	Impact of temperature level innovations on TFP growth	5	-0.0054
τ_θ	Impact of $TVOL$ innovations on TFP growth	5	-0.0265
ρ_x^z	Long-run temperature-related TFP shock persistence	5	0.6
ρ_z	Temperature persistence parameter	5	0.4
ρ_θ	Persistence of volatility shocks to UK temperature	5	0.85
σ_z	Standard deviation of level shocks to UK temperature	5	0.56
σ_θ	Standard deviation of volatility shocks to UK temperature	5	$0.25^*\sigma_z$

Notes: This table reports the set of parameters used to calibrate (at an annual frequency) the model described in Section 4. Parameter sources: 1 = Croce (2014), 2 = Bansal and Ochoa (2011a), 3 = Kung and Schmid (2015), 4 = Donadelli and Grüning (2016), 5 = own calibration.

the elasticity of intertemporal substitution (IES), ψ, to values of 10 and 2, respectively (i.e., the representative agent has preference for the early resolution of uncertainty, since $\gamma > \psi^{-1}$). In line with Bansal and Ochoa (2011b), the annualized subjective discount factor, β, is fixed at 0.988. The consumption share in the utility bundle $\tilde{C}$ is chosen such that the steady-state supply of labor is one third of the total time endowment of the household. Given the other parameters, this is achieved by setting $\nu = 0.3407$. On the final production side, we set the capital share α in the production technology equal to 0.345 as in Croce (2014). Regarding the adjustment cost parameters, τ is set to 0.7 as in Kung and Schmid (2015). The constants α_1 and α_2 are chosen such that there are no adjustment costs in the deterministic steady state. The depreciation rate of capital δ_K is set to 0.06 as in Croce (2014). The parameter μ_a is set to a value of 0.0142, so that the average annual TFP growth rate is 1.42%, as indicated by the UK data. The volatility of the short-run shock, σ_a, is calibrated to match the annual volatility of output growth observed in the macroeconomic data. We then calibrate the parameters of the long-run productivity risk process, x_t, according to empirical estimates, resulting in $\rho_x = 0.97$ and $\sigma_x = 0.12\sigma_a$.[18]

5.2 *Macro and Asset Pricing Implications*

The main results produced by our benchmark calibration (BC) are reported in Table 6, denoted by specification [1]. In line with standard long-run risk models, our framework produces $\mathbb{E}[R_{ex}^{LEV}] = 3.14\%$, a value close to what is observed on the major capital markets around the world. Compared to specification [2], representing a model without temperature volatility effects, we observe that the impact of $TVOL$ on TFP growth significantly affects asset prices. $\mathbb{E}[R_{ex}^{LEV}]$ increases by 11 basis points when volatility effects of temperature are introduced.

Equity volatility also experiences an additional increase by 15 basis points after introducing temperature volatility effects. The correlation between the excess return and temperature volatility is negative with a value of -0.13. The reason for the negative sign is that unexpected increases in $TVOL$ negatively affect firms' productivity and, hence, their return on capital. In the data, the negative correlation is somewhat stronger than in our benchmark model.

The negative effects of $TVOL$ increases on the macroeconomy are reflected by a negative correlation between the volatility of temperature and both TFP and output growth, with values of -0.19 and -0.16, respectively. An important advantage of our model is that the inclusion of temperature volatility risk can explain asset price dynamics and replicate $TVOL$ effects in the data, while it does not affect the long-run moments of macroeconomic quantities.

To analyse how $TVOL$ shocks are transmitted through the economy, we plot the responses of macro quantities to an unexpected increase in $TVOL$ (see Figure 9). This shock negatively affects the temperature-related long-run risk component of productivity growth. While long-run macro shocks have an delayed effect on productivity, an unexpected temperature volatility increase reduces TFP growth on impact by about $0.4pp$. This translates into an immediate decrease in consumption

[18] We estimate the following state-space model:

$$\Delta a_t = 0.0142 + x_{t-1} + \underbrace{\sigma_{a,t}}_{0.015^{***}} \cdot \epsilon_{a,t},$$
$$x_t = \underbrace{\rho_x}_{0.97^{***}} \cdot x_{t-1} + \underbrace{\sigma_{x,t}}_{0.002^{***}} \cdot \epsilon_{x,t},$$

where 0.0142 corresponds to the UK long-run mean of aggregated productivity estimated over the period 1950-2015, ρ_x is the estimated persistence parameter of the long-run productivity component, $\sigma_{a,t}$ and $\sigma_{x,t}$ are the estimated volatilities of the short- and long-run TFP shock, and $\epsilon_{a,t}$ and $\epsilon_{x,t}$ are independent and identically distributed standard normal shocks. Estimates are obtained using the Newton-Raphson optimization procedure with Marquardt step. Huber-White standard errors are employed in order to account for heteroskedasticity. *** indicates significance at 1% level.

Table 6: MODEL VS (UK) DATA: MACROECONOMIC QUANTITIES AND ASSET PRICES

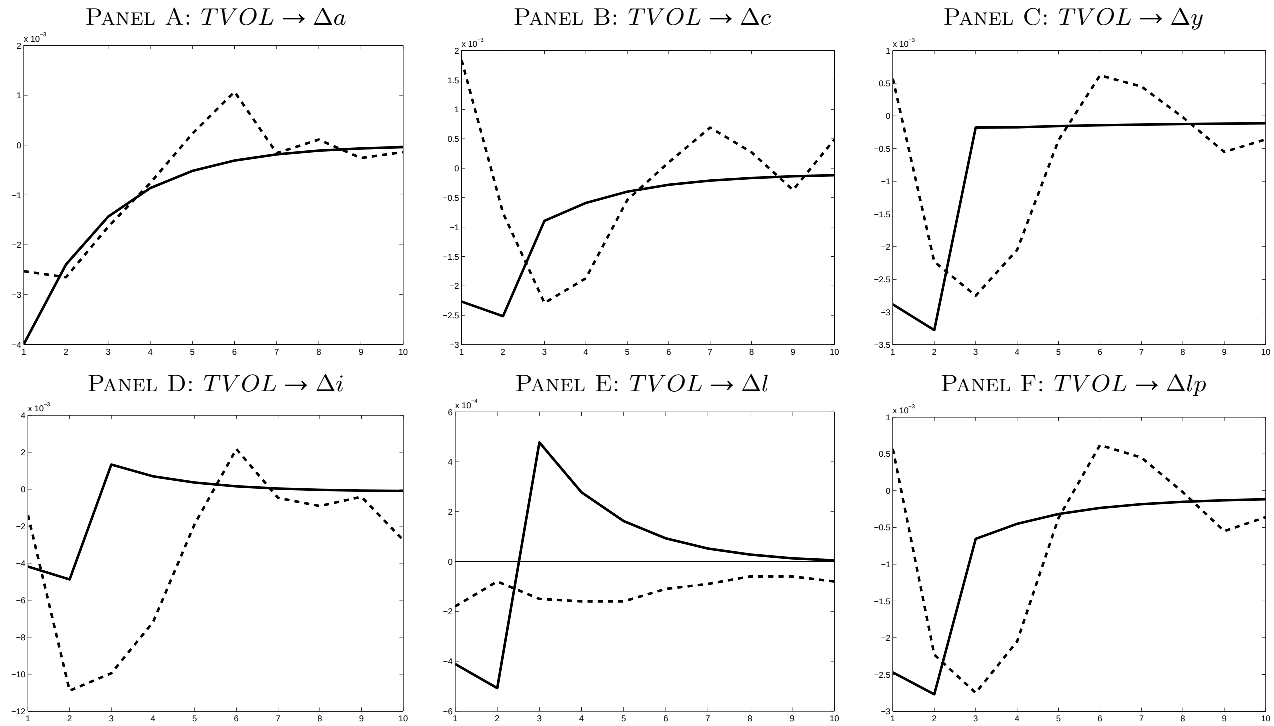
Variable	**Data**	**BC**	$\tau_\theta = 0$	$\rho(\epsilon_x, \epsilon_\theta) = 0.5$	$\rho(\epsilon_x, \epsilon_\theta) = 1$
		[1]	[2]	[3]	[4]
MACRO QUANTITIES					
$\mathbb{E}(\Delta a)$	1.44	**1.43**	1.44	1.43	1.44
$AC1(\Delta a)$	0.25	**0.12**	0.10	0.10	0.08
$\sigma(\Delta y)$	2.02	**2.05**	2.00	2.02	2.00
$\sigma(\Delta l)$	0.26	**0.68**	0.68	0.67	0.67
$\sigma(\Delta c)/\sigma(\Delta y)$	1.02	**0.82**	0.82	0.83	0.84
$\sigma(\Delta i)/\sigma(\Delta y)$	3.08	**1.82**	1.84	1.82	1.81
$\sigma(\Delta l)/\sigma(\Delta y)$	0.13	**0.33**	0.34	0.33	0.34
$\rho(\Delta c, \Delta y)$	0.79	**0.87**	0.86	0.87	0.86
$\rho(\Delta c, \Delta i)$	0.55	**0.53**	0.52	0.52	0.51
$\rho(\Delta l, \Delta y)$	-0.01	**0.58**	0.57	0.56	0.55
$\rho(\Delta i, \Delta l)$	0.08	**0.89**	0.89	0.89	0.89
TEMPERATURE					
$\mathbb{E}(z)$	9.74	**9.74**	9.74	9.74	9.75
$\sigma(z)$	0.60	**0.60**	0.60	0.60	0.61
$\rho(\theta, \Delta a)$	-0.18	**-0.19**	0.00	-0.10	0.00
$\rho(\theta, \Delta y)$	-0.16	**-0.16**	0.00	-0.06	0.00
ASSET PRICES					
$\mathbb{E}[R_{ex}^{LEV}]$	7.31	**3.14**	3.03	2.55	1.99
$\sigma(R_{ex}^{LEV})$	19.78	**5.09**	4.94	4.64	4.17
$\rho(\theta, R_{ex}^{LEV})$	-0.32	**-0.13**	0.00	0.07	0.32

Notes: This table reports the main moments for the benchmark calibration (specification [1]) and two other model specifications. In model [2], we assume that volatility shocks to temperature do not affect long-run productivity growth, i.e., $\tau_\theta = 0$. In model [3] and [4], by imposing $\rho(\epsilon_x, \epsilon_\theta) > 0$, temperature volatility shocks are assumed to be positively correlated with long-run productivity shocks. The levered equity risk premium is defined as $R_{ex}^{LEV} = (1 + \frac{D}{E})(R_t - R_{t-1}^f)$ where financial leverage is imposed by assuming an average debt-to-equity ratio $\frac{D}{E}$ of 1 (see, e.g., Croce, 2014; Hitzemann et al., 2016). Models' entries are obtained from repetitions of small-sample simulations (i.e., averages over 1000 simulations of 100 years). $\mathbb{E}[\cdot]$, $\sigma(\cdot)$, $\rho(\cdot, \cdot)$, and $AC1(\cdot)$ denote mean, volatility, correlation, and first-order autocorrelation, respectively. Means and volatilities are expressed in percentage points. Empirical moments are computed from annual data spanning the period 1950-2015. Additional details on data are provided in Section 3.1.

growth of more than 0.2pp (Panel B) and a decrease in investment of more than 0.4pp, which reduces total output growth by almost 0.3pp (Panel C).

Our production economy model further allows us to analyse the impact of temperature volatility shocks on labor market dynamics. While the effect on labor growth is negative during the first two periods, it becomes positive afterwards due to the income effect. As the agent feels poorer, she reduces consumption of leisure and increases labor supply. Labor productivity growth falls on impact as well, since labor growth decreases less than output growth. Later on, the effect is still negative since labor growth turns positive, while output growth is still negative over a longer horizon. Thus, our model reproduce the negative effects of a temperature volatility shock on macroeconomic quantities found in Figure 4 with a magnitude close to the empirical counterparts. So, modelling temperature volatility shocks within a production economy with endogenous investment and labor

Figure 9: Responses of macro quantities to a $TVOL$ shock

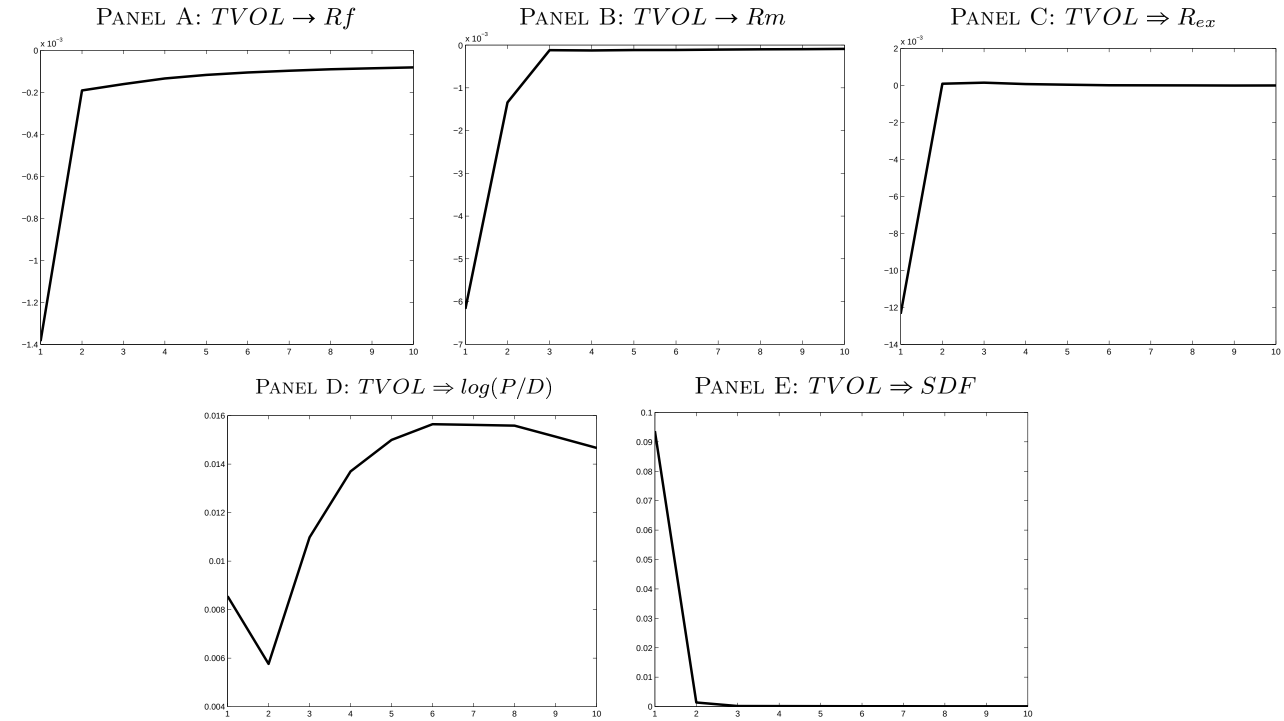


Notes: This figure reports impulse response functions (expressed as percentage annual log-deviations from the steady state) for a length of 10 years of TFP growth, Δa, consumption growth, Δc, output growth, Δy, investment growth, Δi, labor growth, Δl, and labor productivity growth, Δlp, with respect to a $TVOL$ shock. Solid black lines: model-implied impulse responses. Dashed black lines: average empirical impulse responses (i.e., average of the three different VAR models impulse responses estimated and plotted in Figure B.4). All the parameters are calibrated to the values reported in Table 5.

decisions represents the most natural choice.

As found in our VAR analysis, $TVOL$ shocks also affect the financial sector. Impulse responses for financial variables are shown in Figure 10. As unexpected increases in $TVOL$ reduce productivity, firms' profits decline, which also has a negative effect on dividends. Due to the fall in investment, the price of capital depreciates, which implies lower stock market returns (Panel B) and a contemporaneous increase in the stochastic discount factor (Panel E). The price dividend-ratio increases following the shock (Panel D) because dividends decrease more than equity prices in our model. As equity markets experience a contraction, the agent's demand for risk-less securities increases, producing a drop in the risk-free rate (Panel A). As the returns on the aggregate stock market decreases more than the risk-free rate, the excess return declines as well (Panel C). This also means that the equity market does not provide insurance against temperature volatility risk. There is no positive excess return when the marginal utility of the agent is high, i.e. in a bad state of the world. Therefore, temperature volatility risk is associated with increases in the equity premium (see Table 6).

Figure 10: Responses of financial variables to a temperature volatility shock



Notes: This figure reports impulse response functions (expressed as percentage annual log-deviations from the steady state) for a length of 10 years of the log of the price dividend ratio, $log(p/d)$, the pricing kernel, SDF, the equity market return, R_m, the risk-free rate, R_f, and the excess return, R_{ex}, with respect to a temperature volatility shock. All the parameters are calibrated to the values reported in Table 5.

Correlated long-run macro and temperature volatility shocks: To capture possible adaptation to temperature volatility risk, we assume that long-run TFP shocks and $TVOL$ shocks are positively correlated. This may reflect increasing investment by agents in new technologies to shield against higher temperature volatility, and this investment increases productivity. In specification [3], we therefore set $\rho(\epsilon_x, \epsilon_\theta) = 0.5$. The counter-cyclicality between the equity market return and temperature volatility, i.e. $\rho(\theta, R_{ex}^{LEV}) < 0$, almost disappears, which decreases the overall level of risk. As a result, the equity risk premium decreases by about 59 basis points, and equity volatility decreases by 45 basis points compared to the benchmark scenario. In the extreme case of specification [4] we assume a perfect correlation between temperature volatility shocks and long-run productivity shocks, which represents the case where agents perfectly respond to increasing temperature volatility by means of adaption efforts. This results in a sharp drop of the equity premium. Now, the counter-cyclicality between $TVOL$ and TFP actually turns into a pronounced procyclicality of almost the same magnitude.

5.3 *Welfare and Growth Effects of Temperature Volatility Risk*

In the spirit of Bansal and Ochoa (2011b), we measure the economic costs of temperature volatility risk by means of welfare compensation of a change in the level of temperature volatility. The welfare compensation is expressed as a permanent change of agent's lifetime utility relative to the economy with no temperature volatility risk. Formally,

$$\mathbb{E}[U_0((1+\Delta)\tilde{C})] = \mathbb{E}[U_0(\tilde{C}^*)], \tag{9}$$

where Δ represents welfare-costs, and $\tilde{C} = \{\tilde{C}_t\}_{t=0}^{\infty}$ and $\tilde{C}^* = \{\tilde{C}_t^*\}_{t=0}^{\infty}$ denote the optimal consumption paths with and without temperature volatility risk, respectively.

Table 7 reports welfare costs for temperature volatility effects in the benchmark economy and for the cases with positive correlation between $TVOL$ shocks and long-run TFP shocks. In addition, costs are calculated for two values of the intertemporal elasticity of substitution to check if our results are qualitatively robust to whether the substitution effect or the income effect dominates. The first case is represented by $\psi > 1$, and more precisely, we use $\psi = 2$ as in the benchmark specification. To let the income effect dominate we set $\psi = 0.9$.

In our benchmark calibration, welfare costs amount to 9.1% of per capita composite consumption. This means that the bundle consisting of consumption and leisure of an agent living in an economy with temperature volatility risk needs to be increased by 9.1% in every state and at every point in time to give the agent the same utility as in an economy without temperature volatility risk. Since $TVOL$ shocks have a large and persistent effect on productivity and other macroeconomic and financial variables, they produce sizeable welfare costs.

In the case where long-run TFP shocks are positively correlated with $TVOL$ shocks ($\rho(\epsilon_x, \epsilon_\theta) > 0.5$), welfare costs decrease substantially and become negative, which means that there are welfare gains from temperature volatility risk. In specification [2] with a correlation coefficient of 0.5, welfare costs decrease to -41.0%. We interpret the positive correlation between long-run TFP shocks and $TVOL$ shocks as adaptation by agents to temperature uncertainty. Therefore, increases in temperature volatility that reduce TFP growth come with long-run macro shocks which in turn increase TFP growth. This hedge decreases overall risk and welfare costs. In specification [3] where we assume that long-run productivity shocks perfectly respond to temperature volatility shocks with a correlation coefficient of 1, welfare gains from temperature volatility risk are higher accordingly.[19]

In case of a lower value $\psi = 0.9$ of the IES, results change quantitatively, but not qualitatively. With a lower IES the welfare loss in the benchmark case is about one third of the value for $\psi = 2$. Welfare costs are decreasing in the IES, since a lower IES implicitly makes the agent less patient, i.e., future consumption has a lower weight in the value function. This makes temperature volatility risk as a source of long-run macroeconomic risk less costly for the agent.

Table 7: Welfare costs of temperature volatility risk

ψ	**[1]** ($\tau_\theta = -0.0285$) (**BC**)	**[2]** ($\rho(\epsilon_x, \epsilon_\theta) = 0.5$)	**[3]** ($\rho(\epsilon_x, \epsilon_\theta) = 1$)
2.00	9.1%	-41.0%	-71.0%
0.90	3.0%	-13.1%	-29.3%

Notes: This table reports the welfare costs of temperature volatility shocks for two different IES values. Welfare costs are defined as the percentage increase $\Delta > 0$ in composite consumption ($\tilde{C}$) that the household should receive in every state and at every point in time in order to be indifferent between living in an economy with full risk exposure (i.e., $\sigma_z, \sigma_a, \sigma_x > 0, , \sigma_\theta > 0$) and an economy with no temperature volatility risk. Temperature volatility risk is eliminated by imposing $\tau_\theta = 0$. Specification [1] refers to the benchmark calibration (i.e., $\tau_\theta = -0.0285$) while specification [2]and [3] assume a positive correlation between temperature volatility and long-run productivity shocks (i.e., $\rho(\epsilon_x, \epsilon_\theta) > 0$).

Expected Losses: To quantify the long-term effects of $TVOL$ increases, we calculate expected changes in GDP and labor productivity growth for horizons from 1 to 50 years ahead after a temporary positive shock to UK temperature volatility. More specifically, we compare the cumulative growth in an economy in which $TVOL$ negatively affects TFP growth to cumulative growth in an economy without $TVOL$ effects. The shock sizes are one and two standard deviations of temperature volatility changes, i.e., 0.14 and 0.28.

Panels A and B of Table 8 report results for output growth and labor productivity growth. A single initial temperature volatility shock has a sizeable long-run negative impact on both variables as it induces a long-lasting decline in productivity. Over a 50-year horizon, a one-standard deviation shock decreases both cumulative output and labor productivity growth by about 0.95pp. A two-standard deviation shock leads to a fall in cumulative output and labor productivity growth by about 1.9pp each after half a century. Hence, increases in temperature volatility affects economic activity negatively not only in the short but also in the long run by decreasing growth perspectives for output and labor productivity.

[19] In this setting, we assume adaptation to be costless. In order to asses properly the benefits of adaptation, one would need to take into account the costs of these measures. This is left for future research.

Table 8: LONG-RUN EFFECTS OF TEMPERATURE VOLATILITY SHOCKS

Panel A: $\sum_{j=1}^{N} \Delta y_{t+j} - N \cdot \Delta y^*$ Difference in expected output growth after a shock to U.S. temperature					
Shock size	1Y	5Y	10Y	20Y	50Y
1 std. dev. σ_θ	−0.29	−0.67	−0.73	−0.82	−0.94
2 std. dev. σ_θ	-0.58	-1.33	-1.46	-1.64	-1.89
Panel B: $\sum_{j=1}^{N} \Delta lp_{t+j} - N \cdot \Delta lp^*$ Difference in expected labor productivity growth after a shock to U.S. temperature					
Shock size	1Y	5Y	10Y	20Y	50Y
1 std. dev. σ_θ	-0.25	-0.67	-0.75	-0.83	-0.95
2 std. dev. σ_θ	-0.49	-1.33	-1.50	-1.67	-1.90

Notes: This table reports the cumulative change in growth over 1, 5, 10, 20, and 50 years in percentage points after a temporary temperature volatility shock. The cumulative growth in an economy without such a shock is compared to that in an economy with shocks to temperature volatility z_t. Specifically, we report $\left(\sum_{j=1}^{N} \Delta y_{t+j}\right) - N \cdot \Delta y^*$ and $\left(\sum_{j=1}^{N} \Delta lp_{t+j}\right) - N \cdot \Delta lp^*$ where Δy_{t+j} (Δlp_{t+j}) is the log growth rate of total output (labor productivity), and Δy^* (Δlp^*) is the steady state growth rate in the economy without a shock (i.e., with $\sigma_z = 0$). For example, the entry xy for a horizon of 5 years in the first row of Panel A means that cumulative growth over these 5 years has been xy percentage points higher than it would have been without the temperature volatility shock. The amount of lost output (Panel A) and labor productivity (Panel B) growth is reported for temperature volatility shocks amounting to one and two standard deviations, i.e., to 0.14 and 0.28, respectively.

5.4 *Temperature Volatility and Capital Depreciation*

Global climate is projected to continue to change. The effects on the environment of the unstable climate are well known and – based on scientists views – are expected to become even stronger. In particular, temperatures will keep rising, the frost-free season (and growing season) will lengthen, hurricanes will become stronger, more intense and more frequent, and there will be further changes in precipitation patterns in the sense of more droughts and heat waves. More volatile climate conditions are therefore associated with stronger and more frequent extreme weather events. As a result, we should also expect stronger adverse effects of volatility in climate drivers on real economic activity (see Figure 1). Benson and Clay (2004) argue that one of the channels through which natural disasters affect the macroeconomy is the destruction of the stock of capital. Based on these expectations and existing evidence, it is most likely that the increasing number of extreme weather events – induced by unusual weather dynamics – will exacerbate the process through which capital depreciates. In the spirit of Furlanetto and Seneca (2014), we account for a direct effect of temperature volatility (i.e., our climate change-related variable) on the capital stock by assuming a stochastic depreciation rate of capital. More importantly, we assume $TVOL$ and depreciation rate shocks to be positively correlated. This is to stress the fact that innovations to temperature level variations exacerbate the overall effects of climate change and destroy capital more rapidly.

Formally, in the presence of a stochastic deprecation rate, the dynamic equation for capital reads:

$$K_{t+1} = (1 - \delta_{K,t})K_t + G\Big(\frac{I_t}{K_t}\Big)K_t,$$

where

$$\delta_{K,t} = e^{\zeta_t}\delta_K, \quad (10)$$

$$\zeta_t = \rho_k \zeta_{t-1} + \epsilon_{k,t}. \quad (11)$$

Unexpected changes in the depreciation rate are represented by the shock term ϵ_k, and ρ_k measures the persistence of a depreciation shock. Time-varying capital depreciation helps to explain the high volatility of investment observed in the data. We calibrate the standard deviation of depreciation shocks to obtain an investment volatility of 6%, which is close to the data, and set ρ_k to 0.85. The main results produced by the new benchmark calibration featuring depreciation risk (BC) are reported in Table 9, specification [1]. Compared to an economy without depreciation risk (specification [2]), investment volatility significantly increases up to 6%, but this comes at the cost of an increasing volatility in labor and output. Due to higher risk, the equity premium increases by 127 basis points relative to the case with no depreciation shocks.

As pointed out in the beginning of this section, innovations to temperature level variations may exacerbate the overall effects of climate change and destroy capital via the increasing probability of natural disasters. To account for this effect, specifications [3] and [4] assume that temperature volatility shocks and depreciation shocks are positively correlated. Although this assumption reduces the counter-cyclicality of $TVOL$ and the excess return, the equity risk premium increases. To understand this finding it is helpful to look at welfare costs of temperature volatility risk in the presence of stochastic depreciation of capital. The results of this analysis are displayed in Table 10. When $TVOL$ shocks and depreciation shocks are uncorrelated (specification [1]), welfare costs of temperature volatility risk are not much affected compared to Table 7. Introducing a positive correlation between temperature volatility shocks and depreciation shocks (specifications [2] and [3]) increases welfare costs, and this effect is the stronger the higher the correlation. This results from the fact that depreciation risk exacerbates $TVOL$ risk. On the one hand, increasing temperature volatility has a negative effect on TFP growth, which reduces output and consumption. On the other hand, higher temperature volatility increases the depreciation rate, which decreases the capital stock. This has negative effects on production as well, which amplifies the response of consumption. Welfare costs of $TVOL$ risk increase, as the overall volatility of consumption

Table 9: Model vs (UK) data: Macroeconomic quantities and asset prices

Variable	**Data**	**BC**	$\sigma_k = 0$	$\rho(\epsilon_k, \epsilon_\theta) = 0.3$	$\rho(\epsilon_k, \epsilon_\theta) = 1$
		[1]	**[2]**	**[3]**	**[4]**
MACRO QUANTITIES					
$\mathbb{E}(\Delta a)$	1.44	**1.43**	1.44	1.43	1.43
$AC1(\Delta a)$	0.25	**0.12**	0.12	0.12	0.12
$\sigma(\Delta y)$	2.02	**2.96**	2.06	2.99	3.04
$\sigma(\Delta i)$	6.21	**5.94**	3.85	5.94	5.85
$\sigma(\Delta l)$	0.26	**1.15**	0.74	1.15	1.13
$\sigma(\Delta c)/\sigma(\Delta y)$	1.02	**0.79**	0.83	0.80	0.83
$\sigma(\Delta i)/\sigma(\Delta y)$	3.08	**2.02**	1.87	2.00	1.93
$\sigma(\Delta l)/\sigma(\Delta y)$	0.13	**0.39**	0.36	0.39	0.37
$\rho(\Delta c, \Delta y)$	0.79	**0.80**	0.84	0.81	0.83
$\rho(\Delta c, \Delta i)$	0.55	**0.42**	0.46	0.42	0.43
$\rho(\Delta l, \Delta y)$	-0.01	**0.61**	0.56	0.60	0.56
$\rho(\Delta i, \Delta l)$	0.08	**0.92**	0.90	0.91	0.90
TEMPERATURE					
$\mathbb{E}(z)$	9.74	**9.74**	9.74	9.74	9.74
$\sigma(z)$	0.60	**0.61**	0.60	0.61	0.61
$\rho(\theta, \Delta a)$	-0.18	**-0.19**	-0.20	-0.19	-0.19
$\rho(\theta, \Delta y)$	-0.16	**-0.11**	-0.17	-0.21	-0.46
ASSET PRICES					
$\mathbb{E}[R_{ex}^{LEV}]$	7.31	**5.65**	4.29	5.75	6.00
$\sigma(R_{ex}^{LEV})$	19.78	**7.51**	7.04	7.45	7.30
$\rho(\theta, R_{ex}^{LEV})$	-0.32	**-0.12**	-0.14	-0.05	0.14

Notes: This table reports the main moments for the benchmark calibration (specification [1]) and two other model specifications. In model [2], we shut down risk to the depreciation rate of capital, $\sigma_k = 0$. In model [3] and [4], by imposing $\rho(\epsilon_k, \epsilon_\theta) > 0$, temperature volatility shocks are assumed to be positively correlated with depreciation shocks. The levered equity risk premium is defined as $R_{ex}^{LEV} = (1 + \frac{D}{E})(R_t - R_{t-1}^f)$ where financial leverage is imposed by assuming an average debt-to-equity ratio $\frac{D}{E}$ of 1 (see, e.g., Croce, 2014; Hitzemann et al., 2016). Models' entries are obtained from repetitions of small-sample simulations (i.e., averages over 1000 simulations of 100 years). $\mathbb{E}[\cdot]$, $\sigma(\cdot)$, $\rho(\cdot, \cdot)$, and $AC1(\cdot)$ denote mean, volatility, correlation, and first-order autocorrelation, respectively. Means and volatilities are expressed in percentage points. Empirical moments are computed from annual data spanning the period 1950-2015. Additional details on data are provided in Section 3.1.

goes up substantially. The higher the positive correlation between temperature volatility risk and depreciation risk, the stronger is the amplification effect, which increases welfare costs further.

Table 10: Welfare costs of temperature volatility risk

ψ	**[1]** ($\tau_\theta = -0.0215$) (**BC**)	**[2]** ($\rho(\epsilon_k, \epsilon_\theta) = 0.3$)	**[3]** ($\rho(\epsilon_k, \epsilon_\theta) = 1$)
2.00	8.6%	9.7%	11.5%
0.90	3.0%	3.9%	5.4%

Notes: This table reports the welfare costs of temperature volatility shocks for two different IES values in the presence of stochastic depreciation rate of capital. Welfare costs are defined as the percentage increase $\Delta > 0$ in composite consumption ($\tilde{C}$) that the household should receive in every state and at every point in time in order to be indifferent between living in an economy with full risk exposure (i.e., $\sigma_z, \sigma_a, \sigma_x > 0, \sigma_k > 0, \sigma_\theta > 0$) and an economy where temperature volatility risk is shut down. Temperature volatility risk is eliminated by imposing $\tau_\theta = 0$. Specification [1] refers to the benchmark calibration (i.e., $\tau_\theta = -0.0215$) while specification [2] and [3] assume a positive correlation between temperature volatility and depreciation rate shocks (i.e., $\rho(\epsilon_k, \epsilon_\theta) > 0$).

6 Evidence from an Endowment Economy

Using empirical evidence from a bi-variate VAR suggesting that a global temperature shock has a negative effect on consumption growth, Bansal and Ochoa (2011b) develop an endowment economy featuring long-run consumption and temperature risk to compute the welfare costs associated to rising temperatures. In a similar spirit to theirs, we first check whether there is a direct relationship between consumption growth and $TVOL$. The GC test suggests the presence of a negative and significant effect of $TVOL$ on consumption growth for the period 1950-2015 (see Table 11).

Table 11: Granger causality: Consumption growth vs. temperature volatility.

Period	1831-1900	1900-1950	1950-2015
$TVOL \rightarrow \Delta c$	0.609 (+)	0.997 (+)	0.092* (–)
$\Delta c \rightarrow TVOL$	0.566 (+)	0.355 (+)	0.762 (–)

Notes: p-values for the bootstrap test statistics are reported. ** and * denote significance, respectively at the 1 and 5% significance level. The sign of the causality is reported in parentheses. The number of lags is two and it is chosen using Akaike information criterion.

A bi-variate VAR impulse response analysis shows that, two and three years after it occurs, a $TVOL$ shock produces a drop in consumption growth of (approx) 0.4pp. This effect lasts for almost six years (see Figure 11). Based on this empirical evidence, we can account for the direct effect of $TVOL$ shocks on consumption growth in the spirit of Bansal and Ochoa (2011b) and thus test whether $TVOL$ risk still produces non-negligible welfare costs once we abstract from capital and labor decisions. We view this robustness check as a pure quantitative exercise to examine the sensitivity of our results to a different modeling choice. The model is briefly outlined here below.

The representative household is equipped with recursive preferences, as in Epstein and Zin (1989):

$$U_t = \left[(1-\beta)\tilde{C}_t^{1-\frac{1}{\psi}} + \beta\Big(\mathbb{E}_t[U_{t+1}^{1-\gamma}]\Big)^{\frac{1-1/\psi}{1-\gamma}}\right]^{\frac{1}{1-1/\psi}}. \tag{12}$$

The intertemporal budget constraint is:

$$W_{t+1} = (W_t - C_t)R_{c,t+1}, \tag{13}$$

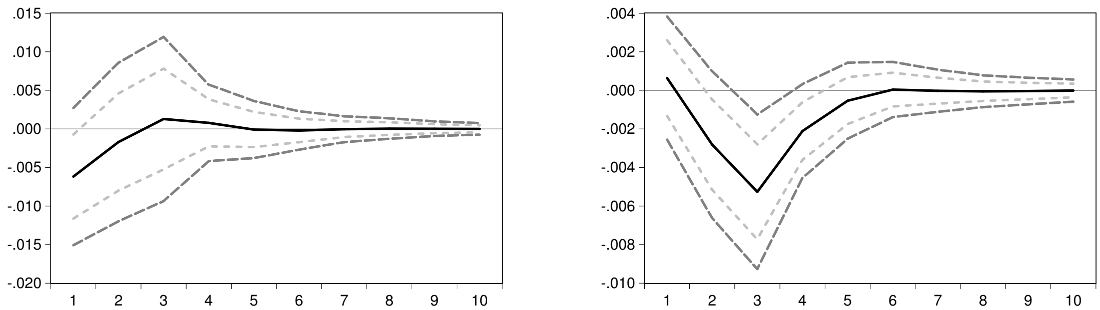
and the log SDF is:

$$m_{t+1} = \theta Log(\delta) - \frac{\theta}{\psi}\Delta(C_{t+1}) + (\theta-1)r_{c,t+1}, \tag{14}$$

where $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$.

Figure 11: Impulse-responses of consumption growth (ΔC) to temperature volatility ($TVOL$) shocks.

Panel A: $TVOL \Rightarrow \Delta C$ (1900-1950) Panel B: $TVOL \Rightarrow \Delta C$ (1950-2015)



Notes: This figure depicts generalized impulse response functions of consumption growth (ΔC) to a one-standard-deviation shock in temperature volatility ($TVOL$). The impulse-response functions (IRFs) are obtained by estimating a bi-variate VAR(2) with a constant. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

Consumption growth and temperature dynamics are represented by the following system

$$
\begin{aligned}
\Delta c_{t+1} &= \mu_c + x_t + x_t^z + \sigma_c \epsilon_{c,t+1} \\
x_t &= \rho_x x_{t-1} + \sigma_x \epsilon_{x,t} \\
x_t^z &= \rho_x^z x_{t-1}^z + \tau_z \sigma_z \epsilon_{z,t} + \tau_\theta \sigma_\theta \epsilon_{\theta,t+1} \\
z_{t+1} &= \mu_z + \rho_z (z_t - \mu_z) + e^{\theta_{t+1}} \sigma_z \epsilon_{z,t+1} \\
\theta_{t+1} &= \rho_\theta \theta_t + \sigma_\theta \epsilon_{\theta,t+1},
\end{aligned}
\tag{15}
$$

where the shocks $\epsilon_{c,t+1}$, $\epsilon_{x,t}$, $\epsilon_{\theta,t+1}$ and $\epsilon_{z,t+1}$ are independent of each other and are each distributed i.i.d. standard normally. The unconditional expected growth rate of consumption is μ_c. In this economy, short-run consumption shocks are induced by $\epsilon_{c,t}$, whereas $\epsilon_{x,t}$, $\epsilon_{\theta,t}$, and $\epsilon_{z,t}$ indicate long-run shocks affecting the persistent stochastic components in consumption growth x_t and x_t^z. The persistence of long-run consumption and temperature-related productivity shocks is measured by ρ_x and ρ_x^z, respectively. In this framework, the two distinct long-run components for consumption and temperature shocks feature the same timing of those innovations. As for long-run consumption shocks, temperature related shocks impact consumption growth with one lag, as suggested by the data.

To calibrate the model we again rely on the bi-variate VAR estimation results and set the parameters to match the consumption dynamics from the data (i.e., consumption growth volatility). The effect of a $TVOL$ shock on consumption growth is depicted in Figure 11. It is rather persistent and leads to a drop in consumption growth by more than 0.4pp after three years. We therefore assume in the model that a $TVOL$ shock has a lagged effect on consumption growth. By imposing τ_θ = -0.218 and $\rho_x^z = 0.6$, we let the endowment economy produce a drop of 0.4pp in consumption growth following a $TVOL$ shock. As suggested by our bivariate analysis, the negative impact of consumption growth produced by the model lasts for several years.[20] The standard parameters β, γ, and ψ are taken from Bansal and Ochoa (2011b) and are set to 0.988, 10, and 1.5 respectively. Except for the IES, these are also the values used in our production framework. The parameters governing the consumption process, μ_c and σ_c, are calibrated to match the unconditional mean and volatility of consumption growth, which implies values of 0.0256 and 0.02, respectively. Since consumption growth exhibits a high autocorrelation in the data (0.47), we set the persistence of long-run consumption shocks ϵ_x to a high value of 0.99. The standard deviation of these long-run shocks, σ_x, is assumed to be a small fraction of the volatility of short-run consumption shocks, i.e. $\sigma_x = 0.044 \cdot \sigma_c$ as in Bansal and Yaron (2004). Naturally, the parameters governing the evolution of UK temperature remain as in Section 5.

Simulated moments and welfare costs are displayed in Table 12. As in the data, our benchmark endowment economy featuring $TVOL$ effects (specification [1]) produces a negative correlation between $TVOL$ and both consumption growth and the equity market return. Compared to an economy with no $TVOL$ effects (specification [2]), this additional source of risk produces a small equity risk premium of 3bps. On the other hand, it entails sizeable welfare costs. These amount to 13% of lifetime consumption and are comparable with the magnitude found in our production economy. Note that in this endowment economy, welfare costs are higher as we match the volatility of consumption growth which is larger compared to the one obtained in our production economy framework. This robustness test shows that the substantial welfare costs from $TVOL$ risk are still obtained when modelling the interaction between consumption and temperature dynamics in an endowment economy that abstracts from labor and investment decisions.

7 Concluding Remarks

We show novel empirical evidence that increasing uncertainty about temperature variations (i.e., temperature volatility) negatively (positively) affects aggregate productivity, economic activity, and asset valuations in the UK after (before) 1950. We further show that temperature volatility risk has carried a positive risk premium in the UK equity market over the past decades. In summary,

[20]For space consideration, the model-implied impulse response of consumption growth to a $TVOL$ shock is not reported but is available from the authors upon request.

Table 12: Model vs (UK) data: Macroeconomic quantities, asset prices, and welfare

Variable	**Data**	**BC**	$\tau_\theta = 0$
		[1]	**[2]**
MACRO QUANTITIES			
$\mathbb{E}(\Delta c)$	2.56	2.57	2.57
$\sigma(\Delta c)$	2.05	2.08	2.02
TEMPERATURE			
$\mathbb{E}(z)$	9.74	9.75	9.75
$\sigma(z)$	0.60	0.63	0.63
$\rho(\theta, \Delta c)$	-0.09	-0.17	0.00
ASSET PRICES			
$\mathbb{E}(R_{ex}^{LEV})$	7.31	1.71	1.68
$\sigma(R_{ex}^{LEV})$	19.78	2.96	2.94
$\rho(\theta, R_{ex}^{LEV})$	-0.32	-0.06	0.00
WELFARE			
$LOG(U/C)$	-	-2.29	-2.16
Δ	-	13.2%	-

Notes: This table reports the main moments for the benchmark "endowment economy" calibration (specification [1]) and the endowment economy with no temp-vol risk. (specification [2]). Models' entries are obtained from repetitions of small-sample simulations (i.e., averages over 1000 simulations of 100 years). $\mathbb{E}[\cdot]$, $\sigma(\cdot)$, $\rho(\cdot,\cdot)$, and $AC1(\cdot)$ denote mean, volatility, correlation, and first-order autocorrelation, respectively. Means and volatilities are expressed in percentage points. Empirical moments are computed from annual data spanning the period 1950-2015. Additional details on data are provided in Section 3.1.

our novel evidence suggests that the adverse effects of climate change belong to the post-war era.

We suggest a model for a production economy featuring long-run macro and temperature volatility risk to explain these empirical findings. In the model temperature volatility shocks (i) dampen productivity growth, the growth rate of key macro-aggregates, and equity valuations and (ii) command a positive risk premium, consistent with post-war UK data. Our model is then used to quantify the temperature volatility-related adverse effects on expected growth and welfare. The associated welfare costs are substantial, and positive temperature volatility shocks reduce long-run growth prospects. When temperature volatility shocks are associated with faster depreciation of capital (through increasing occurrence of natural disasters), welfare costs are exacerbated. However, if the economy immediately reacts to changes in temperature volatility by means of long-run technology improvements, such costs can be totally offset or at least mitigated.

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A Empirical Methodology

In this section we briefly describe the methodology employed to examine the relationship between temperature volatility, aggregate productivity, macro quantities (such as output, consumption, and investment), and financial variables. In Section A.1, we first introduce the Granger Causality (GC) test which we use to examine the causality between TFP growth and temperature volatility over the period 1800-2015. In Section A.2, we review the "generalized" VAR framework as proposed by Pesaran and Shin (1998). A generalized approach is used to obtain impulse responses of macroeconomic and financial aggregates that do not depend on the ordering of the variables in the system. This property is important for our analysis given that the there is uncertainty about the true causal ordering of the variables. Moreover, for robustness purposes, we describe the local projections methodology of Jordà (2005) and Jordà (2009), which does not require the specification of a multivariate dynamic system and is robust to a potential misspecification of the data generating process.

A.1 *Granger Causality Test*

A time series variable x is said to Granger-cause a time series variable y, if y can be better predicted using the past values of both x and y than by just using the past values of y alone. Tests of Granger Causality (GC) can be based on a vector autoregressive model, a multivariate MA-representation, or an OLS regression.[21] In this paper we choose the last approach.[22] The test is performed by regressing (separately) each variable on lagged values of itself and the other:

$$
\begin{aligned}
y_t &= \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i} + \sum_{i=1}^{p} \gamma_i x_{t-i} + u_t \\
x_t &= \beta_0 + \sum_{i=1}^{p} \beta_i x_{t-i} + \sum_{i=1}^{p} \gamma_i y_{t-i} + u_t
\end{aligned}
$$

The simple F-test is used to examine the null hypothesis $H_0 : \gamma_1 = \gamma_2 = \cdots = \gamma_p = 0$. A rejection of the null hypothesis implies the presence of GC. Obviously, all variables have to be stationary to avoid "spurious" results. The choice of lag length p is important for this test, and we determine the appropriate maximum lag length for the variables using the Schwartz Information Criterion (SIC). To get time-varying estimates, we search for causality over different sub-periods using the modified bootstrap test suggested by Balcilar et al. (2010, 2014). As demonstrated for example by Mantalos et al. (2000), the residual-based bootstrap method improves the critical values and the true size of the test.

A.2 *Generalized Impulse Response Functions*

Consider the m-dimensional VAR(p) model:

$$
y_t = \sum_{i=1}^{p} \Phi_i y_{t-1} + \varepsilon_t, \tag{A.1}
$$

[21] See Hamilton (1994) for a review of such tests.

[22] We also checked the GC results running a VAR and the results are very similar to the regressions.

where ε_t is an *iid* error term with zero mean and covariance matrix Σ. Assuming weak stationarity, y_t can be rewritten via an infinite moving average representation:

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \tag{A.2}$$

where the $m \times m$ coefficient matrix A_i is obtained using the following recursive relation:

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}, \;\; i = 1, 2, \cdots \tag{A.3}$$

Let Ω_{t-1} denote the information set available at the beginning of time t. Then Pesaran and Shin (1998) define the generalized impulse response function (GIRF) of y_t to the shock δ_i at horizon n as

$$GIRF_y(n, \delta_i, \Omega_{t-1}) = E(y_{t+n}|\varepsilon_{it} = \delta_i, \Omega_{t-1}) - E(y_{t+n}|\Omega_{t-1}), \tag{A.4}$$

where Ω_{t-1} and δ_i represent the information set and the shock to the ith equation that the expectations are conditioned on, respectively. Ω_{t-1} consists of the matrix of initial values needed to compute the conditional expectations in (A.4).[23] Assuming that ε_t has a multivariate normal distribution, we have

$$E(\varepsilon_t|\varepsilon_{it} = \delta_i) = (\sigma_{1i}, \sigma_{2i}, \cdots, \sigma_{mi})' \sigma_{ii}^{-1} \delta_i = \Sigma e_i \sigma_{ii}^{-1} \delta_i, \tag{A.5}$$

where e_i is an $m \times 1$ selection vector with the ith element equal to 1 and all other elements equal to 0. The $m \times 1$ vector of the unscaled and scaled GIRF are given by

$$\left(\frac{A_n \Sigma e_i}{\sqrt{\sigma_{ii}}}\right)\left(\frac{\delta_i}{\sqrt{\sigma_{ii}}}\right), \;\; n = 0, 1, 2, \cdots \tag{A.6}$$

$$\Psi_i^g(n) = \sigma_{ii}^{-\frac{1}{2}} A_n \Sigma e_i, \;\; n = 0, 1, 2, \cdots, \tag{A.7}$$

where (A.7) is obtained from (A.6) by setting $\delta_i = \sqrt{\sigma_{ii}}$. Central to the GIRF is δ, the hypothesized vector of shocks δ_i for $i = 1, ..., p$. When one variable is shocked, other variables also vary as implied by the matrix structure of covariances in the system. The impulse responses emerging from the GIRF are unique and invariant to the ordering of the variables of the system (Pesaran and Shin, 1998).

A.3 *Local projection impulse response function*

Jordà (2005) suggests to estimate impulse response functions (IRFs) without prior recourse to an auxiliary VAR model. The author applies insights from the forecasting literature to the issue of estimating IRFs. Jordà (2005) proposes to project y_{t+n} onto a linear space generated by $(y_{t-1}, \cdots, y_{t-p})'$ to estimate the local projection impulse response function (LPIRF) of y_{t+n} to a shock δ_i as

$$y_{t+n} = \alpha^n + P_1^n y_t + \cdots + P_p^n y_{t-p+1} + u_{t+h}, \;\; n = 1, \cdots, H; \;\; P_1^0 = I. \tag{A.8}$$

[23] In our analysis, for robustness check, we estimate also a Bayesian VAR (BVAR) using the Minnesota prior. Using the Bayesian approach, we compute the generalized impulse responses simply by averaging out the history uncertainties, future uncertainties, and parametric uncertainties.

By construction, P_1^n can be interpreted as the response of y_{t+n} to a reduced-form disturbance in period t:

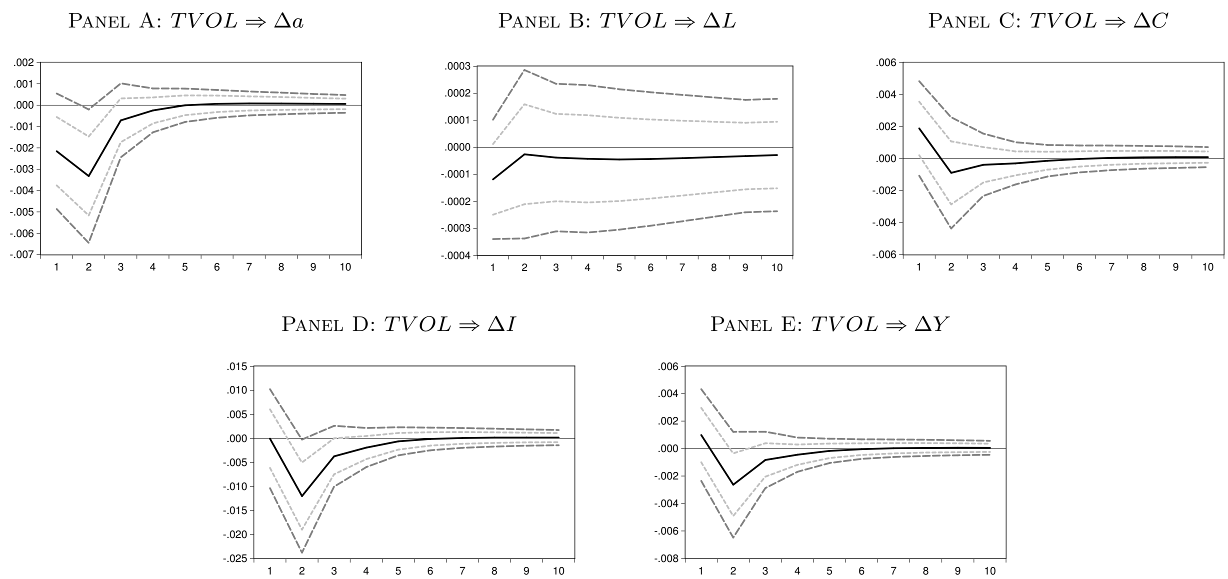
$$LPIRF_y(n, \delta_i) = P_1^n = E(y_{t+n}|e_i = \delta_i, y_t, \cdots, y_{t-p}) - E(y_{t+n}|y_t, \cdots, y_{t-p}), \quad n = 1, \cdots, H. \quad \text{(A.9)}$$

Note that when the data generating process is the VAR model in (A.1), the impulse responses calculated by local projections are equivalent to the impulse responses obtained with VAR. Further details on this point can be found in Jordà (2005).

B Robustness Tests

B.1 *Cholesky Identification*

Figure B.1: Impulse response of macro-variables to $TVOL$ shocks (1950-2015): Cholesky Identification.

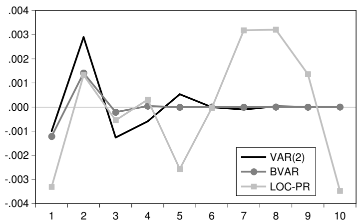


Notes: This figure depicts orthogonalized impulse responses of TFP growth (Δa), labor growth (ΔL), consumption growth (ΔC), investment growth (ΔI), and output growth (ΔY) to a one-standard-deviation shock in temperature volatility ($TVOL$). The orthogonalization is performed via a Cholesky decomposition. Impulse-response are obtained by estimating a VAR(1) with the six variables (in this order): $TVOL$, Δa, ΔI, ΔC, ΔY, ΔL, and a constant. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

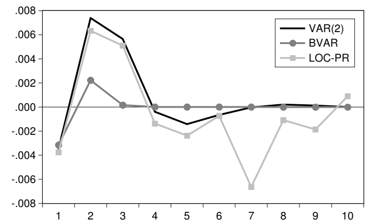
B.2 *Different VAR Models*

Figure B.2: Impulse-responses of TFP growth to $TVOL$ shocks: Evidence from three different VAR models

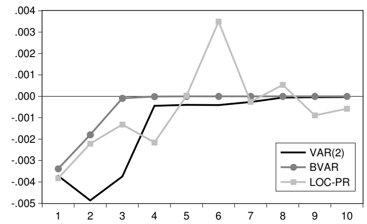
Panel A: $TVOL \Rightarrow \Delta a$ (1800-1900)



Panel B: $TVOL \Rightarrow \Delta a$ (1900-1950)



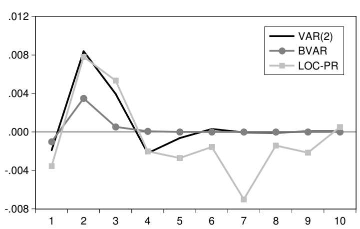
Panel C: $TVOL \Rightarrow \Delta a$ (1950-2015)



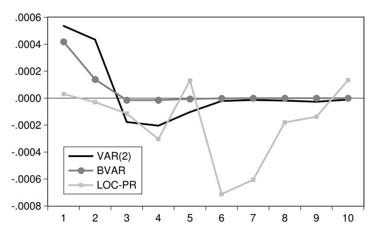
Notes: This figure depicts generalized impulse response functions (IRFs) of TFP growth (Δa) to a one-standard-deviation shock in temperature volatility ($TVOL$). Solid black line: IRFs of VAR with two lags (VAR(2)). Dark gray line with circles: IRFs of Bayesian VAR (BVAR), estimated using Minnesota prior, with one lag. Light gray line with squares: local projection IRFs (LPIRF) with lag length determined by the Akaike Information Criterion (AIC), assuming a maximum lag length of 2. All estimations include a constant. Three different periods are considered: (i) 1800-1900 (PANEL A); (ii) 1900-1950 (PANEL B); (iii) 1950-2015 (PANEL C).

Figure B.3: Impulse-responses of macro-variables to $TVOL$ shocks (1900-1950): Evidence from three different VAR models

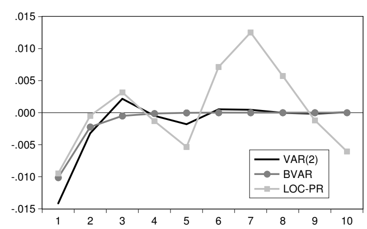
Panel A: $TVOL \Rightarrow \Delta a$



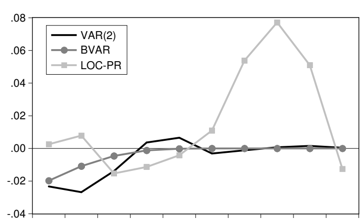
Panel B: $TVOL \Rightarrow \Delta L$



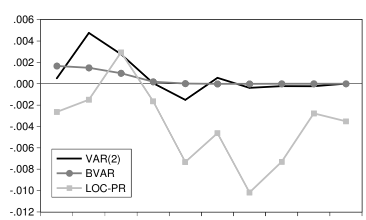
Panel C: $TVOL \Rightarrow \Delta C$



Panel D: $TVOL \Rightarrow \Delta I$

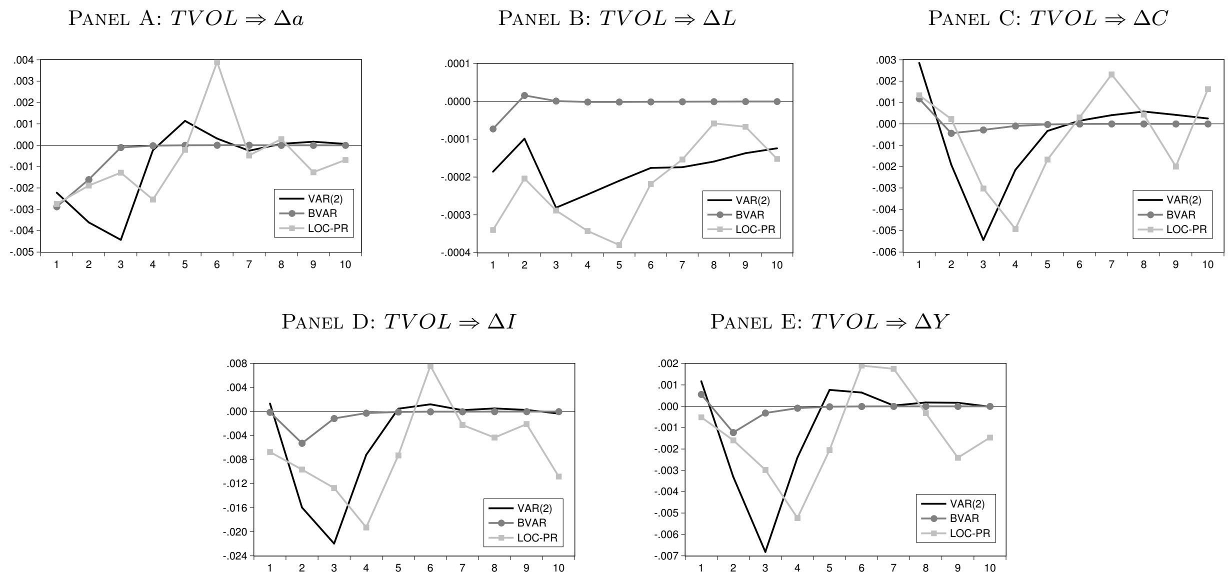


Panel E: $TVOL \Rightarrow \Delta Y$



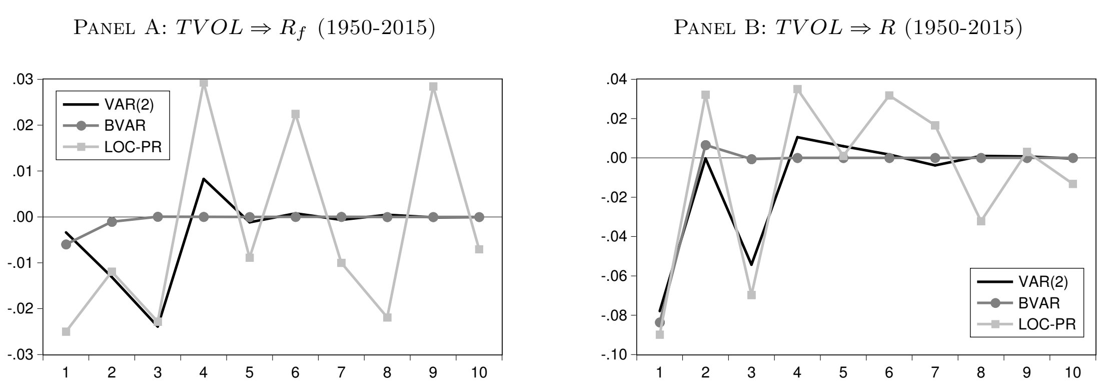
Notes: This figure depicts generalized impulse response functions (IRFs) for TFP growth (Δa), labor growth (ΔL), consumption growth (ΔC), investment growth (ΔI), and output growth (ΔY) with respect to a one-standard-deviation shock in temperature volatility ($TVOL$). Solid black line: IRFs of VAR with two lags (VAR(2)). Dark grey line with circles: IRFs of Bayesian VAR (BVAR), estimated using Minnesota prior, with one lag. Light grey line with squares: local projection IRFs (LPIRF) with lag length determined by the Akaike Information Criterion (AIC), assuming a maximum lag length of 2. All estimations include a constant.

Figure B.4: Impulse-responses of macro-variables to $TVOL$ shocks (1950-2015): Evidence from three different VAR models.



Notes: This figure depicts generalized impulse response functions (IRFs) for TFP growth (Δa), labor growth (ΔL), consumption growth (ΔC), investment growth (ΔI), and output growth (ΔY) with respect to a one-standard-deviation shock in temperature volatility ($TVOL$). Solid black line: IRFs of VAR with two lags (VAR(2)). Dark grey line with circles: IRFs of Bayesian VAR (BVAR), estimated using Minnesota prior, with one lag. Light grey line with squares: local projection IRFs (LPIRF) with lag length determined by the Akaike Information Criterion (AIC), assuming a maximum lag length of 2. All estimations include a constant.

Figure B.5: Impulse-responses of the risk-free rate (R_f) and the equity return (R) to $TVOL$ shocks: Evidence from three different VAR models.

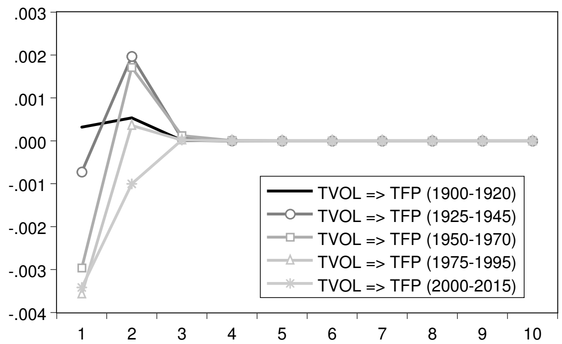


Notes: This figure depicts generalized impulse response functions for the risk-free rate (R_f) and the equity return (R) to a one-standard-deviation shock in temperature volatility ($TVOL$). Solid black line: IRFs of VAR with two lags (VAR(2)). Dark grey line with circles: IRFs of Bayesian VAR (BVAR), estimated using Minnesota prior, with one lag. Light grey line with squares: local projection IRFs (LPIRF) with lag length determined by the Akaike Information Criterion (AIC), assuming a maximum lag length of 2. All estimations include a constant.

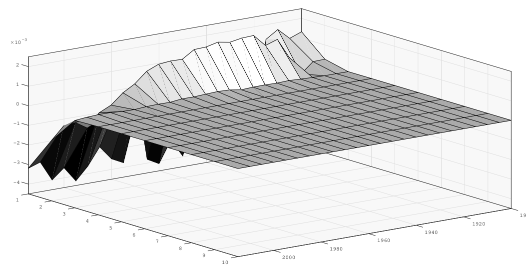
B.3 *“Time-Varying” VAR*

Figure B.6: Dynamics Impulse-Responses of TFP growth (Δa) to $TVOL$ shocks

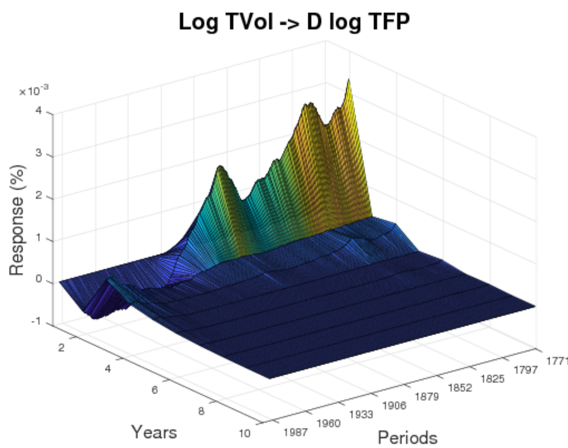
Panel A



Panel B



Panel c

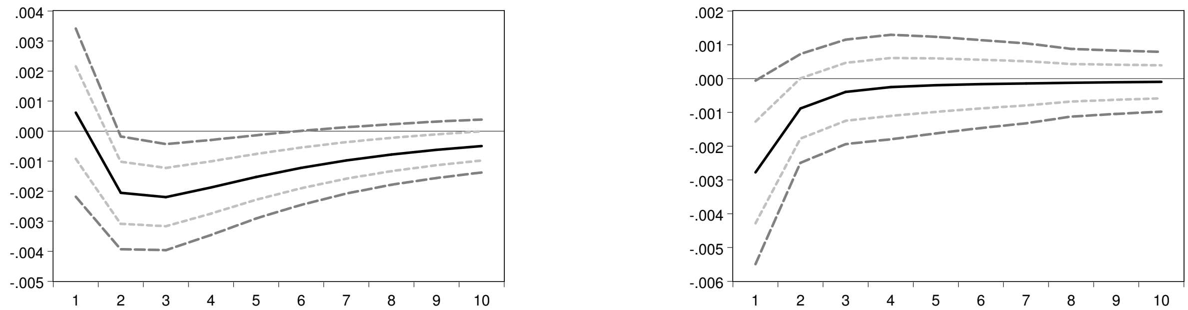


Notes: This figure depicts the dynamics of the impulse response of TFP growth (Δa) to $TVOL$ shock. In Panels (A) and (B) IRFs are estimated from a constant parameter Bayesian VAR model (one lag) estimated with a rolling window or 50 years. Impulse responses in Panel A represent 20 years response averages for different sub-periods. In Panel (C) IRFs are estimated from a time-varying parameter vector autoregressive (i.e., TVP-VAR). The TVP-VAR includes our measure of temperature volatility, the temperature level (as control) and the TFP growth and has been estimated using annual data for the period 1760-2015.

B.4 *A Different Proxy for Temperature Volatility: Inter-Annual TVOL*

Figure B.7: Impulse-responses of TFP growth (Δa) to a Temp-Vol Shock: Inter-Annual Temperature Volatility ($TVOL^i$)

Panel A: $TVOL^i \Rightarrow \Delta a$ (1950-2015, 10-year rolling window) Panel B: $TVOL^i \Rightarrow \Delta a$ (1950-2015, 15-year rolling window)

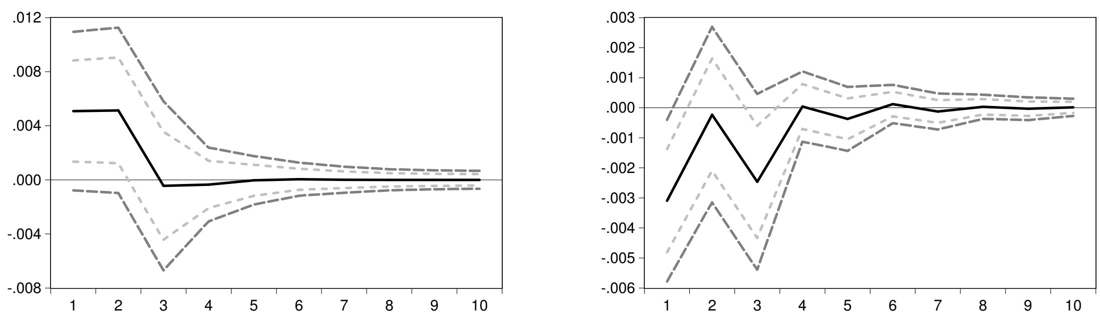


Notes: This figure depicts generalized impulse responses of TFP growth (Δa) to a one-standard-deviation shock in inter-annual temperature volatility ($TVOL^i$). $TVOL^i_t = |\sigma_t(n) - \bar{\sigma}_{1659-1759}|$, for $t = 1950, ..., 2015$, where $\sigma_t(n)$ represents the standard deviation computed using a rolling window of length n years, and $\bar{\sigma}_{1659-1759}$ is the average inter-annual standard deviation observed in the pre-industrial revolution period. n is equal to 10 (Panel A) and 15 (Panel B). Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

B.5 *Rainfall Volatility*

Figure B.8: Impulse-responses of TFP growth (Δa) to a rainfall volatility ($RVOL$) shock.

Panel A: $RVOL \Rightarrow \Delta a$ (1900-1950) Panel B: $RVOL \Rightarrow \Delta a$ (1950-2015)

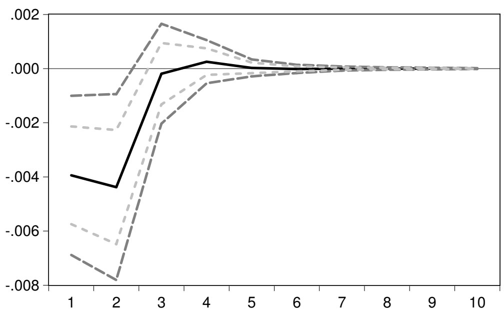


Notes: This figure depicts generalized impulse response of TFP growth (Δa) to a one-standard-deviation shock in rainfalls volatility ($RVOL$). Rainfalls volatility is represented by the intra-annual volatility, computed in each year as standard deviation of monthly observations. Monthly rainfall observations are collected from several climate stations operating in UK for the period 1900-2015 (Source: https://www.metoffice.gov.uk/public/weather/climate-historic). To minimize contamination by local meteorological and instrumental conditions, we amalgamate all independent stations into one single average rainfall series. Impulse-responses are obtained by estimating a bi-variate VAR(1). A constant is included. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

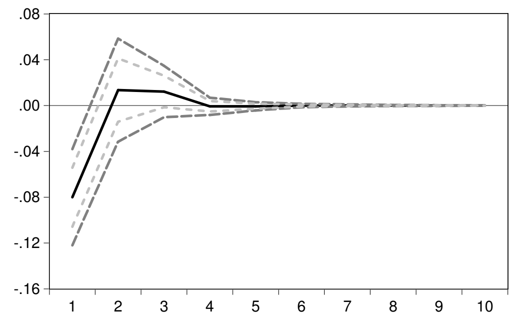
B.6 *Controlling for equity market dynamics*

Figure B.9: Impulse-responses of TFP growth (Δa) and equity return (R) to $TVOL$ shocks

Panel A: $TVOL \Rightarrow \Delta a$ (1950-2015)



Panel B: $TVOL \Rightarrow R$ (1950-2015)



Notes: This figure depicts generalized impulse response functions (GIRFs) of TFP growth (Δa) and the equity return (R) with respect to a one-standard-deviation shock in temperature volatility ($TVOL$). Impulse-responses are obtained by estimating a tri-variate VAR(1) with a constant. Solid "black" lines: IRFs. Dashed "dark grey" line: 90% confidence bands. Dashed "light grey" line: 68% confidence bands.

C Additional Cross-Sectional Tests

Table C.1: Risk Premium of Temp-Vol Shocks: Pre-2007

Panel A:		Risk Premia
Fama-McBeth	Intercept	$\lambda_{\Delta TVOL}$
UK12	18.720	0.455
	[5.886]	[1.486]
UK40	13.917	0.186
	[4.600]	[1.257]
EU100	14.573	0.125
	[3.420]	[0.581]
Panel B:		**Risk Premia**
Avg Returns	Intercept	$\lambda_{\Delta TVOL}$
UK12	18.720	0.455
	[16.356]	[5.123]
UK40	13.917	0.186
	[14.042]	[2.048]
EU100	14.573	0.125
	[36.574]	[1.226]

Notes: This table reports the estimates of the temp-vol risk premium. Test assets are: (i) twelve UK portfolios (UK12) with six portfolios formed on size and book-to-market and six portfolios formed on size and momentum (Source: Stefano Marmi's Data Library) (ii) 40 UK portfolios (40UK) with 10 portfolios formed on price-earnings, 10 portfolios formed on price to book, 10 portfolios formed on price to cash flow, and 10 portfolios formed on gross profit margin (Source: Stefano Marmi's Data Library) (iii) 100 EU portfolios (100EU) with 25 portfolios formed on size and book-to-market, 25 portfolios formed on size and operating profitability, 25 portfolios formed on size and investment, and 25 portfolios formed on size and momentum (Source: Kenneth R. French's Data Library). Data on UK (EU) portfolios run from 1989 (1991) to 2007. The t-statistics in square brackets for the risk premium are adjusted for autocorrelation and heteroskedasticity following Newey and West (1987).

Table C.2: Risk Premium of Temp-Vol Shocks (GREAT RECESSION)

Panel A:			Risk Premia		
Fama-McBeth	Intercept	$\lambda_{\Delta mkt}$	$\lambda_{\Delta a}$	λ_{GR}	$\lambda_{\Delta TVOL}$
UK12	7.185	3.623	-0.090	-0.159	0.518
	[0.810]	[0.380]	[-0.325]	[-1.139]	[2.315]
UK40	8.043	3.392	0.287	-0.158	0.137
	[2.641]	[0.635]	[0.926]	[-1.563]	[1.060]
EU100	1.168	9.256	0.689	-0.338	0.261
	[0.215]	[1.364]	[2.522]	[-2.794]	[1.610]
Panel B:			**Risk Premia**		
Avg Returns	Intercept	$\lambda_{\Delta mkt}$	$\lambda_{\Delta a}$	λ_{GR}	$\lambda_{\Delta TVOL}$
UK12	7.185	3.623	-0.090	-0.159	0.518
	[1.413]	[0.850]	[-0.517]	[-2.411]	[2.832]
UK40	8.043	3.392	0.287	-0.158	0.137
	[5.101]	[2.028]	[1.936]	[-2.371]	[1.995]
EU100	1.168	9.256	0.689	-0.338	0.261
	[0.236]	[1.989]	[3.180]	[-3.644]	[2.473]

Notes: This table reports the estimates of the temp-vol risk premium. Test assets are: (i) twelve UK portfolios (UK12) with six portfolios formed on size and book-to-market and six portfolios formed on size and momentum (Source: Stefano Marmi's Data Library) (ii) 40 UK portfolios (40UK) with 10 portfolios formed on price-earnings, 10 portfolios formed on price to book, 10 portfolios formed on price to cash flow, and 10 portfolios formed on gross profit margin (Source: Stefano Marmi's Data Library) (iii) 100 EU portfolios (100EU) with 25 portfolios formed on size and book-to-market, 25 portfolios formed on size and operating profitability, 25 portfolios formed on size and investment, and 25 portfolios formed on size and momentum (Source: Kenneth R. French's Data Library). GR represents a dummy for the 2008-2009 Great Recession. Data on UK (EU) portfolios run from 1989 (1991) to 2016. The t-statistics in square brackets for the risk premium are adjusted for autocorrelation and heteroskedasticity following Newey and West (1987).