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**Article**

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# Time-heterogeneous impacts of global temperature cycle on world business cycle

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## ABSTRACT

We study the statistical relationship between the world business cycle and the global temperature cycle. To amplify the signal-to-noise ratio, we estimate a two-state latent dynamic process from the original data using the endogenous regime-switching methodology. Subsequently, we apply a time-varying structural VAR analysis to identify the time-heterogeneous relationship between the extracted latent factors. Our findings provide empirical evidence that the global mean temperature cycle has a negative impact on the world business cycle during super El Niño periods, which are characterized by relatively high temperature variance records given the past information.

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Climate change; global temperature anomaly; world business cycle; structural VAR model



## JEL CLASSIFICATION

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## 1. Introduction

The economic consequences of climate change are a central issue for climate economists. It is widely recognized that climate change negatively impacts national economies through extreme weather events, loss of arable land, and rising sea levels. A substantial body of literature has examined the relationship between climate change and economic growth, with efforts to quantify its economic costs. Ideally, these impacts should be analyzed separately from both long-term and short-term perspectives. Nevertheless, such analyses are often constrained by the limited availability of time-series data and the absence of suitable econometric methodologies. Despite these obstacles, accurately estimating the economic costs of climate change continues to be a matter of paramount importance for governments, policymakers, and private sector stakeholders.

Among the various approaches available, this study addresses two key econometric issues to examine the short-run statistical relationship between world economic activity and global temperature: the time-heterogeneous impacts of climate change and the issue of measurement error. First, the relationship between world economic activity and temperature is unlikely to be time-homogeneous. It is well established that fluctuations in global temperature have historically been closely linked to outcomes in weather-dependent sectors, particularly agriculture. In the early stages, rising global temperatures would reduce agricultural productivity, driving up product prices, increasing inflationary

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pressures, and lowering labor productivity. These factors, in turn, could slow economic growth and negatively impact the manufacturing sector.

Moreover, the nonlinear relationship between annual average temperature and economic output has been explored in the literature (Schlenker & Roberts, 2009; Burke et al., 2015, *inter alia*). The effects of temperature fluctuations vary by country, depending on the average and variance of temperature experienced. For instance, rising temperatures may benefit high-latitude countries while negatively impacting those in low-latitude regions. Consequently, the overall effect of global climate events on the world economy is largely shaped by the geographic distribution of wealthier nations, such as the G-7. Importantly, the composition of these wealthy nations has shifted significantly over the past 150 years, indicating that the economic consequences of global climate change have also evolved over time.

Second, both economic and temperature data are susceptible to measurement errors and noise, complicating the data collection process. Specifically, generating the national consumption data involves aggregating thousands of household survey responses to represent the entire population. This process is not only costly but also prone to biases, including selection and response biases, which can compromise the quality of the economic data. Moreover, temperature data may be affected by uncertainties related to the timing of measurements and the representativeness of measurement locations. Additionally, irregular fluctuations in both global temperature and economic activity introduce non-systematic variations, further complicating the analysis. As a result, the true underlying relationship between world economic activity and global temperature may be obscured by these measurement errors, noise, and idiosyncratic fluctuations.

The existing literature has primarily focused on examining the time-invariant economic impacts of local temperature on the country-level real GDP while addressing the issue of omitted variable bias. Researchers have typically employed cross-sectional or panel fixed-effect regression models at the country or regional level, utilizing annual data Dell et al. (2012), Hsiang et al. (2013), Burke et al. (2015), Hsiang (2016), Auffhammer (2018), Kalkuhl and Wenz (2020), Newell et al. (2021), Chang et al. (2023), and Meierrieks and Stadelmann (2024). These models often rely on temporal aggregation or first differencing over longer periods to distinguish permanent effects from transitory effects. However, they would provide only an overall temperature effect for the sample period, obscuring the time-heterogeneous impacts of climate change. Utilizing the advanced very high-resolution radiometers aboard the National Oceanic and Atmospheric Administration's afternoon-viewing satellites, meanwhile, Richmond et al. (2007) construct a Net Primary Production (NPP) metric, which measures the energy used by plants for storage, growth, and reproduction.<sup>1</sup> Coupled with real GDP, labor, and capital data, they estimate panel cointegration and panel error correction models based on an extended Cobb-Douglas production function, finding that a one percent increase in NPP raises real GDP by 0.13%.

In contrast to existing studies, we focus on identifying the time-heterogeneous short-run relationship between the world business cycle and the global temperature cycle on a global scale within a time-series framework. Utilizing the endogenous regime-switching methodology by Chang et al. (2017), we first conduct a descriptive analysis to identify the

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<sup>1</sup>Detailed information for AVHRR/NOAA is available here: [https://www.class.noaa.gov/data\\_available/avhrr/index.htm](https://www.class.noaa.gov/data_available/avhrr/index.htm)

cyclical behaviors in world GDP growth rates and global temperature anomalies, while also removing idiosyncratic fluctuations from these variables. Note that measurement or idiosyncratic errors would only impact the short-run relationship, which is the primary focus of our study. To account for time heterogeneity in the relationship between the world business cycle and the global temperature cycle, we then employ a time-varying bivariate structural VAR model.

The empirical findings of our analysis provide significant economic implications. While conventional statistical tests suggest a weak relationship between world economic activity and global temperature by rejecting the null hypothesis of their linkage, our approach reveals an interesting story. Specifically, we find that the global mean temperature has negatively impacted world economic activity during super El Niño periods, with this time-heterogeneous relationship identified through an amplified signal-to-noise ratio in the original process. Our estimation results confirm a time-heterogeneous relationship between the world business cycle and the global mean temperature cycle, which is consistent with existing climate economics literature (Nam, 2021).

The remainder of the paper is organized as follows. [Section 2](#) provides detailed information about the world GDP and temperature data. Specifically, we explain the imputation of the world GDP growth rate to construct a measure of world economic activity and the extraction of the stationary component from global temperature anomaly distributions over the past 150 years. In [Section 3](#), we present a descriptive analysis of the cyclical behavior of the original process using the endogenous regime-switching approach by Chang et al. (2017). [Section 4](#) provides a regression analysis that accounts for time heterogeneity, and we conclude with [Section 5](#). The appendix includes a robustness check for the imputation method discussed in [Section 2](#).

## 2. Data

In this section, we provide detailed information on the world economic activity and global temperature dynamics. It is important to note that both economic and temperature data exhibit strong seasonality. Utilizing higher frequency data, such as quarterly or monthly observations, could introduce undesirable seasonality effects, potentially leading to spurious causality. In this case, statistically significant relationships observed at higher frequencies may be driven by omitted variables or seasonal cycles, rather than reflecting true causality between economic and temperature data. To mitigate these issues, we rely on yearly observations for both world economic activity and global temperature, which helps in accurately identifying the relationship of interest.

### 2.1. World economic activity

We measure the world economic activity using the world GDP growth rate. The literature analyzing the impact of global mean temperature on world economic production typically employs country-level GDP panel data spanning only 50–60 years (Burke et al., 2015; Dell et al., 2012; Kalkuhl & Wenz, 2020; Newell et al., 2021, *inter alia*). However, the endogenous regime-switching model, developed by Chang et al. (2017), necessitates a reasonably large sample for the time-series data to ensure efficient and stable parameter estimation. Shorter time spans, such as a 70-year sample period, would result in

inefficient and unreliable estimates. To ensure robust and reliable estimates from the endogenous regime-switching model, it is essential to utilize long-term time-series GDP data that aligns with the time span of global temperature anomaly data. In this context, we adopt an imputation method to extend the world GDP growth rate data to cover approximately 150 years.

The data source providing the longest annual observations is the Maddison Project Database (Bolt & Van Zanden, 2014).<sup>2</sup> Specifically, this source provides world GDP level data for the years 1870, 1900, 1913, 1940, and 1951–2010. Another source for global GDP data is the Total Economy Database (TED), which offers yearly observations from 1950 to 2015.<sup>3</sup> Both data sources report world GDP in millions of 1990 US dollars (converted at Geary-Khamis PPPs). To construct world GDP data with a long time span, we combine both data sources using the Friedman-Chow-Lin type imputation method (Chow & Lin, 1971, 1976; Friedman, 1962).

Specifically, we scale the log of the sum of available country-level GDP data and linearly interpolate the missing data between the four available points (1870, 1900, 1913, 1940) to cover the period up to 1949. For the period after 1950, we use world GDP data from the TED source (1950–2015). By calculating the first difference for the imputed data from 1870 to 1949 and the log difference for the TED data from 1950 to 2015, we obtain the world GDP growth rate for the period 1870–2015. The list of available country-level GDP on the Maddison website is provided in Table 1.

The detailed procedure for the Friedman-Chow-Lin type imputation strategy is described as follows. Let  $x_t$  represent the logarithm of the sum of available country-level GDP at time  $t$ , and let  $y_t$  denote the logarithm of world GDP, available only for the years 1870, 1900, 1913, and 1940. The missing data points for the intervening years are linearly interpolated using the following equation:

$$y_t^j = s_t^i * x_t^i + \left( \frac{j}{m_i + 1} \right) (y_{t^i} - s_t^i * x_{t^i}^i) \quad (1)$$

where  $i = 1, 2, 3, 4$  is the period index,  $j = 0, 1, 2, \dots, m_i$  represents the interpolation step with  $m_1 = 29, m_2 = 12, m_3 = 26$ , and  $m_4 = 9$ , and  $t \in [t^i, t^i] = [1870, 1900), [1900, 1913), [1913, 1940), [1940, 1950)$ , corresponding to each

**Table 1.** List of available countries over different periods.

Period	Available Countries
1870 to 1899	Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Sweden, Switzerland, UK, Portugal, Spain, Australia, New Zealand, Canada, USA, Brazil, Chile, Uruguay, Indonesia, Japan, Sri Lanka.
1900 to 1912	24 above + India, Argentina, Colombia, Mexico, Peru, Venezuela.
1913 to 1939	30 above + Taiwan, Greece, 14 small WEC (Western European Countries).
1940 to 1949	33 above + Turkey, Nicaragua, Honduras, Guatemala, El Salvador, Ecuador, Cuba, Ireland, Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Russia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan.

<sup>2</sup><http://www.ggdnet/maddison/maddison-project/data.htm>

<sup>3</sup>The Conference Board Total Economy Database, September 2015, <http://www.conference-board.org/data/economydatabase/>

period index. The scale coefficients  $s_t^i$  are calculated as step function values of 1.06, 1.03, 1.02, and 1.01 for the respective time periods  $t$  [1870,1900), [1900,1913), [1913,1940), and [1940,1950). This indicates that in the years 1870, 1900, 1913, and 1940, the logarithm of world GDP reached approximately 106%, 103%, 102%, and 101% of the logarithm of the sum of available country-level GDP in those respective years.<sup>4</sup> For example, the imputed log world GDP in 1880 is calculated as:

$$y_{1880} = 1.06 * x_{1880} + \left(\frac{10}{30}\right)(y_{1900} - 1.06 * x_{1900})$$

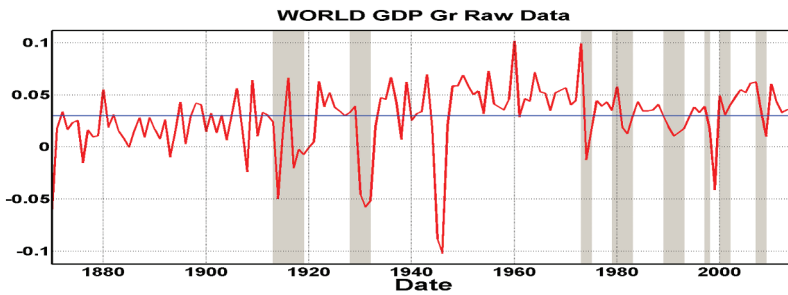
To characterize the world business cycle, we exploit the information of both strongly defined and weakly defined global recession periods. The International Monetary Fund (IMF) defines a global recession as “a decline in annual per-capita real World GDP (purchasing power parity weighted), backed up by a decline or worsening for one or more of the seven other global macroeconomic indicators: Industrial production, trade, capital flows, oil consumption, unemployment rate, per-capita investment, and per-capita consumption”. Since World War II, by this definition, there were only four global recessions (in 1975, 1982, 1991, and 2009), and all of them only last a year. Moreover, the IMF argued that a global annual real GDP growth rate of *3.0 percent or less* was “equivalent to a global recession.” By this measure, there were six global recessions from 1970 to 2009: 1974–75, 1980–83, 1990–93, 1998, 2001–02, 2008–09. The corresponding episodes are provided in Table 2.

In addition to the defined periods above, we consider World War I and its aftermath (1914–19) and the Great Depression (1929–32) as the global recession periods. Note that there has been no study identifying a global recession immediately following World War II. While most countries experienced positive growth rates during this period, several major economies suffered significant recessions, including Germany (from 302,457 to 143,381), the United Kingdom (from 347,035 to 331,985), the United States (from 1,644,761 to 1,305,357), Japan (from 205,214 to 102,607 and subsequently to 111,492), and India (from 272,503 to 258,164). Given this context, we do not consider this period as a global recession. The world GDP growth rate with defined global recession periods (using shaded bars) from 1870 to 2015 is illustrated in Figure 1. Note that the blue line indicates

**Table 2.** Major economic crises.

Period	Crisis Description
1974-75	The oil crises
1980-83	The early 1980s crisis
1990-93	The deregulation crisis
1998	Asian and Russian financial crisis
2001-02	The early 2000s recession (mainly in developed countries), related to the Dot-com bubble
2008-09	Global financial crisis or Great Recession

<sup>4</sup>The data supporting the findings of this study are available from <https://drive.google.com/file/d/1Mi5j-BQpuCTSF5JvEduPYB4a7UQ6DPu/view?usp=sharing>.



**Figure 1.** World GDP growth rate from 1870 to 2015.

a threshold value of the global recession based on the IMF definition (less than a growth rate of 3 percent). While most economic recession events are effectively captured by the imputed world GDP growth rate, not all can be fully explained. Imperfections in data quality may contribute to the inability to account for certain recession periods.

## 2.2. Global temperature dynamics

We employ two measures for global temperature dynamics: the global mean temperature anomaly and the global variance temperature anomaly. Temperature data are expressed as anomalies in degrees Celsius relative to the monthly average temperature during the base period (1961–1990) for the HadCRUT4 dataset.<sup>5</sup> To generate these measures, we calculate the global mean and variance temperature anomalies from the global temperature anomaly distribution using HadCRUT4 data provided by Morice et al. (2012), with 99% support as described in Miller and Nam (2020), Miller (2023), and Chang et al. (2020). To identify short-run or medium-run relationships, we extract the stationary component from the global mean and variance temperature anomalies using the HP filter, with a commonly used smoothing parameter ( $\lambda$ ) value of 6.25 for yearly data (Ravn & Uhlig, 2002).

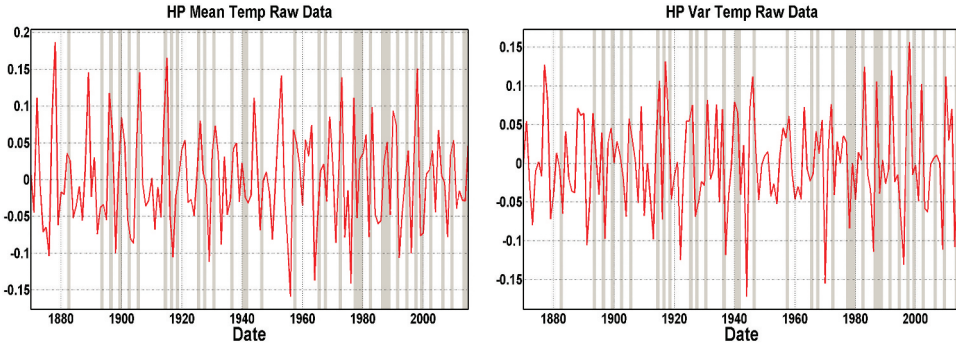
To characterize the global temperature cycle, we incorporate climate information from well-known medium-frequency temperature cycles, such as the ENSO and sunspot cycles. The ENSO cycle typically lasts four to five years and persists for 9–12 months, while the solar cycle is an approximately 11-year cycle reflecting changes in the Sun’s activity. The terms “solar maximum” and “solar minimum” refer to periods of maximum and minimum sunspot counts, respectively.<sup>6</sup> In Figures 2, we illustrate the HP-filtered global mean and variance temperature anomalies from 1870 to 2015. The El Niño events and years of maximum sunspot counts are shaded in these figures.<sup>7</sup>

<sup>5</sup>Source: <https://www.metoffice.gov.uk/hadobs/hadcrut4/>

<sup>6</sup>[https://en.wikipedia.org/wiki/Solar\\_cycle](https://en.wikipedia.org/wiki/Solar_cycle)

<sup>7</sup>[https://www.esrl.noaa.gov/psd/enso/past\\_events.html](https://www.esrl.noaa.gov/psd/enso/past_events.html), [https://en.wikipedia.org/wiki/List\\_of\\_solar\\_cycles](https://en.wikipedia.org/wiki/List_of_solar_cycles). Un-fortunately, ENSO index data are unavailable prior to 1900.





**Figure 2.** Hp-filtered global mean (left) and variance (right) temperature anomaly from 1870 to 2015.

### 3. Descriptive analysis

In this section, we provide a descriptive analysis for the world business cycle and global temperature cycle that are both extracted by the endogenous regime switching in the mean model. Chang et al. (2017) develop a regime-switching model whose regime is determined by an endogenous autoregressive latent factor. Their endogenous regime switching in the mean model is given by

$$\gamma(L)(y_t - \mu_t) = \sigma u_t \quad (2)$$

where  $\gamma(z) = 1 - \gamma_1 z - \dots - \gamma_k z^k$  is a  $k$ -th order polynomial,  $\mu_t = \mu(s_t)$ ,  $s_t = 1\{w_t \geq \tau\}$ , and  $w_t = \alpha w_{t-1} + v_t$  with

$$\begin{pmatrix} u_t \\ v_{t+1} \end{pmatrix} = {}_d\mathbb{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right). \quad (3)$$

In the model, the observed time series variable  $y_t$  alternates between two regimes based on an underlying latent process  $w_t$ . More specifically, equation (2) captures the  $k$ -th order autoregressive dynamics of the deviations of  $y_t$  from its regime-specific mean  $\mu_t$ , where  $\mu_t = \mu(s_t)$ , and  $s_t$  is a binary state variable indicating the regime at time  $t$ . The regime state  $s_t$  is determined by whether the latent factor  $w_t$  exceeds a threshold  $\tau$ . The latent factor  $w_t$  itself follows an autoregressive process with parameter  $\alpha$ .

Note that they call this endogenous regime switching model because a shock  $u_t$  to observed time series  $y_t$  at time  $t$  affects the regime at time  $t + 1$  with an endogeneity parameter  $\rho$ , as specified in equation (3). More importantly, the extracted factors  $w_t$  determine time periods of boom-recession for the world business cycle, and time periods of high-low for the global temperature cycle. In this light, we call the extracted factors from the world GDP growth rate, and HP-filtered global mean and variance temperature anomalies of the world business cycle and global mean and variance temperature cycles, respectively.

The AR(1) endogenous regime switching in the mean model needs seven parameters to be estimated using a modified Markov switching filter, requiring the computationally burdensome estimation procedure. To achieve a global maximizer, we utilize both the

profile likelihood surface algorithm and Global and Multistart (G/M) search algorithms. The considered optimization procedures are listed as follows.

- (1) Without generating the profile likelihood surface and G/M search algorithms, directly estimate the whole parameters,  $\underline{\mu}, \bar{\mu}, \tau, \sigma, \gamma, \alpha, \rho$ .
- (2) With generating the profile likelihood surface and without G/M search algorithms, sequentially estimate the parameters,  $\underline{\mu}, \bar{\mu}, \tau, \sigma, \gamma$  and then  $\underline{\mu}, \bar{\mu}, \tau, \sigma, \gamma, \alpha, \rho$ .
- (3) Without generating the profile likelihood surface and with G/M search algorithms, directly estimate the whole parameters,  $\underline{\mu}, \bar{\mu}, \tau, \sigma, \gamma, \alpha, \rho$ .
- (4) With generating the profile likelihood surface and G/M search algorithms, sequentially estimate the parameters,  $\underline{\mu}, \bar{\mu}, \tau, \sigma, \gamma$  and then  $\underline{\mu}, \bar{\mu}, \tau, \sigma, \gamma, \alpha, \rho$ .

### 3.1. World business cycle

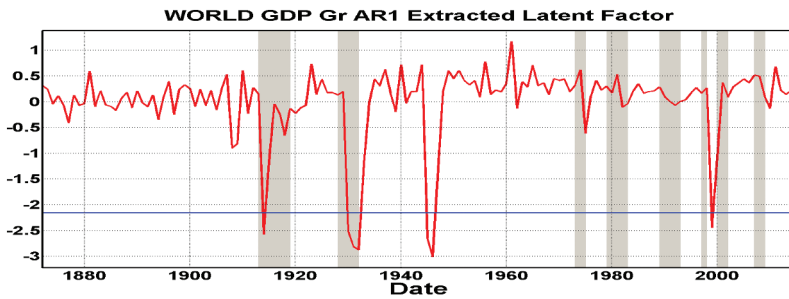
The estimates for world GDP growth rate with AR (1) endogenous regime switching in the mean model are provided in Table 3. Although scheme 1 provides somewhat high standard errors for the parameters,  $\gamma, \alpha$ , and  $\rho$ , all parameters of AR(1) endogenous regime switching in mean model are generally significant in the sense that the reliable schemes 2 and 3 provide low standard errors.

The parameters  $\underline{\mu}$  and  $\bar{\mu}$  indicate mean values of low and high states of world GDP growth rate, which identify that a mean of the high state of world GDP growth rate is 3.3 percent and that of the low state of world GDP growth rate is  $-5.3$  percent. Note that the extracted factor,  $w_t$  is interpreted as the indicator of the world business cycle, which follows a stationary process having zero mean and unit variance, and therefore the estimate of the parameter  $\tau, -2.15$  represents a threshold value, which defines two different regimes of world business cycle indicator. In this light, the estimate of the parameter  $\tau$  shows that world economy for the last 150 years has stayed at the high state except for four periods, which are marked with a blue line in Figure 3.

The estimates of the parameters,  $\alpha$  and  $\rho$ , which indicate the degree of persistence of the world business cycle and the degree of endogeneity, reveal several interesting points for the world business cycle. First, the degree of persistence of the world business cycle (0.66) is not high, implying predictable dynamics, and its sign is positive, meaning that a positive growth rate typically brings a positive growth rate. This positive persistence implies that there have been stable technological developments and positive innovations that have grown the world economy steadily.

**Table 3.** ERS AR(1) estimates for world GDP growth rate.

	Est.	S.E. (1)	S.E. (2)	S.E. (3)
$\underline{\mu}$	-0.0529	0.0088	0.0080	0.0083
$\bar{\mu}$	0.0334	0.0104	0.0021	0.0027
$\tau$	-2.1511	1.0382	0.0576	0.1443
$\sigma$	0.0206	0.0027	0.0012	0.0013
$\gamma$	0.2764	1.8914	0.0647	0.0641
$\alpha$	0.6632	0.7565	0.0683	0.1643
$\rho$	0.3385	0.6762	0.0702	0.0788
llk	331.0551			

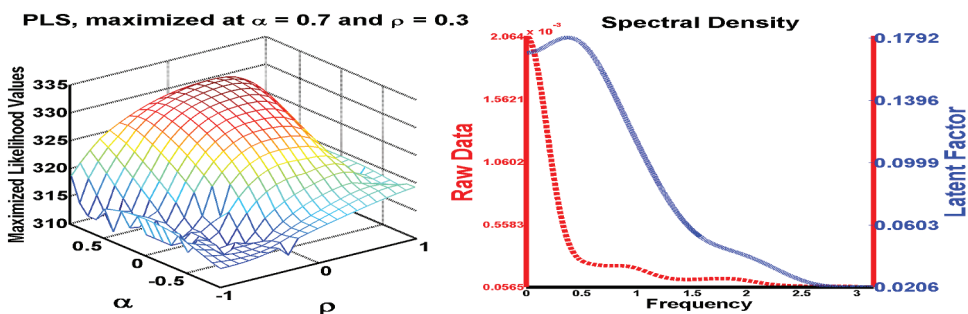


**Figure 3.** Extracted factor for world GDP growth rate from 1872 to 2015.

Second, the endogeneity of the regime-switching is estimated as a value, 0.34, implying that only 34 percent of a shock at time  $t$  to world GDP growth rate  $y_t$  is exploited to determine the regime at time  $t + 1$ . As indicated by the estimate of AR(1) parameter  $\gamma$  (0.28), the world GDP growth rate follows a reverting process to both its state-dependent mean ( $\mu_t$ ) and its global mean  $\mathbb{E}[y_t]$ . As explained in Chang et al. (2017) for the case of a positive estimate  $\hat{\rho}$ , however, a positive shock  $u_t$ , albeit it makes  $y_t$  revert to the state-dependent mean  $\mu_t$ , increases the probability of having high regime in the state-dependent mean  $\mu_{t+1}$  of  $y_{t+1}$ , and therefore the state-dependent mean ( $\mu_t$ ) moves to anti-reverting direction. Further, regime-switching is more likely to occur if  $y_t$  is located between the two state-dependent means.

As illustrated in Figure 4, the profile likelihood surface, which shows maximized log-likelihood values across fixed  $\alpha$  and  $\rho$  with the concentrated maximum likelihood method, proves that the estimation of AR(1) endogenous regime switching in the mean model identifies a global maximum, and clearly describes that the persistence and endogeneity are important to understand the world business cycle.

More importantly, the estimated spectral density in Figure 4 could not reveal the reasonable length of cycle for world GDP growth rate, but identify the 16-year world business cycle. As indicated by the magnitudes of the estimated spectral densities, furthermore, the volatility of the extract factor is greater than that of the original process, implying that the endogenous regime switching methodology not only attenuates the noise in the original process but also amplifies the signal of that process.



**Figure 4.** Profile likelihood surface and spectral densities for world GDP growth rate.

The estimation results provide an economic implication that the world economy has a boom-bust cycle with 16-year period. It is worth noting that 16-year cycle is estimated from real-world GDP growth rate (log differenced real-world GDP level) whereas the periodicity of the 6–32 quarters for the U.S. business cycle is estimated from HP-filtered log real U.S. GDP data (Christiano & Fitzgerald, 2003). Note that we estimate the world business cycle from world GDP growth rate data, instead of HP-filtered log real-world GDP data, because it is more plausible that the effect of global temperature is more likely influential on the high-frequency component of world economic activity extracted by the first difference filter.

### 3.2. Global temperature cycle

The estimates for HP-filtered global mean and variance temperature anomalies from AR (1) endogenous regime switching in the mean model are provided in Tables 4 and 5, respectively. Since we take the HP-filter on global mean and variance temperature anomalies, the filtered data would be interpreted as anomaly-level differences from HP-filtered trend. Unfortunately, the estimates of the parameters  $\bar{\mu}$ ,  $\tau$ , and  $\gamma$  for global mean temperature anomaly are insignificant, which implies that global mean temperature anomaly has only one state with one mean value ( $-0.03^{\circ}\text{C}$  difference from HP-filtered trend) for the sample period. Further, the observed global mean temperature anomaly would be better explained by the white noise process rather than the AR(1) process.

Nonetheless, the persistence and endogeneity parameters  $\alpha$  and  $\rho$  are highly significant, which implies that the global mean temperature process is linked to an AR(1) latent process with strong endogeneity. In particular, 95% of a shock to an observed process at time  $t$  is exploited to drive another stationary process. This is an interesting result in the sense that a white noise process drives an AR (1) stationary process. Probably, the

**Table 4.** ERS AR(1) estimates for hp-filtered global mean temperature anomaly.

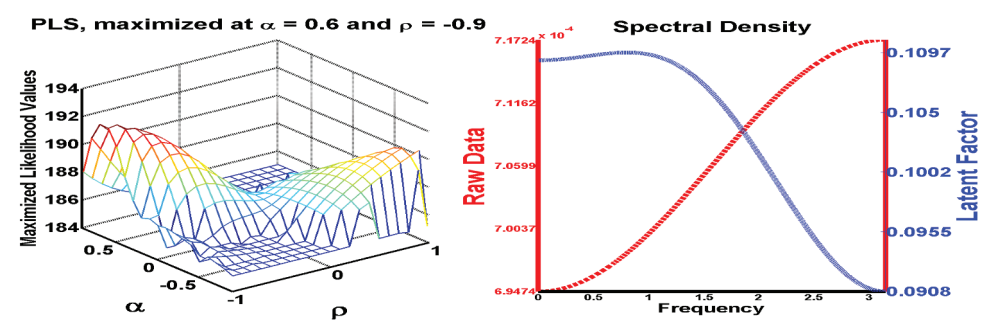
	Est.	S.E. (1)	S.E. (2)	S.E. (3)
$\mu$	-0.0330	0.0888	0.0095	0.0112
$\bar{\mu}$	0.0348	0.1018	0.0201	0.0829
$\tau$	0.0078	0.6663	0.2368	1.6678
$\sigma$	0.0573	0.0159	0.0056	0.0217
$\gamma$	-0.0435	0.3336	0.0899	0.3649
$\alpha$	0.6135	0.1433	0.1580	0.2155
$\rho$	-0.9507	0.1166	0.1807	0.2729
llk	192.0907			

**Table 5.** ERS AR(1) estimates for hp-filtered global variance temperature anomaly.

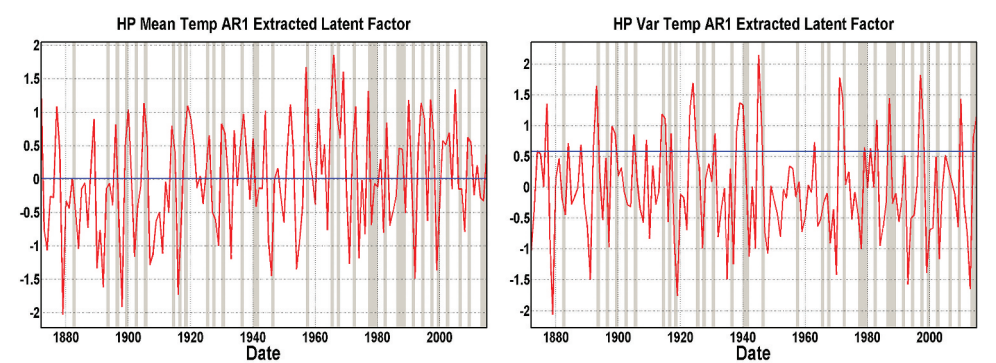
	Est.	S.E. (1)	S.E. (2)	S.E. (3)
$\mu$	-0.0167	0.1727	0.0097	0.0070
$\bar{\mu}$	0.0364	0.1785	0.0091	0.0160
$\tau$	0.5827	0.2604	0.1473	0.5087
$\sigma$	0.0555	0.0042	0.0059	0.0040
$\gamma$	-0.1183	0.0931	0.1024	0.0733
$\alpha$	0.6070	0.1564	0.1443	0.1077
$\rho$	-0.9304	0.1030	0.0831	0.0703
llk	203.3999			

observed global mean temperature anomaly data is contaminated by the substantial amount of noise, which masks the persistence in the original process. As indicated in spectral densities in Figure 5, global mean temperature anomaly follows a white noise or weak anti-persistent process. However, the latent process, driven by observed  $y_t$  but free from noise, has 6–7-year cycles, and it turns out to be consistent with the ENSO cycle. The global mean temperature cycle, which is the latent factor extracted from the global mean temperature anomaly, is depicted in the left panel of Figure 6.

Contrary to the global mean temperature anomaly, the global variance temperature anomaly has several interesting features obtained by the endogenous regime-switching approach. All estimates except for the parameter  $\gamma$  of AR(1) endogenous regime switching in the mean model are significant, showing that there has been a two-state-dependent mean in the global variance temperature anomaly. Specifically, the low state mean is  $-0.02$  deviation from the HP-filtered trend, and the high state mean is  $+0.04$  deviation from the HP-filtered trend. Moreover, it possesses a strong endogeneity in the sense that 93% of a shock at time  $t$  is exploited to determine the regime at time  $t + 1$ . Note that the global variance temperature anomaly has two reverting means: one is its global mean  $E[y_t]$  and another is state-dependent mean ( $\mu_t$ ). The negative sign of the estimate,  $\hat{\rho}$  implies that a positive shock to the original process,  $y_t$ , increases the probability of having



**Figure 5.** Profile likelihood surface and spectral densities for HP-filtered global mean temperature anomaly.



**Figure 6.** Extracted factor for hp-filtered global mean (left) and variance (right) temperature anomaly from 1872 to 2015.

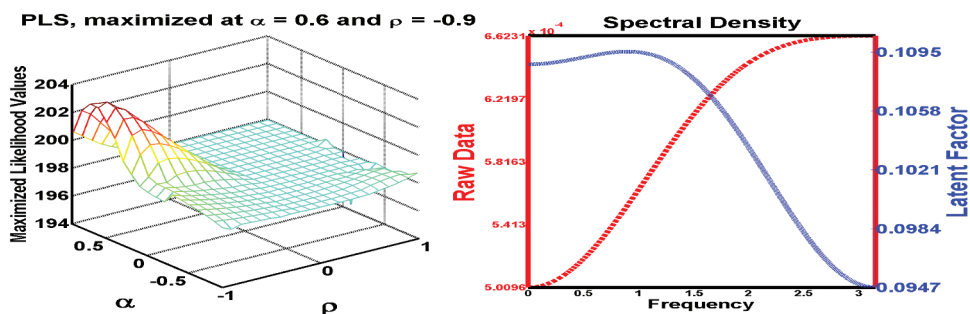
a low regime in the state-dependent mean  $\mu_{t+1}$  of  $y_{t+1}$  and therefore the shock lets the state-dependent mean also revert to its global mean.

The global variance temperature cycle is illustrated in the right panel of Figure 6. A blue line (0.58) is a regime threshold that determines two different states of the global variance temperature cycle, implying that the global variance temperature anomaly has changed its state frequently, unlike the world business cycle. It is important to note that the high state of the global variance temperature cycle usually happens during the years of El Niño events and maximum sunspot counts, which are shaded in Figure 6. Similar to the global mean temperature cycle, moreover, the spectral densities in Figure 7 show that the global variance temperature anomaly is severely contaminated by the noise, in the sense that there has been no distinct cycle in the original process. However, the extracted global variance temperature cycle has 6–7-year periods, which is coherent with the ENSO cycle.

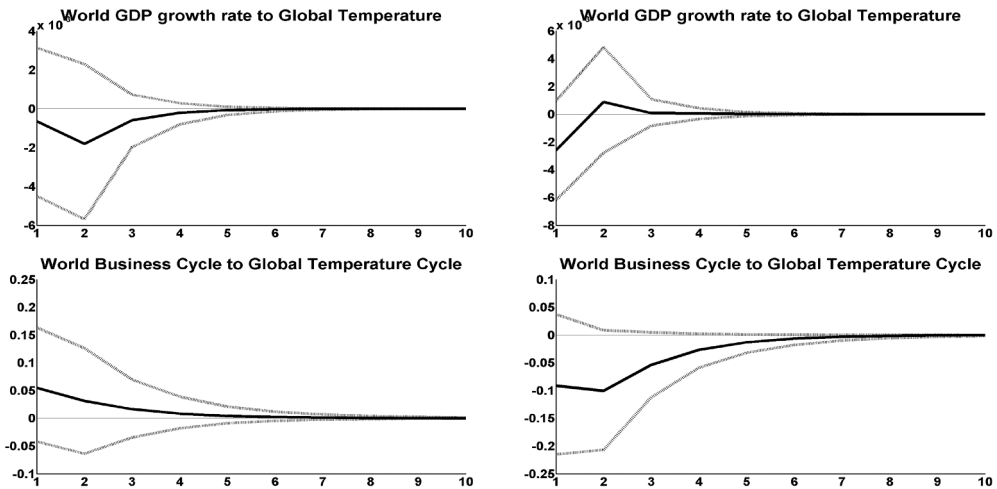
### 3.3. The baseline estimation results

Before we establish the statistical relationship between world economic activity and global temperature, we first provide the estimation results from the fixed coefficient VAR model as a benchmark case. The estimation results from the bivariate structural VAR(1) model indicate that all median IRFs are *insignificant* at 90% confidence level, which are presented in Figure 8. Note that we impose a short-run restriction by putting temperature first, and IRFs are generated from 1,000 bootstrapping samples.

Not surprisingly, regardless of whether we employ the original data or the extracted factor or mean temperature or variance temperature, the LS estimation results generated from a linear regression of world economic activity on global temperature with an intercept indicate that a slope coefficient is also insignificant at the conventional confidence level with the  $R^2$  value less than 0.05. Note that the estimation results listed above are obtained under the time-invariant relationship between less-noise contaminated data. In this light, we may conclude that world economic activity and global temperature hold a weak linear relationship.



**Figure 7.** Profile likelihood surface and spectral densities for hp-filtered global variance temperature anomaly.



**Figure 8.** IRFs of world GDP growth rate to hp-filtered global mean (top left) and variance (top right) temperature shocks, and IRFs of world business cycle to hp-filtered global mean (bottom left) and variance (bottom right) temperature cycle shocks.

#### 4. Regression analysis

In this section, we present a regression analysis that addresses the two statistical issues mentioned earlier. Specifically, we employ a time-varying structural VAR model using the extracted latent factors. To implement this, we utilize the Gibbs sampling procedure within a Bayesian framework, recognizing that the strength of the Bayesian approach lies in its ability to effectively handle nonlinearity and complexity in the model.

Given the limited availability of yearly macroeconomic variables, we employ a bivariate VAR model consisting of global temperature and world economic activity. Edelstein and Kilian (2007) show that a bivariate VAR model can yield results qualitatively similar to those of a VAR model with additional endogenous variables, assuming that changes in climate events are predetermined. Although there is a possibility of omitted variable bias, we argue that it is unlikely to significantly affect our empirical results. Even if some global macroeconomic variables are omitted, more specifically, the direction of bias could be identifiable based on the correlation between the omitted variables, the temperature variable, and world economic activity. In this light, any potential bias would not alter the sign or general interpretation of the impulse responses.

As demonstrated by Richmond et al. (2007), who incorporate labor and capital variables alongside the NPP variable in their model, labor productivity can be influenced by temperature dynamics. Given that labor productivity positively impacts world economic activity, the impulse responses may be overestimated (underestimated) if historical temperature dynamics have been positively (negatively) correlated with labor productivity. Our estimation results suggest that the global mean temperature anomaly negatively impacts world economic activity, leading us to postulate that global mean temperature has been negatively correlated with labor productivity. Consequently, the obtained impulse responses might be underestimated, implying that the estimated negative impulse response represents a lower bound of the true effects.



#### 4.1. Time-varying structural VAR with stochastic volatility model

We consider the structural VAR(1) model with time-varying parameter and stochastic volatility in the spirit of Cogley and Sargent (2005) and Primiceri (2005), which is given by

$$\begin{aligned} Y_t &= C_t + B_t Y_{t-1} + u_t \\ &= C_t + B_t Y_{t-1} + A_t^{-1} \Sigma_t \varepsilon_t \end{aligned} \quad (4)$$

where  $A_t$  is the lower-triangular matrix as given by

$$A_t = \begin{pmatrix} 1 & 0 & \dots & 0 \\ a_{21,t} & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1,t} & a_{n2,t} & \dots & 1 \end{pmatrix} \quad (5)$$

and the diagonal matrix  $\Sigma_t$  is

$$\Sigma_t = \begin{pmatrix} \sigma_{1,t} & 0 & \dots & 0 \\ 0 & \sigma_{2,t} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_{n,t} \end{pmatrix} \quad (6)$$

and the dynamics of the vector of time-varying coefficients,  $C_t$  and  $B_t$ , and the vector of non-zero and non-one elements of the matrix  $A_t$ ,  $\alpha_t$  and the vector of the diagonal elements of the matrix  $\Sigma_t$ ,  $\sigma_t$  is as follows.

$$\begin{aligned} C_t &= C_{t-1} + v_{1t} \\ B_t &= B_{t-1} + v_{2t} \\ \alpha_t &= \alpha_{t-1} + \zeta_t \\ \log \sigma_t &= \log \sigma_{t-1} + \eta_t \end{aligned}$$

The innovations are assumed to be jointly normally distributed with zero-mean and the following variance-covariance matrix.

$$V = \text{Var} \begin{pmatrix} \varepsilon_t \\ v_t \\ \zeta_t \\ \eta_t \end{pmatrix} = \begin{pmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{pmatrix} \quad (7)$$

where  $I_n$  is an  $n$ -dimensional identity matrix,  $Q$ ,  $S$  and  $W$  are positive definite matrices as described in Primiceri (2005).

As noted by Cogley and Sargent (2005) and Baumeister and Peersman (2013), estimating time-varying coefficients can be misleading if the heteroscedastic variance structure of the disturbance term is not accounted for. The time variation in the coefficients may be driven by the time-varying size of shocks and their contemporaneous effects. In our model,  $Y_t$  is a  $2 \times 1$  vector of endogenous variables that includes yearly global temperature and yearly world economic activity.  $C_t$  is a vector of time-varying intercepts, and  $B_t$  is a  $2 \times 2$  matrix of time-varying coefficients on the lagged endogenous variables. The number of lags is set to  $p = 1$  to avoid seasonality in yearly observations,



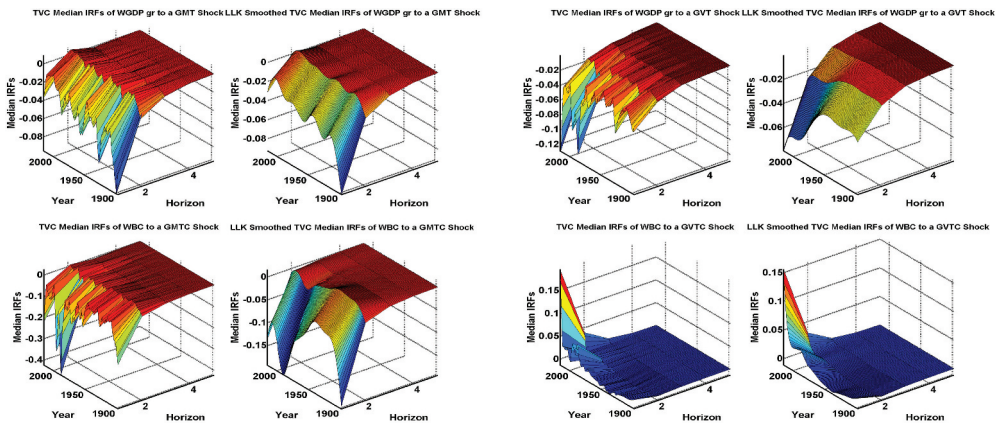
and  $u_t$  represents heteroscedastic reduced-form innovations that are normally distributed with zero mean and a time-varying covariance matrix  $\Omega_t$  (i.e.,  $A_t \Omega_t A_t' = \Sigma_t \Sigma_t'$ ). The reader is referred to Primiceri (2005) for details.

The sample period spans from 1870 to 2015, with the first 25 observations (17% of the total sample) serving as a training sample to calibrate the prior distribution, following standard practice as provided in Primiceri (2005). The actual analysis period begins in 1895. To demonstrate that there are no significant changes in the extracted latent factor of the endogenous regime-switching model through the imputation process, we provide the simulation results in the [Appendix](#), titled “Robustness Check for Friedman-Chow-Lin Type Imputation”. We employ the normal-inverse gamma prior distributions as outlined by Primiceri (2005). To compute the time-varying impulse responses, we introduce a unit variance structural shock to the temperature equation, performing 20,000 replications and basing our inference on the final 5,000 replications.

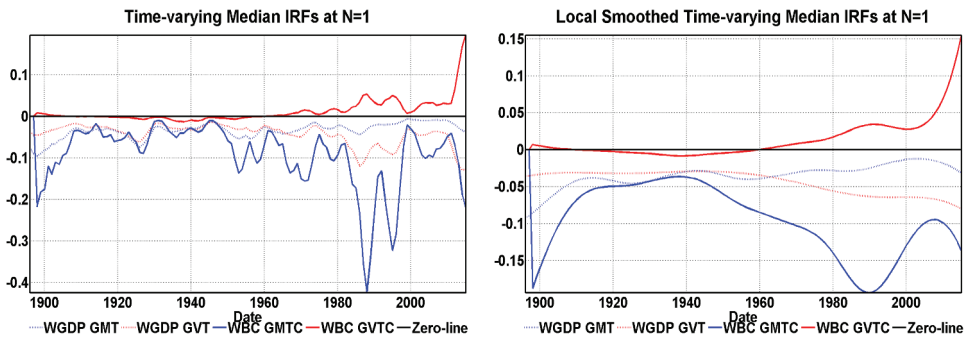
#### 4.2. Time-varying impulse responses of world economic activity

In this section, we present the estimated time-varying impulse responses of the world business cycle to a shock in the global temperature cycle. For notational convenience, we denote the world GDP growth rate as WGDP, the global mean temperature anomaly as GMT, the global variance temperature anomaly as GVT, the world business cycle as WBC, the global mean temperature cycle as GMTC, and the global variance temperature cycle as GVTC.

The left panels of [Figure 9](#) display the three-dimensional time-varying median impulse responses, while the right panels present their locally smoothed versions using a local linear kernel to illustrate the smoothed IRF trends over time. For further detail, [Figure 10](#) compares the impulse response functions (IRFs) of WGDP to a GMT shock, WGDP to a GVT shock, WBC to a GMTC shock, and WBC to a GVTC shock at a one-period horizon. Additionally, the figure compares the locally smoothed IRFs at the same horizon.



**Figure 9.** Three-dimensional time-varying median IRFs.



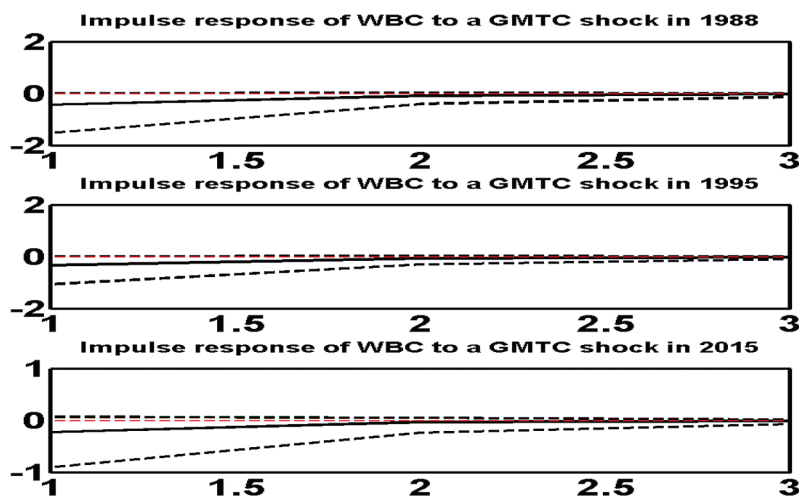
**Figure 10.** Time-varying median IRFs (left) and their local linear kernel smoothed IRFs (right) at  $N = 1$ .

As expected, the magnitudes of the IRFs for the original processes are much smaller than those of the extracted factors, indicating that the low signal-to-noise ratio of the original processes likely obscured the true relationships. Furthermore, the locally smoothed IRFs reveal that WBC and GMTC have been negatively related, with this negative relationship strengthening over time. Meanwhile, the relationship between WBC and GVTC was weak before 1960 but has become positive and stronger thereafter. Notably, the impulse responses of WBC to shocks in GMTC and GVTC are particularly pronounced in 1988, 1995, and 2015, which correspond to the super El Niño periods.

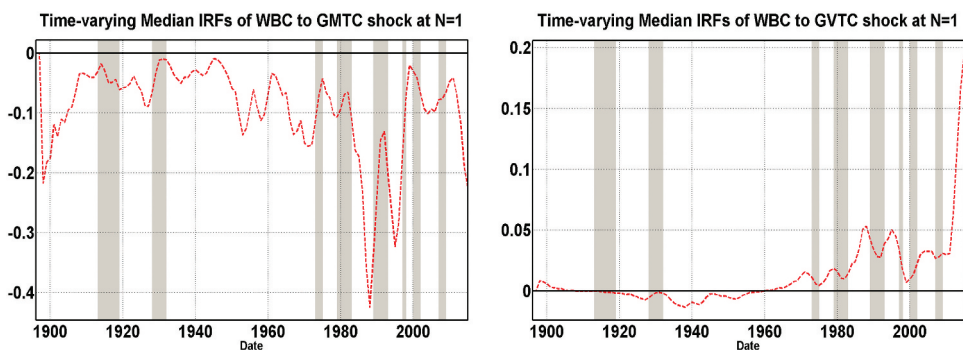
It is important to note that Chang et al. (2020) provide a statistical analysis of the dynamics of the global temperature anomaly distribution. Specifically, they found unit-root behavior in both global mean and variance temperature anomalies, suggesting that the global mean temperature anomaly exhibits a stochastically increasing trend (i.e., global warming), while the global variance temperature anomaly shows a stochastically decreasing trend (i.e., global compression). Considering the concept of an optimal temperature derived from the concavity of the response function of economic production to temperature changes (Burke et al., 2015), we can conjecture that the global mean temperature has likely exceeded the optimal mean temperature level, while the global variance temperature has likely fallen below the optimal variance temperature level since around 1960.

Since a positive one standard deviation shock increases the deviation of the global mean temperature from its optimal level, while the global variance temperature helps restore it to the optimal level, we can infer that the WBC would be negatively impacted by a shock in the GMTC level but positively impacted by a shock in the GVTC level after 1960. To illustrate this, Figures 11 and 12 present the median impulse response of WBC to a shock in GMTC with 68% credible intervals for selected years. The estimated impulse responses in these figures indicate that WBC was negatively affected by GMTC but positively affected by GVTC in the selected years. However, as the effects of GVTC were statistically insignificant, we have not included these results in the paper.

It is important to recognize that global recession periods should be attributed to non-climate causes. Generally speaking, it is unlikely that the 2008–2009 global recession was climate-driven, even though those years were relatively warm. Figure 12 presents the



**Figure 11.** Selected impulse response functions with the median (solid line) and 68% credible intervals (dotted line). The red dotted line represents the horizontal axis at zero.



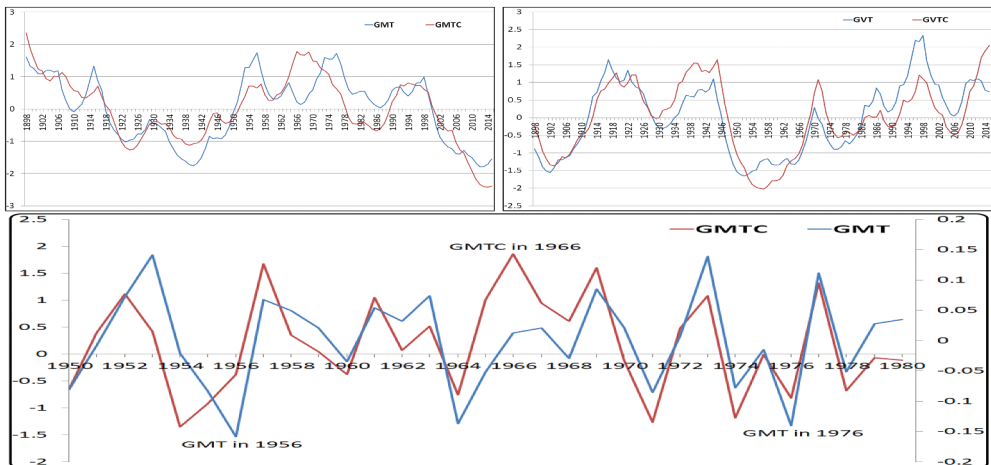
**Figure 12.** Time-varying median IRFs of WBC to a shock of GMTC (left) and GVTC (right) at  $N = 1$  with shaded global recession periods.

time-varying median IRFs (not smoothed using a local linear kernel) at a one-period horizon to assess the impact of global mean and variance temperature cycles on the world business cycle during global recession periods. The global recession periods are shaded in the figure. The estimated IRFs clearly show that the global recessions were not driven by climate events but by other economic factors.

Lastly, it is worth identifying the time periods when the dynamics of world income and global temperature were obscured by substantial noise. The stochastic volatility of the global temperature equation is technically defined as the conditional standard deviation of the one-year-ahead unforecastable component of global temperature dynamics (Elder & Serletis, 2009, 2010; Jo, 2014). Therefore, the estimated stochastic volatility allows us to identify unexpected temperature movements conditional on past information, suggesting that the volatility observed in both global temperature cycle equations represents an unexplained component due to the past temperature information.

Given that the endogenous regime-switching methodology amplifies the signal-to-noise ratio of the observed original process, the stochastic volatility dynamics of the global temperature equation, which are not observed in the global temperature cycle equation, can be considered as the noise component in the original process. On the other hand, the volatility dynamics of the global temperature cycle equation, which are not observed in the global temperature equation, can be interpreted as unexpected movements of the latent signal component conditional on past information. In this context, the extracted volatility of the global temperature cycle equation can identify the pure errors in the one-year-ahead forecasting exercise by excluding erratic movements over the entire sample period.

The top panel of [Figure 13](#) presents the standardized posterior medians of the log stochastic volatilities,  $\log \sigma_t$ , for the global temperature variables. Interestingly, there are periods where the  $\log \sigma_t$  of GMT exhibit distinct dynamics from those of GMTC, while the GVT and GVTC display similar behavior throughout the sample period. Specifically, GMT demonstrates a different pattern from GMTC between 1950 and 1980, indicating that the dynamics observed in GMT around 1956 and 1976 were likely noise components, whereas the dynamics around 1966 reflected unexpected movements of the latent signal component. The bottom panel of [Figure 13](#) compares the GMT level with the GMTC level from 1950 to 1980, showing that GMT in 1956 and 1976 was lower than the historical GMT level. Notably, the super El Niño episodes in 1988, 1995, and 2015 were not unexpected movements of the global mean temperature process, either conditionally or unconditionally. However, in the context of the unconditional global variance temperature anomaly, these super El Niño episodes were unexpected events conditional on past information.



**Figure 13.** The standardized posterior medians of the log stochastic volatilities,  $\log \sigma_t$ , of the global mean (top left) and variance (top right) temperature variables, and the comparison between GMT and GMTC between 1950 and 1980 (bottom).

## 5. Concluding remarks

Despite its weak statistical linkage, this paper establishes a statistical relationship between the world GDP growth rate and global temperature anomaly by addressing two key econometric issues: the time-homogeneous relationship and noise-contaminated original processes. To address these issues, we employ a time-varying structural VAR model with latent factors extracted using the endogenous regime-switching methodology. This approach allows us to isolate the signal from an original process affected by substantial noise. Additionally, the time-varying structural VAR model facilitates the identification of the statistical relationship during specific periods of interest.

The estimated time-varying median impulse responses of the world business cycle to a shock in the global temperature cycle provide interesting economic implications in a qualitative sense. The temperature–income relationship has traditionally been elusive in standard regression analyses. However, with this new approach, we find that the global mean temperature cycle has negatively affected the world business cycle during super El Niño periods (1988, 1995, and 2015). In contrast, the impacts of the global variance temperature cycle during these periods were not statistically significant. These estimation results suggest an economic implication: there exists a nonlinear and time-heterogeneous relationship between the world business cycle and the global mean temperature cycle.

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## Appendix Robustness Check for Friedman-Chow-Lin Type Imputation

In Section 2.1., we employ the Friedman-Chow-Lin type imputation method to generate the historical world GDP growth rate from 1870 to 2015. Since the number of available country-level GDP is different before the year of 1950, we need to check if implemented imputation is properly conducted. To do so, we estimate the AR(1) endogenous regime switching in the mean model using the following non-imputed datasets.

- (1) Benchmark: real-world GDP growth rate artificially generated by the Friedman-Chow-Lin type imputation from 1870 to 2015 (the data this paper uses).
- (2) Data1: non-imputed 24 countries real GDP growth rate from 1871 to 2008.
- (3) Data2: non-imputed 30 countries real GDP growth rate from 1901 to 2008.
- (4) Data3: non-imputed 33 countries real GDP growth rate from 1914 to 2008.

The estimation results of the AR (1) endogenous regime switching in the mean model are provided in Table 6, and estimated profile likelihood surfaces and spectral densities are provided in Figure 14. The estimates in Table 6 are roughly similar, although the estimates  $\hat{\alpha}$  and  $\hat{\rho}$  are slightly different. Furthermore, all non-imputed data provide similar profile likelihood surfaces and spectral densities with those in Figure 4.

In addition, we compare the real GDP growth rate and their latent factors from 1916 to 2008 for each case in Figure 15. Roughly speaking, all non-imputed real country-level GDP growth rates and their extracted latent factors from 1916 to 2008 show similar patterns. However, the benchmark data have a slightly bigger scale after 1950. Note that we use TED data, instead of Maddison data, from 1950 because we need to obtain growth rate data from 2008 to 2015. In this light, the reason we have a different scale for the benchmark case is not that of the imputation strategy but because we use TED growth rate data from 1950.

**Table 6.** Robustness check for Friedman-Chow-Lin type imputation.

Estimates	Benchmark	Data1	Data2	Data3
$\mu$	-0.053	-0.071	-0.056	-0.067
$\bar{\mu}$	0.033	0.033	0.035	0.036
$\tau$	-2.151	-2.615	-2.157	-3.114
$\sigma$	0.021	0.020	0.019	0.018
$\gamma$	0.276	0.256	0.297	0.330
$\alpha$	0.663	0.767	0.697	0.862
$\rho$	0.339	0.123	0.287	0.165
llk	-331.055	-318.528	-251.751	-228.387



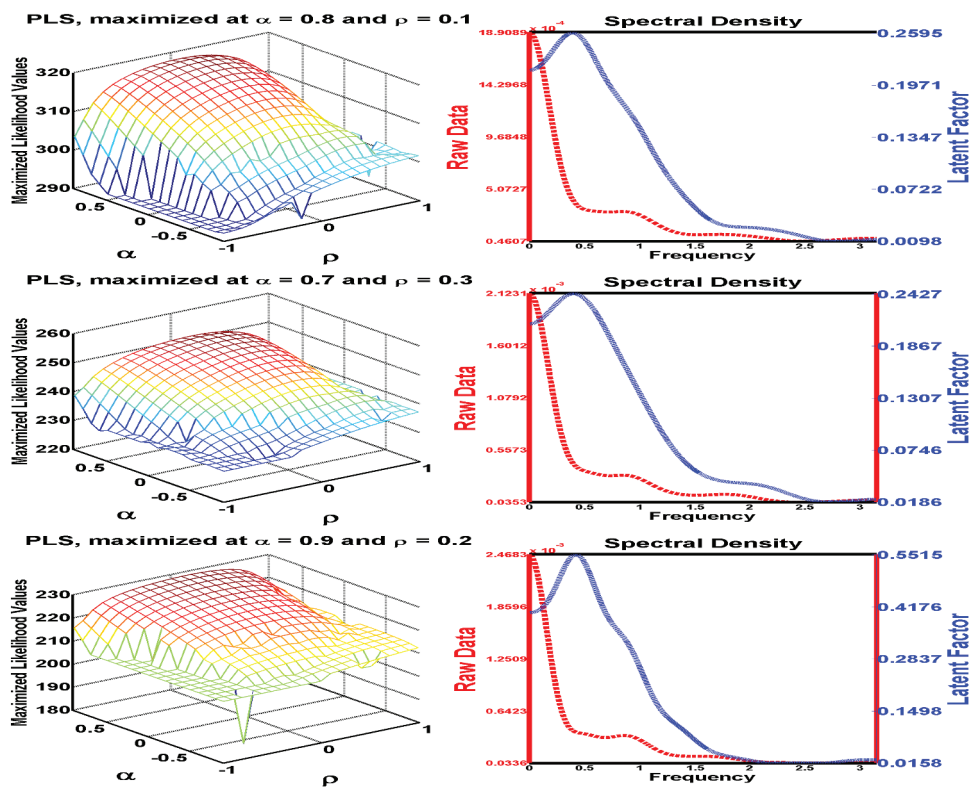


Figure 14. Profile likelihood surfaces and spectral densities from data1 (top), data2 (middle), and data3 (bottom) cases.

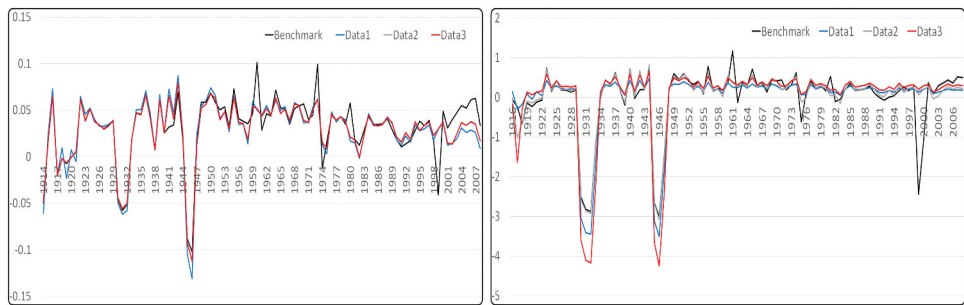


Figure 15. The data comparisons for robustness check of imputation method: world GDP growth rate (left) and their latent factors (right).