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Article

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Climate change and the influence of monetary policy in China

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ABSTRACT

We investigate whether climate change affects the efficiency of monetary policy. We use temperature shocks, calculated as temperature deviations from historical average temperatures, to proxy climate change, and utilize a threshold vector autoregression model (TVAR) to estimate the impact of expansionary and tight monetary shocks on economic output under high and low regimes of temperature shocks. Our results characterize a climate change regime-dependent monetary policy. Expansionary monetary policy is less efficient and the negative impact of tight monetary policy is enhanced, when climate change is severe. The results can be explained by the climate-induced credit constraint of commercial banks. Higher temperature shocks lead to increases in banks' nonperforming loan ratios, which results in larger credit constraints of banks. Banks tend to be more prudent in credit expansion, and the bank credit channel of monetary policy transmissions is weakened.

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KEYWORDS
Climate change; monetary policy; regime dependency; bank credit channel

1. Introduction

Does climate change affect the efficiency of monetary policy? This is an important question in climate finance. Monetary policy is regarded as one of the most important tools to mitigate economic inefficiency caused by climate change (Baranzini et al., 2017; Maestre-Andrés et al., 2019). Answering this question enhances the understanding of the economic and financial consequences of climate change and provides useful guidance for climate-based monetary policy formulations (L. P. Hansen, 2022).

Theoretically, expansionary monetary policy should be less efficient when climate change is severe. Climate change has been recognized worldwide as a new and non-negligible source of economic and financial instability (Dafermos et al., 2018; Giglio et al., 2021). Climate change and its induced natural disasters have negative shocks to economic activities and lead to the devaluation of collaterals (Burke et al., 2015; Dell et al., 2009, 2012; Letta & Tol, 2019). Because climate change affects economic activities and the valuation of collaterals, the debt payments of corporations and households will deteriorate (Dafermos et al., 2018; Hosono et al., 2016; Klomp, 2014). The ratio of nonperforming loans of commercial banks will increase, exposing banks to greater credit constraints and making banks more prudent to expand credit (Abbas et al., 2021; Abou-

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El-Sood, 2016; Pool et al., 2015). The credit channel of monetary policy transmissions is weakened by climate change, and thus, expansionary monetary policy is less influential when climate change is severe. Similarly, the negative impact of tight monetary policy on economic output should be exemplified when climate change is severe. Central bank should care for the climate change proactively by using the traditional monetary policy (C. Chen et al., 2021). Although these theories are well understood, the empirical evidence is still limited. Here are the research questions: Is the influence of monetary policy affected by climate change? How to describe the impact of climate change on the influence of monetary policy? How to explain the impact of climate change on the influence of monetary policy?

In this paper, we provide empirical evidence on the impact of climate change on monetary policy by examining the responses of economic output to monetary shocks under climate change regimes. We use temperature shocks, which are calculated as temperature deviations from historical average temperatures, to proxy climate change (Hong et al., 2019; Russell et al., 2014; Song & Fang, 2023). In the empirical analysis, we utilize a TVAR framework to reveal the impact of monetary policy on output, and the temperature shock is regarded as the threshold variable. Monetary policy (M2), output (GDP), and price level (CPI) are included as other endogenous variables. We perform one-standard-deviation unanticipated positive and negative monetary shocks separately and estimate the generalized impulse responses of output to shocks under high- and low-temperature regimes. Moreover, we explain our results through climate-induced credit constraints in the bank credit channel.

Our results are summarized as follows. First, we find that the influence of monetary policy is climate change regime dependent. Temperature shocks weaken the efficiency of monetary expansions and worsen the effects of monetary tightening. Second, previous literature shows that the effects of expansionary and tight monetary policies are asymmetric, and we show that asymmetries are more apparent under high-temperature regimes. Third, we provide empirical evidence to explain the path through which climate change affects the effectiveness of monetary policy by confirming the credit constraints of commercial banks. Temperature shocks worsen economic activities, which increases corporations' and households' loan default rates and banks' non-performing loan ratios. Consequently, banks have greater credit constraints and are prudent in expanding credit under high-temperature regimes, suggesting that the credit channel of monetary policy is weakened.

Our study contributes to the literature on the role of climate change in monetary policy implementation. We provide empirical evidence that the efficiency of monetary policy is influenced by climate change, characterized as climate change regime dependency, which is meaningful to monetary policy in the context of climate change (C. Chen et al., 2021; George & Anastasios, 2018). Our results confirm the theoretical findings of C. Chen et al. (2021) and suggest that policymakers should consider climate change in monetary policy formulations proactively. Expansionary monetary policy could be more aggressive when temperatures are higher, and tight monetary policy could be more conservative when climate change is severe.

Our paper is also related to the rich literature on the transmission of monetary policy shocks. We find that climate change dynamics affect monetary policy efficiency (Aastveit et al., 2017; Boivin & Giannoni, 2006; Caggiano et al., 2014). Specifically, we empirically

confirm the climate-induced credit constraint of commercial banks, which has only been investigated in theory (Berg & Schrader, 2012; Hosono et al., 2016). Increases in temperature lead to higher bank non-performing loan ratios and greater credit constraints, which make banks more prudent in extending credit. The credit constraint weakens the bank credit channel of monetary policy and thus provides an explanation for the impact of climate change on the influences of monetary policies from a micro perspective.

The remainder of our paper is organized as follows. Section 2 presents a literature review. Section 3 describes the TVAR model and the data. Section 4 reports our main results and robustness checks. Section 5 explains our results, and Section 6 concludes.

2. Literature review and theoretical analysis

2.1. Literature review

Monetary policy plays an important role in adapting to climate-related risks, and central banks should incorporate climate risks into their policy frameworks to maintain economic and financial stability (Dikau & Volz, 2021). Most of the previous literature explores how central banks use monetary policy to support the transition to a low-carbon economy.

On the one hand, monetary policy acts as a complementary instrument for climate policy to cope with climate risks. It is not sufficient to realize the desired objectives by only implementing climate policies, and it is of great importance to consider additional policy instruments (Baranzini et al., 2017; Campiglio, 2016; Engle et al., 2018; Maestre-Andrés et al., 2019; Rozenberg et al., 2013). Monetary policy is regarded as an appropriate tool to address such problems (Benmir & Roman, 2020; Chan, 2020). Annicchiarico and Dio (2017) utilize an extended environmental dynamic stochastic general equilibrium model to reveal that central banks should integrate climate change into monetary policy. Chan (2020) investigates the interactions among climate change, monetary and fiscal policies using an environmental DSGE model and demonstrate that carbon taxation should complement monetary policy but not respond to fiscal policy, in which carbon emissions and household welfare can be maintained as dynamically stable. Moreover, because of market failures, Campiglio (2016) finds that carbon pricing itself is not effective enough to enhance banking credit for low-carbon sectors, whereas monetary policy contributes to attenuating the constraints of bank lending, especially in emerging economies, for which central banks take powerful controls on credit allocation and use more monetary policy instruments.

On the other hand, some studies propose new climate-related monetary policy instruments that integrate climate objectives into monetary policy and evaluate their effects. Böser and Senni (2020) propose climate-oriented monetary policy instruments, including green quantitative easing, green reserve requirements and a green collateral framework. They find that these instruments can make firms adopt cleaner technologies across the entire economy, reduce carbon dioxide emissions and mitigate climate damage. Boneva et al. (2022) incorporate climate change objectives into monetary policy and discuss a couple of actions central banks can take to mitigate climate change. McConnell et al. (2022) investigate several green monetary policy instruments and

point out that it is the most promising conduit to incorporate brown collateral haircuts into the collateralized lending framework of central banks.

However, studies on the effects of climate change on monetary policy are currently quite limited. George and Anastasios (2018) use an indirect method to assess the impacts of climate change on monetary policy. They incorporate total factor productivity (TFP) shocks derived from climate change uncertainty into the integrated assessment model (IAM) and then suggest that climate change uncertainty leads to larger and more persistent fluctuations in economic activity. By embodying more novel environmental features, such as the concealed emissions and potential penalties, and climate policy in the E-DSGE model, C. Chen et al. (2021) find that climate policy is a factor affecting price level and welfare. McKibbin et al. (2021) point out that supply shocks from climate change disrupt central banks' ability to forecast and manage inflation and highlight that climate risks in the monetary framework will make monetary policy more effective.

In summary, one stream of literature mainly focuses on monetary policy as a complementary instrument for climate policy to mitigate climate risks and focuses on incorporating climate objectives into monetary policy. Another stream of literature highlights the role of monetary policy in dealing with climate risks and achieving sustainable development. However, there are several issues to be addressed. First, a large number of previous studies suggest that climate change can impair agricultural yields, industrial output, and economic growth, which are primary monetary policy concerns. However, few studies have simultaneously considered climate change, monetary policy, and output in a framework to discuss the effectiveness of monetary policy in the context of climate change (Carleton & Hsiang, 2016; Dell et al., 2012). Second, though many studies provide theories that relate climate change to monetary policy, the number of empirical examinations is quite limited. Evaluating the reactions of monetary policy to climate shocks is beneficial to more explicitly recognize climate risks, which is the foremost prerequisite of central banks to craft optimal monetary policy to attain objectives. These studies also provide evidence for how central banks should adjust monetary policy conditional on climate change and new perspectives for adapting to climate risks in monetary policy transmission. Third, previous studies have not shown empirical evidence on the influential mechanism that explains how climate change affects the efficiency of monetary policy. China has a bank-based financial system, which implies that the bank credit channel is important in monetary policy transmission. If climate change affects the bank credit channel, then it will definitely affect the influence of monetary policy. In the following analyses, we aim to address these issues using TVAR models and bank-level micro data.

2.2. Theoretical analysis and hypothesis development

The effective implementation of monetary policy depends not only on the efforts of the government, which formulates feasible monetary policy, but also, more importantly, on the transmission of monetary policy (Acharya et al., 2020; K. Chen et al., 2018). For example, when banks face strict regulatory and financial constraints or are undercapitalized, the transmission channel of monetary policy may be hampered, leading to less effective expansive monetary policy (Acharya et al., 2020). Meanwhile,

the transmission channel mainly relies on financial institutions or the financial market, and climate change is regarded as a new source of financial instability (Giglio et al., 2021; Mishkin, 1996, 2001; Walsh, 2017). Therefore, it is conceivable for us to explore the path through which climate change affects monetary policy from the view of transmission channels.

We focus on evidence from China. Despite being the largest developing economy, its financial market is not well developed and its financial system primarily relies on the banking system (Hou et al., 2018; Klingelhöfer & Sun, 2019; H. Li et al., 2021). There are several other transmission channels of monetary policy, such as the interest rate channel, asset price channel, and exchange rate channel (Bernanke & Blinder, 1992; Kashyap & Stein, 1995; Mishkin, 1996, 2001; Walsh, 2017). In China, the (bank) credit channel dominates all other monetary policy transmission channels, whose contributions are relatively limited. In this regard, we analyze the role of banks in explaining the impact of climate change on the transmission of monetary policy.

According to the literature, temperature shocks have negative consequences for economic activities and human behavior. High temperatures lead to decreases in firm profitability through labor productivity, total factor productivity (TFP), and operation costs. First, temperature is negatively associated with labor productivity. High temperatures tend to harm human physiological functions, cognitive capacities, and psychological health, resulting in losses in labor productivity (S. Chen et al., 2018; Deschênes & Moretti, 2009; Hsiang, 2010; Seppänen et al., 2006; Somanathan et al., 2021; Zheng et al., 2019; Zivin et al., 2015). Second, high temperatures reduce TFP growth. Donadelli et al. (2017) indicate that temperature risk has a long-lasting negative effect on TFP, which worsens the welfare cost. Third, temperature shocks increase enterprise operation costs. Pankratz et al. (2023) document that administrative, selling, and general expenses increase when firms are exposed to high temperatures over prolonged periods of time, leading to rising operation costs.

Based on the relationship between temperature shocks and firm profitability, temperature shocks tend to exacerbate the credit channel. High temperatures weaken firm profitability, which deteriorates the firm balance sheet and firms' ability to repay loans from banks. The non-performing loan ratios of banks correspondingly increase, causing banks to suffer capital losses and to reduce lending to maintain the regulatory capital ratio (Abbas et al., 2021; Abou-El-Sood, 2016; Sandra et al., 2016). In addition, increases in the non-performing loan ratios could signal an economic downturn, and commercial banks could become more prudent and conservative in lending to firms (Kollmann et al., 2010; Pool et al., 2015). Weakened firm profitability is also closely related to greater adverse selection and moral hazard, which hinders banks from lending to these firms.

Overall, high temperatures weaken firm profitability and increase the default probabilities of bank loans, thus resulting in higher bank non-performing loan ratios. These consequences make banks more risk averse and prudent in expanding credit and dampen the efficiency of monetary policies. This is the climate-induced credit constraint, as theoretically stated by Berg and Schrader (2012) and Hosono et al. (2016). Therefore, we propose the following hypotheses:

H1: When climate change is severe, the positive impact of expansionary monetary policy is less efficient and the negative impact of tight monetary policy is enhanced.

H2: Climate change affects the efficiency of monetary policy by weakening the bank credit channel of monetary policy transmission.

3. Econometric model and data descriptions

3.1. TVAR model specification

We employ a TVAR model to examine the regime-dependent nonlinear effects of monetary policy in the context of climate change (Lo & Zivot, 2001; Tsay, 1998). The TVAR model has the following characteristics and advantages. First, the TVAR model is a nonlinear multivariate system with regime switching. We can transform the model into several distinct linear VARs. These VARs correspond to several regimes based on the threshold variable (in this paper, the threshold is the climate change variable), and the coefficients of VAR models are unique to each regime. Second, the TVAR model allows the threshold variable to be endogenous. This indicates that the regime can switch after shocks occur (Afonso et al., 2018; Balke, 2000; Ferraresi et al., 2015; Jörg, 2020)

To investigate whether climate change affects the influence of monetary policy, we use temperature shocks as a proxy for climate change and as the threshold variable. The model with two regimes is specified as follows:

$$Y_t = A_1 + \phi_1(L)Y_t + (A_2 + \phi_2(L)Y_t)\mathrm{I}\left(y^*_{t-d} > \gamma\right) + \varepsilon_t, \tag{1}$$

where Y_t is the vector of all endogenous variables, including temperature shocks, monetary policy, price level, and output. In this paper, and the sample period is from 2004Q2 to 2021Q4 (additional information on these variables can be found in Section 3.2).[1] We set the ordering as temperature shocks, monetary policy, price level, and output in the baseline TVAR model. The ordering in the vector of endogenous variables reflects the way in which variables interact.[2] y^*_{t-d} is the threshold variable for temperature shocks at time $t-d$, and d is the lag length. I is an indicator function that equals 1 when y^*_{t-d} is more than threshold γ and 0 otherwise. This setting means that regime switching occurs at time t if the threshold variable at time $t-d$ exceeds γ. A_1 and A_2 are the vectors of the constant term. $\phi_1(L)$ and $\phi_2(L)$ are lag polynomial matrices. ε_t is the vector of structural shocks.

To reveal the responses of endogenous variables to shocks, we employ the generalized impulse response function (GIRF) to compute impulse responses (Koop et al., 1996). Moreover, the GIRF allows us to investigate the effects of shocks of distinct directions and sizes. The GIRF is described as follows:

[1] Since the main objectives of People's Bank of China implementing monetary policy are maintaining price stability and stimulating economic growth, we select three other variables, monetary policy, price level and output, in baseline TVAR model (H. Chen et al., 2017; K. Chen et al., 2018).

[2] For example, temperature shocks are ordered first, indicating that temperature shocks do not contemporaneously react to all other variables. Output is ordered last, indicating that output contemporaneously reacts to all other variables. We also use other orderings in robustness checks.

$$GIRF_y(h, \Omega_{t-1}, u_t) = E[y_{t+h}|\Omega_{t-1}, u_t] - E[y_{t+h}|\Omega_{t-1}], \tag{2}$$

where y is the response variable, h is the horizon, Ω_{t-1} denotes historical information and u_t is the shock. The response of variable y at horizon h is that the expectation of variable y at period $t+h$ imposing shock u_t conditional on history Ω_{t-1} deducts the expectation of variable y at period $t+h$ without shock u_t conditional on history Ω_{t-1}, which is calculated under the framework of linear VAR. In regard to the TVAR model, it is necessary to calculate impulse responses for each regime.

3.2. Data descriptions

3.2.1. Temperature data

Following previous studies, temperature shocks are calculated as temperature deviations from historical average temperatures, which indicate the trend of global warming and unanticipated temperature changes (Hong et al., 2019; Song & Fang, 2023). The temperature data for China are obtained from the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA). The NCEI database of NOAA provides weather data monitored by every meteorological station around the world. To calculate temperature shocks in China, we follow three steps. First, we select stations located in China. Because missing data at each station are a challenge for calculating average temperatures, we remove stations that recorded data for fewer than 350 days per year, resulting in a remaining 260 stations. Next, we collect temperature data from these stations and take the quarterly average of the daily temperatures at each station. Finally, we compute the quarterly average temperatures of these stations ($Temperature_t$) and remove the trend by subtracting the historical H-year averages from quarterly average temperatures:

$$tempv_t = Temperature_t - \frac{1}{H}\sum_{j=1}^{H} Temperature_{t-4*j}. \tag{3}$$

The historical average temperatures are computed using H = 30/25/20-year moving averages (M. E. Kahn et al., 2021). Figure 1 plots the temperature shocks in China. We find that most temperature shocks are greater than zero, which reflects a trend of global warming. Temperature shocks have larger fluctuations in the first and fourth quarters, which is consistent with the findings of Dell et al. (2012) and S. Kahn et al. (2019). The sample period spans from 2004Q2 to 2021Q4.

3.2.2. Macroeconomic data

The money stock and interbank-offered rate are usually employed as proxies of monetary policy. The interbank-offered rate has the drawbacks of forward-looking expectations and inconsistent movement with monetary policy, while money stocks predominantly act as the intermediate target of monetary policy in China (K. Chen et al., 2018; Heryan & Tzeremes, 2017; R. Li & Tian, 2018).[3] To proxy monetary policy, we use the monetary stock growth rate, which is calculated as the year-on-year growth rate of money stocks

[3]The Central Economic Work Conference in China decides on the M2 growth target for the next coming year at the end of this year. In the next year, the government adjusts the actual M2 growth from quarter to quarter subject to the annual M2 growth target. M2 growth also serves mainly for the economic growth (K. Chen et al., 2018).

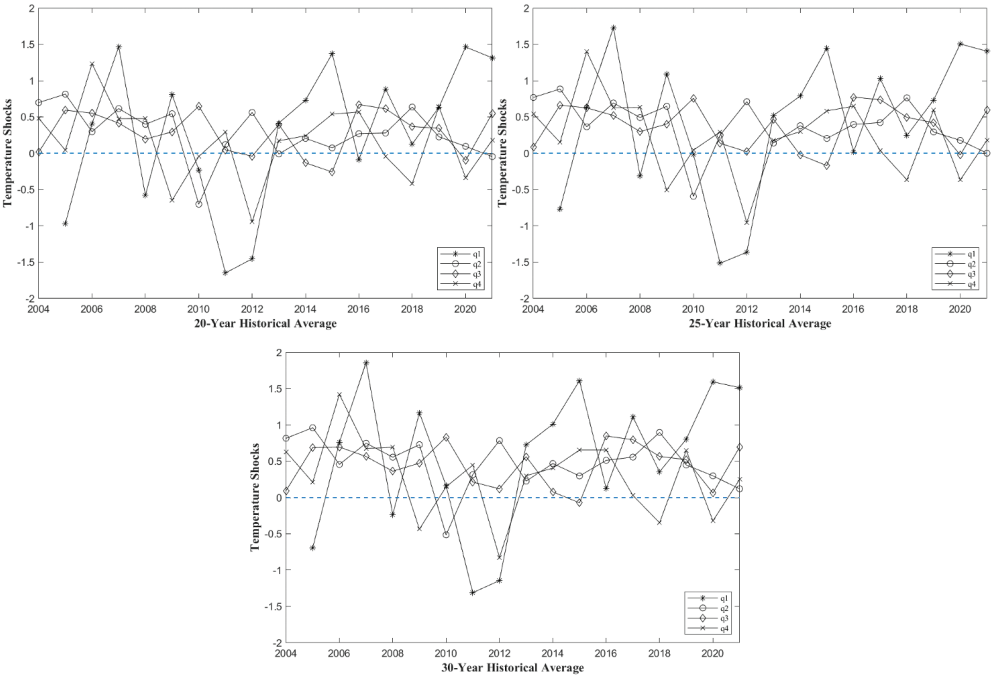

Figure 1. Quarterly temperature shocks. This figure displays the quarterly temperature shocks, which are computed as temperatures that deviate from historical 30/25/20-year moving averages. The sample period is from 2004Q2 to 2021Q4.

(M2). In the TVAR model, we include the consumer price index (CPI) and economic output (GDP), which is calculated as the year-on-year growth rate of gross domestic product. We utilize Census X-12 to seasonally adjust the quarterly time series. The data are all collected from the WIND database, and the sample period spans from 2004Q2 to 2021Q4, corresponding to the sample period for climate change.[4]

We perform the augmented Dickey–Fuller (ADF) test to check the variables' stationarity, which is a vital prerequisite for applying a TVAR model (Banerjee et al., 1993; Said & Dickey, 1984). The null hypothesis of the ADF test is that the variable contains a unit root, and the alternative hypothesis is that the variable is generated by a stationary process. Table 1 shows the results of the ADF test for all variables, including specifications. We find that all tests reject the null hypothesis at the 1% significance level. All the variables are stationary. The summary statistics for all the variables included in the TVAR models can also be found in Table 1.

[4]Due to the availability of monthly GDP data, we have to utilize quarterly data in the baseline TVAR model. Some readers may conjecture that the TVAR results can be biased by the small sample size. We address this concern by using monthly industrial production in Section 4.3.3. The results with a larger sample size remain robust.

Table 1. Summary statistics and unit root test.

Panel A: Unit root test

Variables	Specification (c, t, l)	ADF statistics	Critical values 1%	5%	10%
tempv_30	(c, 0, 0)	−7.742***	−3.552	−2.914	−2.592
tempv_25	(c, 0, 0)	−7.591***	−3.552	−2.914	−2.592
tempv_20	(c, 0, 0)	−7.624***	−3.552	−2.914	−2.592
M2	(c, t, 0)	−4.369***	−4.106	−3.480	−3.168
GDP	(c, 0, 0)	−4.531***	−3.552	−2.914	−2.592
CPI	(c, 0, 0)	−5.123***	−3.552	−2.914	−2.592

Panel B: Summary Statistics

Variables	Mean.	Std.	Min.	Max.	Sample period
tempv_30	0.449	0.559	−1.457	1.812	2004Q2 to 2021Q4
tempv_25	0.357	0.567	−1.610	1.720	2004Q2 to 2021Q4
tempv_20	0.255	0.561	−1.695	1.560	2004Q2 to 2021Q4
M2	0.144	0.048	0.080	0.290	2004Q2 to 2021Q4
GDP	0.086	0.034	−0.070	0.182	2004Q2 to 2021Q4
CPI	0.026	0.019	−0.016	0.080	2004Q2 to 2021Q4

This table reports the augmented Dickey-Fuller (ADF) unit root test results and summary statistics for variables in the TVAR model, including temperature shocks, monetary policy (M2), price level (CPI) and output (GDP). Panel A reports the results for the ADF unit root tests, and Panel B reports summary statistics including the average, standard deviation, minimum, maximum and the sample period. The variables tempv_30, tempv_25 and tempv_20 reflect quarterly temperatures that deviate from historical 30/25/20-year moving averages. The letters c, t, and l in the model specification indicate drift, trend and lag order terms, respectively. The null hypothesis of the ADF test is that the variable contains a unit root, and the alternative is that the variable is generated by a stationary process. ***, ** and * denote 1%, 5%, and 10% significance levels, respectively.

4. Empirical results

4.1. Nonlinearity test

Before estimating the TVAR model, we apply the nonlinearity test to examine whether it is reasonable to employ the TVAR model in this paper and determine the number of regimes to set (B. E. Hansen, 1999; Lo & Zivot, 2001). To answer these two questions, we perform three nonlinearity tests, in which the null hypotheses include the "linear VAR versus two-regime TVAR model (1vs2)", "linear VAR versus three-regime TVAR model (1vs3)" and "two-regime TVAR model versus three-regime TVAR model (2vs3)". We

Table 2. Nonlinearity test.

Threshold variables	Lag order	Test type	LR statistics	P value
tempv_30	1	1vs2	54.702	0.004
tempv_30	1	1vs3	88.915	0.014
tempv_30	1	2vs3	34.213	0.470
tempv_25	1	1vs2	54.018	0.008
tempv_25	1	1vs3	90.168	0.014
tempv_25	1	2vs3	36.150	0.444
tempv_20	1	1vs2	49.162	0.018
tempv_20	1	1vs3	83.307	0.038
tempv_20	1	2vs3	34.146	0.476

This table reports the results of the nonlinearity test of B. E. Hansen (1999) and Lo and Zivot (2001). The threshold variables are tempv_30, tempv_25 and tempv_20, respectively, which reflect quarterly temperatures that deviate from historical 30/25/20-year moving averages. "1vs2", "1vs3" and "2vs3" test the null hypothesis of "linear VAR versus the alternative of one threshold TVAR", the null hypothesis of "linear VAR versus the alternative of two thresholds TVAR" and the null hypothesis of "one threshold TVAR versus the alternative of two thresholds TVAR", respectively.

take the value of 1 for the lag order based on the AIC and BIC. Table 2 reports the results of the nonlinearity tests. According to the "1vs2" and "1vs3" tests, all the statistics reject the null hypothesis of linear VAR at the 1% or 5% significance levels, indicating the presence of multiple regimes. In this respect, employing the TVAR model is preferable. Comparing the two-regime TVAR model with the three-regime TVAR model, the results show that we should not reject the null hypothesis of a two-regime TVAR model. Therefore, we employ a TVAR model with two regimes for temperature shocks and evaluate the efficiency of monetary policy under high- and low-temperature shocks.[5]

4.2. Results from the TVAR model

To explore the impact of climate change on the influence of monetary policy, we use the GIRFs to analyze the output responses to positive and negative policy shocks. We separately perform one-standard-deviation unanticipated positive and negative monetary policy shocks to the TVAR models. Figure 2 shows the impulse responses for TVAR models using temperature shocks as threshold variables for the first 20 quarters. The dashed and solid lines denote the impulse responses under the high regime and low regime of temperature shocks, respectively.

The first column shows the responses of the output to one-standard-deviation positive monetary policy shocks. The output positively responds to monetary policy shocks, which aligns with conventional economic theory. We mainly focus on the differences in impulse responses under high and low regimes of temperature shocks. The influences of monetary policy under high and low regimes of temperature shocks are apparently distinctive. The responses of output are always positive under low regimes, and GDP increases by at most approximately 0.4%. The effect of monetary shocks on output during hotter periods is slightly negative for the first two-quarters and becomes positive for the following quarters. Such lagged effects of monetary policy shocks can occur due to insufficient information, as stated by Kerssenfischer (2019). Moreover, the output only increases by approximately 0.1% following the monetary shock when tempv_30 and tempv_20 are used as threshold variables under high regimes. More importantly, the responses of output under high regimes are lower than those under low regimes, implying that the effect of monetary expansion is less efficient when temperatures are higher than historical averages.

The second column displays impulse responses to one-standard-deviation negative monetary policy shocks, which correspond to tight monetary policies. The output negatively responds to negative shocks. Under low regimes of temperature shocks, the output falls by at most approximately 0.5%, and under high regimes, it falls by at most approximately 0.9%. Output is more sensitive to negative monetary shocks under high-temperature regimes. In addition, the effects of tight monetary shocks are stronger than the effects of expansionary shocks, and such asymmetric effects are quite similar to the results in Cover (1992) and Florio (2004).

Figure 2 indicates that temperature shocks weaken the efficiency of monetary expansions and worsen the effects of monetary tightening, which corresponds to a temperature-regime dependency in monetary policy transmission. The patterns of

[5]The nonlinearity test and TVAR models are estimated using R software.

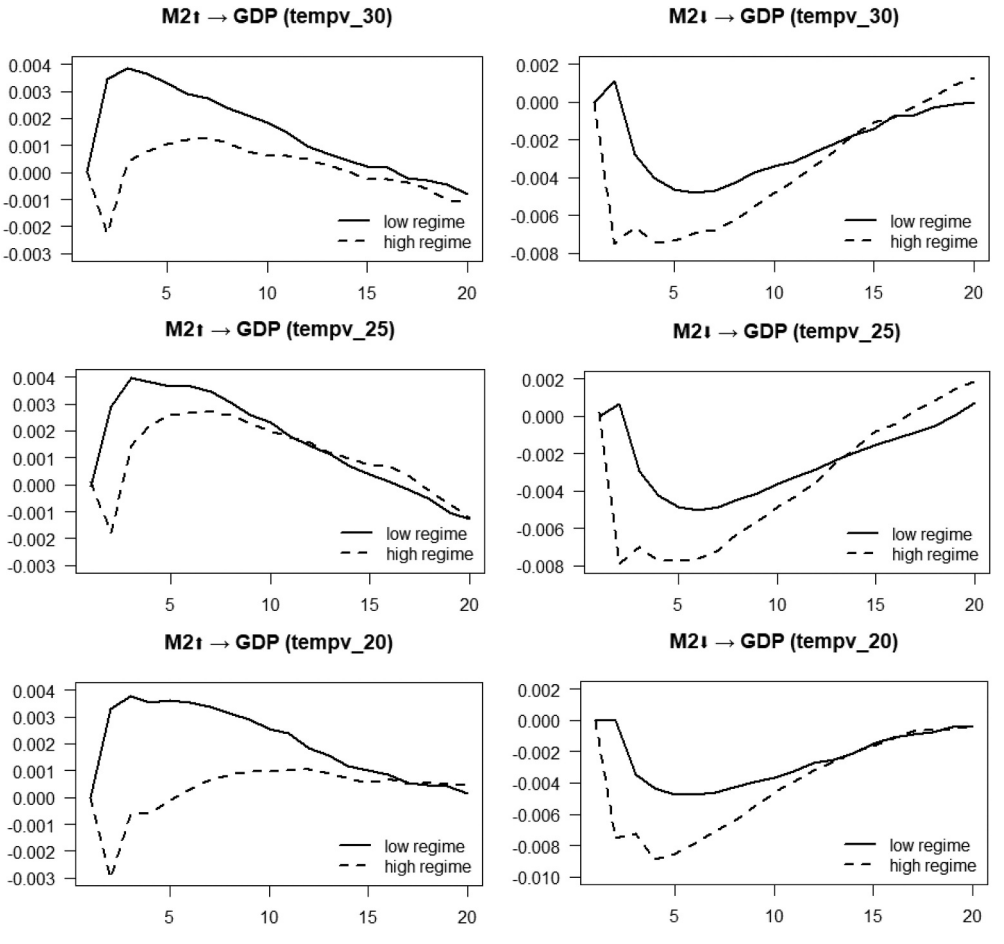

Figure 2. Impulse responses for TVAR models with Y=[tempv_H, M2, CPI, GDP]. This figure shows the output responses to monetary policy shocks conditional on high- and low-temperature shocks. Temperature shocks are tempv_30, tempv_25 and tempv_20, which reflect quarterly temperatures that deviate from historical 30/25/20-year moving averages. The first column shows impulse responses of output to one-standard-deviation positive monetary policy shocks, and the second column shows impulse responses of output to one-standard-deviation negative monetary policy shocks. Dashed lines and solid lines denote the impulse responses under high and low regimes of temperature shocks.

regime-dependent impulse responses are consistent with the theoretical results of Sandra et al. (2016) and George and Anastasios (2018). We also empirically confirm the results of George and Anastasios (2018), who argue that climate change leads to larger fluctuations in economic outputs and lengthens the duration of divergence to steady states. Overall, Hypothesis H1 is confirmed.

4.3. Robustness checks

4.3.1. Alternative orders of endogenous variables

We consider alternative orderings of endogenous variables in TVAR models. In the TVAR model in Section 4.2, we order these variables based on the assumption that temperature shocks have an immediate impact on the other variables but do not contemporaneously respond to other shocks, and that they are the same as monetary policy. However, economic growth also leads to an increase in carbon dioxide emissions and climate fluctuations. The assumption for the model in Section 4.2 may not be appropriate, and the impulse responses may change (Copeland & Taylor, 2004). To determine if and to what

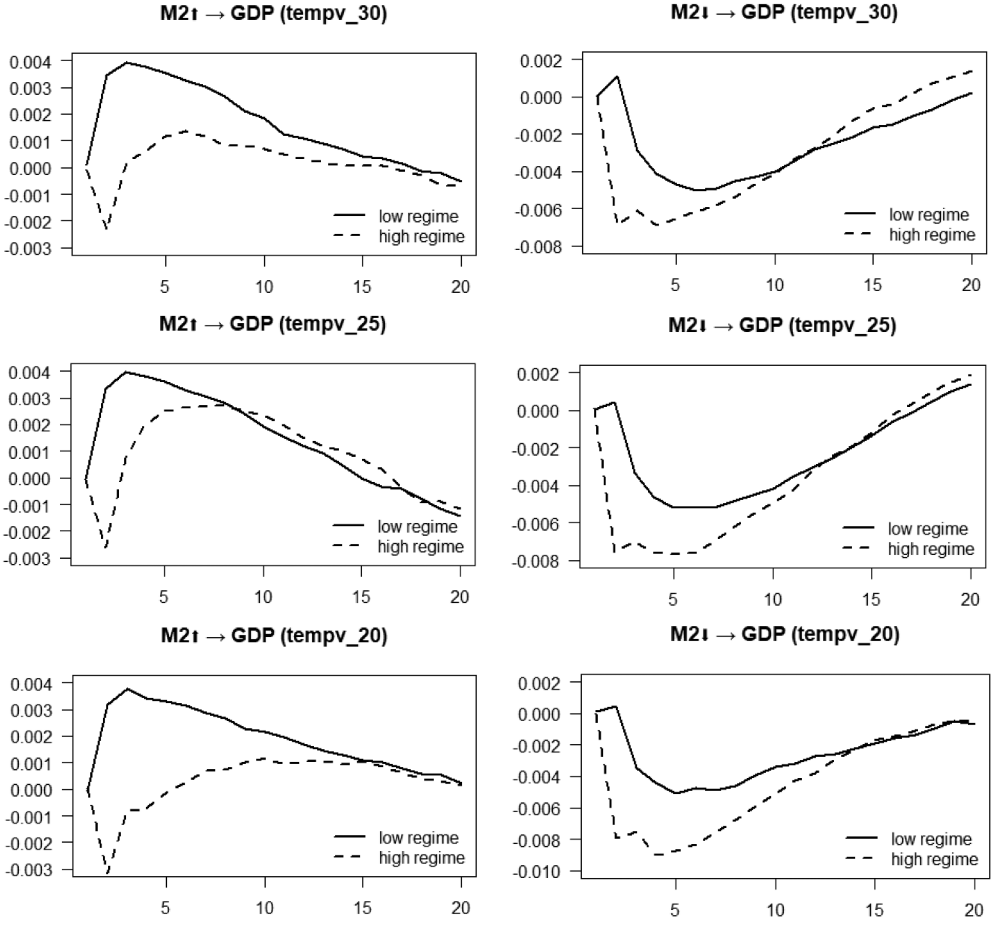

Figure 3. Impulse responses for the TVAR model with Y=[M2, tempv_H, CPI, GDP]. This figure shows the impulse responses to monetary policy shocks to output under high- and low-temperature shocks. Temperature shocks are tempv_30, tempv_25 and tempv_20, which reflect quarterly temperatures that deviate from historical 30/25/20-year moving averages. The first column shows impulse responses of output to one-standard-deviation positive monetary policy shocks, and the second column shows impulse responses of output to one-standard-deviation negative monetary policy shocks. Solid lines denote the impulse responses under low-temperature shocks, and dashed lines are under high regimes of temperature shocks.

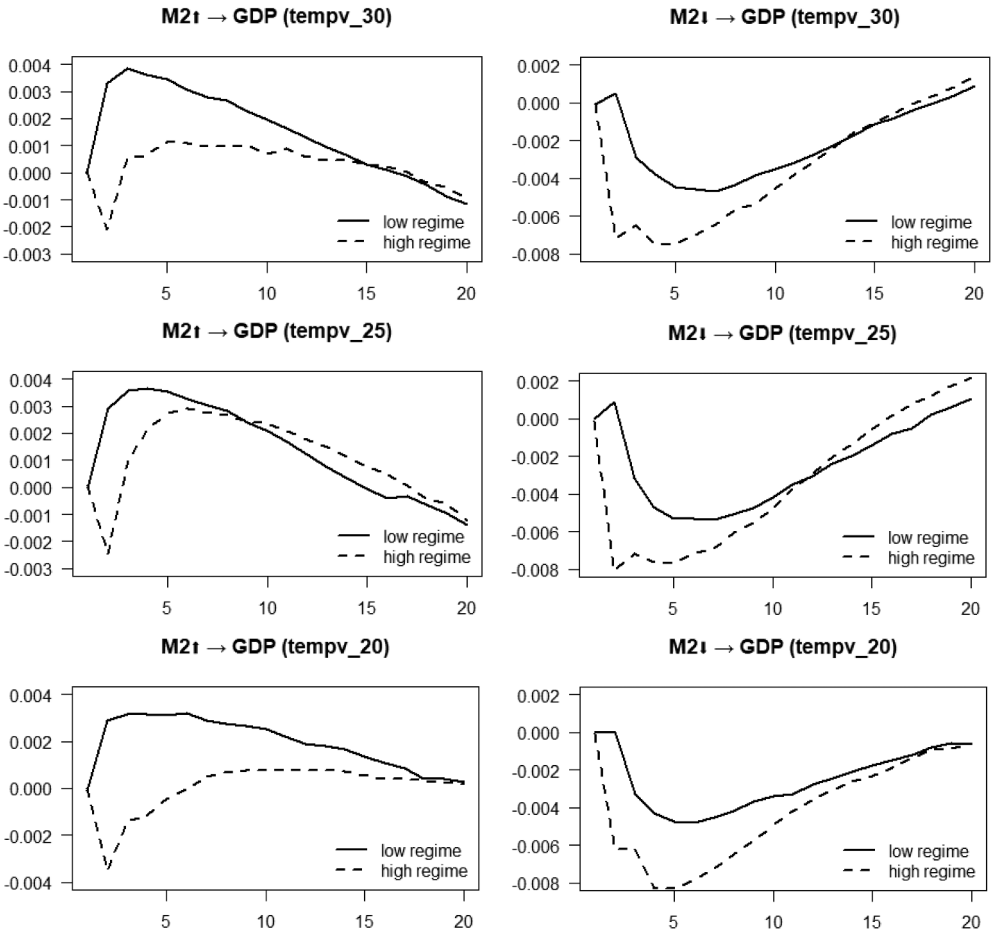

Figure 4. Impulse responses for the TVAR model with Y=[M2, CPI, GDP, tempv_H]. This figure shows the impulse responses to monetary policy shocks to output under high- and low-temperature shocks. Temperature shocks are tempv_30, tempv_25 and tempv_20, which reflect quarterly temperatures that deviate from historical 30/25/20-year moving averages. The first column shows impulse responses of output to one-standard-deviation positive monetary policy shocks, and the second column shows impulse responses of output to one-standard-deviation negative monetary policy shocks. Solid lines denote the impulse responses under low-temperature shocks, and dashed lines are under high regimes of temperature shocks.

extent the assumption could affect our results, we employ four possible alternative orders of the endogenous variable vectors to see if our results remain the same.

Figures 3–6 show that the impulse responses of output to monetary shocks under high and low regimes of temperature shocks are the same as those shown in Figure 2. Our empirical findings are not sensitive to the order of the endogenous variables, confirming their robustness.

4.3.2. Controlling for fiscal policy

Fiscal policy is also an important factor that influences economic growth, and our results may be biased in the absence of fiscal policy. To address this potential issue, we include

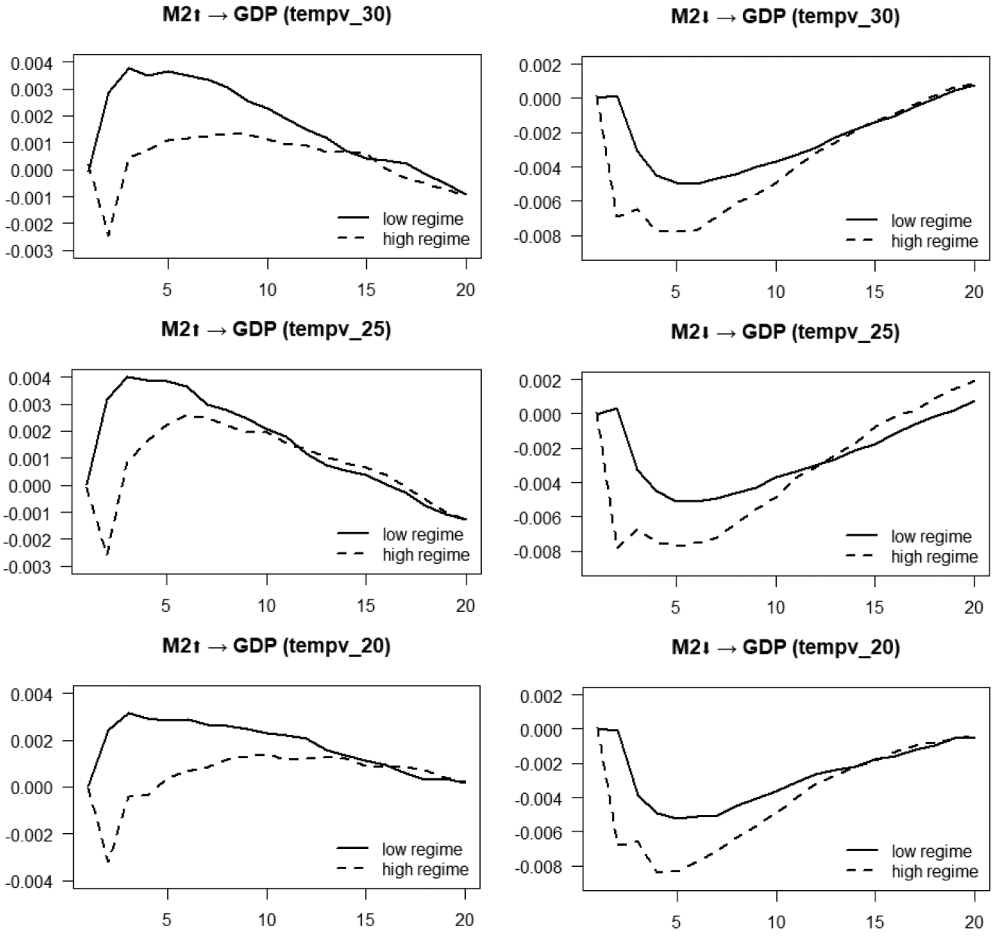

Figure 5. Impulse responses for the TVAR model with Y=[CPI, GDP, tempv_H, M2]. This figure shows the impulse responses to monetary policy shocks to output under high- and low-temperature shocks. Temperature shocks are tempv_30, tempv_25 and tempv_20, which reflect quarterly temperatures that deviate from historical 30/25/20-year moving averages. The first column shows impulse responses of output to one-standard-deviation positive monetary policy shocks, and the second column shows impulse responses of output to one-standard-deviation negative monetary policy shocks. Solid lines denote the impulse responses under low-temperature shocks, and dashed lines are under high regimes of temperature shocks.

the fiscal policy variable (fp) in the endogenous variable vector. Fiscal policy is proxied by the year-on-year growth rate of public expenditure, which is collected from the National Bureau of Statistics of China. The endogenous variable vector becomes $Y = [tempv\_H, M2, fp, CPI, GDP]$.

Figure 7 shows the impulse responses of monetary policy controlling the effects of fiscal policy. Unsurprisingly, the responses of output to monetary shocks become weaker. For example, the output increases by at most approximately 0.3% under the low regime, and the response is 0.2% under the high regime of temperature shocks with 20-year historical averages after a one-standard-deviation positive monetary shock. The efficiency of monetary policy is still lower when the weather is hotter.

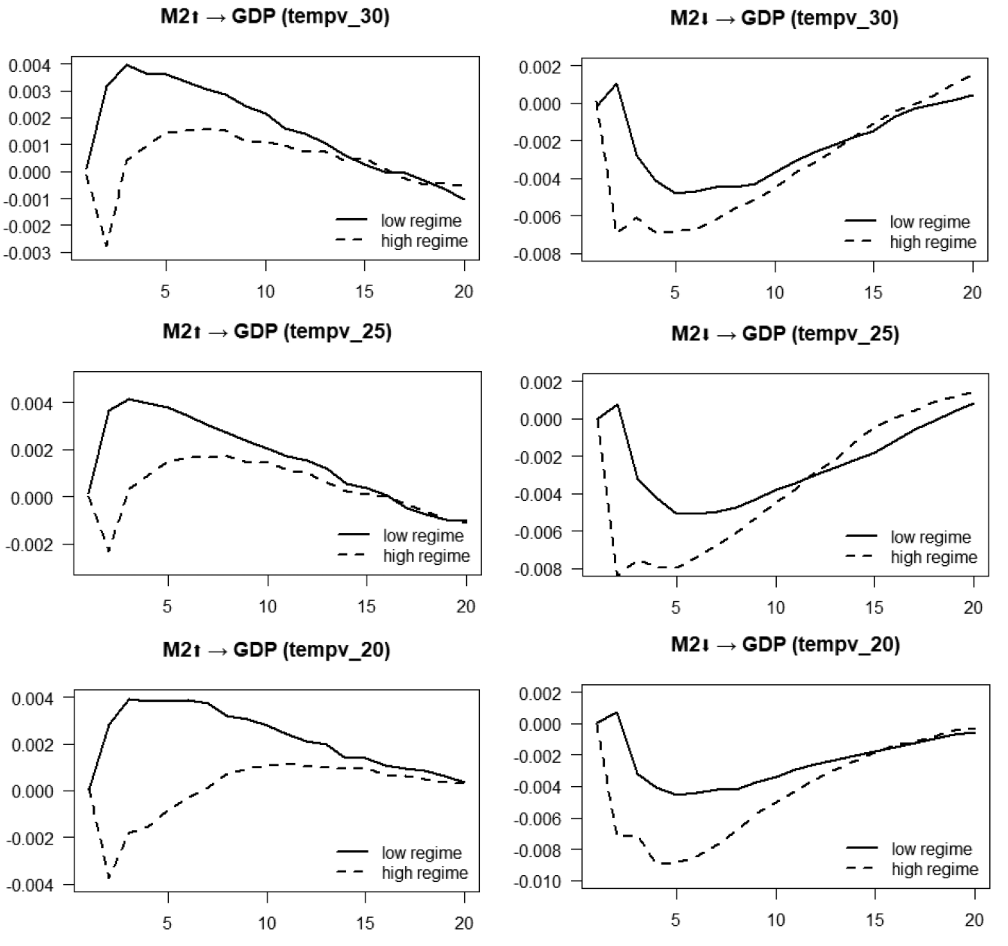

Figure 6. Impulse responses for the TVAR model with Y=[CPI, GDP, M2, tempv_H]. This figure shows the impulse responses to monetary policy shocks to output under high- and low-temperature shocks. Temperature shocks are tempv_30, tempv_25 and tempv_20, which reflect quarterly temperatures that deviate from historical 30/25/20-year moving averages. The first column shows impulse responses of output to one-standard-deviation positive monetary policy shocks, and the second column shows impulse responses of output to one-standard-deviation negative monetary policy shocks. Solid lines denote the impulse responses under low-temperature shocks, and dashed lines are under high regimes of temperature shocks.

4.3.3. Alternative variables for output

We use an alternative indicator of output. We replace the growth rate of GDP with the growth rate of industrial production and re-estimate the TVAR model. The results in Figure 8 show that using an alternative proxy of output does not affect our empirical results. In addition, we use monthly data for another robustness check to alleviate the bias from using a relatively small sample size of quarterly data. The impulse response results are shown in Figure 9. With a larger sample size, the results are consistent with the baseline results.

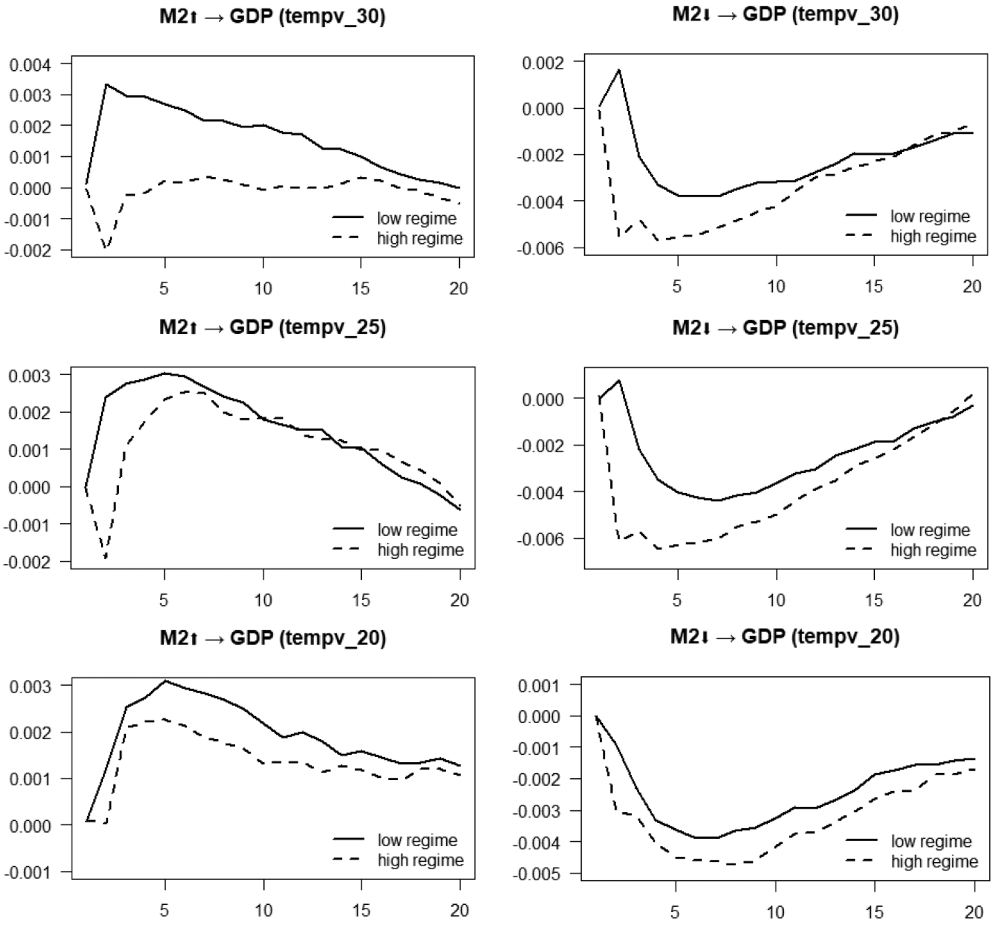

Figure 7. Impulse responses for the TVAR model with Y = [tempv_H, M2, fp, CPI, GDP]. This figure shows the impulse responses to monetary policy shocks to output under high- and low-temperature shocks. Temperature shocks are tempv_30, tempv_25 and tempv_20, which reflect quarterly temperatures that deviate from historical 30/25/20-year moving averages. The first column shows impulse responses of output to one-standard-deviation positive monetary policy shocks, and the second column shows impulse responses of output to one-standard-deviation negative monetary policy shocks. Solid lines denote the impulse responses under low-temperature shocks, and dashed lines are under high regimes of temperature shocks.

5. Influential mechanism: the climate-induced credit constraint

Hypothesis H2 indicates that high temperatures weaken firm profitability, increase the default probabilities of bank loans, and result in higher bank non-performing loan ratios. Commercial banks will be more risk averse and prudent in expanding credit, which weakens the efficiency of monetary policies. This climate-induced credit constraint is used to explain the impact of climate change on monetary policy efficiency (Berg & Schrader, 2012; Hosono et al., 2016). To empirically examine the climate-induced credit constraint, we employ Equations (4)–(6).

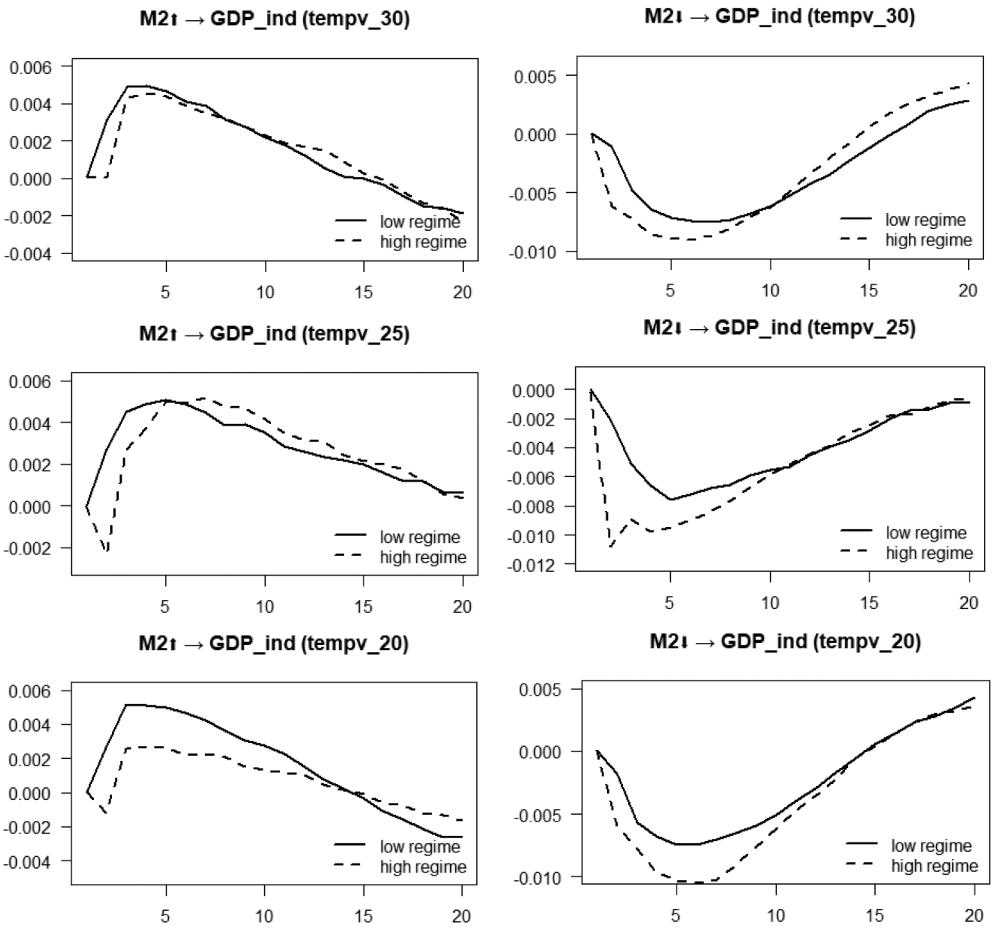

Figure 8. Impulse responses for the TVAR model with Y=[tempv_H, M2, CPI, GDP_ind]. This figure shows the impulse responses to monetary policy shocks to output under high- and low-temperature shocks. Temperature shocks are tempv_30, tempv_25 and tempv_20, which reflect quarterly temperatures that deviate from historical 30/25/20-year moving averages. The first column shows impulse responses of output to one-standard-deviation positive monetary policy shocks, and the second column shows impulse responses of output to one-standard-deviation negative monetary policy shocks. Solid lines denote the impulse responses under low-temperature shocks, and dashed lines are under high regimes of temperature shocks.

$$loan_{i,t} = \alpha_1 + \beta_1 tempv\_H_t + \phi_1 controls_{i,t} + \eta_i + \varepsilon_{i,t} \tag{4}$$

$$npl_{i,t} = \alpha_2 + \beta_2 tempv\_H_t + \phi_2 controls_{i,t} + \eta_i + \varepsilon_{i,t} \tag{5}$$

$$loan_{i,t} = \alpha_3 + \beta_3 tempv\_H_t + \gamma_3 npl_{i,t} + \phi_3 controls_{i,t} + \eta_i + \varepsilon_{i,t} \tag{6}$$

where $loan_{i,t}$ denotes the growth rate of the bank loan scale calculated by the first difference of log total loans, $tempv\_H_t$ denotes the temperature shocks as mentioned above, $npl_{i,t}$ denotes the log non-performing loan ratio of banks, and $controls_{i,t}$ denotes bank-level variables, which include bank size (lnsize), log total assets of banks, the capital ratio (cap), the liquidity ratio (liq), the ratio of liquid assets to total assets, the ratio of

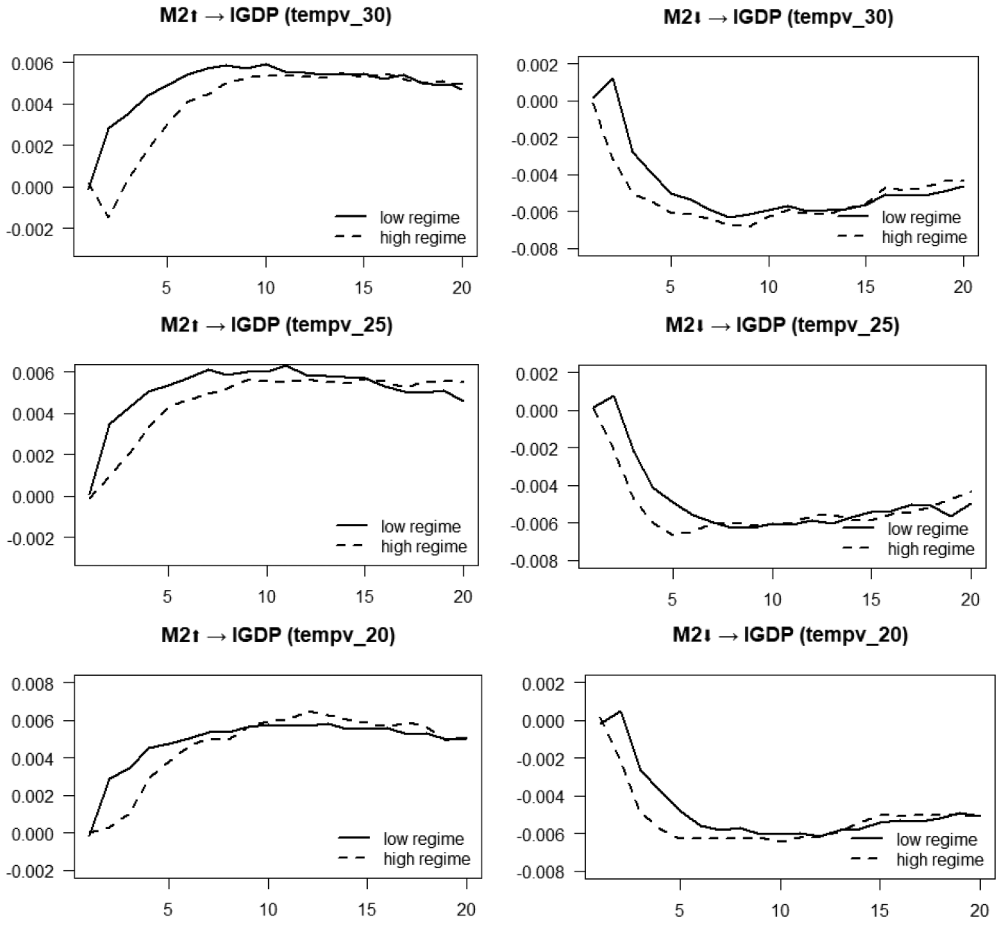

Figure 9. Impulse responses for the TVAR model with Y=[tempv_H, M2, CPI, IGDP]. This figure shows the impulse responses to monetary policy shocks to output under high- and low-temperature shocks. We replace quarterly data with monthly data in TVAR model. Temperature shocks are tempv_30, tempv_25 and tempv_20, which reflect monthly temperatures that deviate from historical 30/25/20-year moving averages. The first column shows impulse responses of output to one-standard-deviation positive monetary policy shocks, and the second column shows impulse responses of output to one-standard-deviation negative monetary policy shocks. Solid lines denote the impulse responses under low-temperature shocks, and dashed lines are under high regimes of temperature shocks.

owners' equity to total assets. We also include macroeconomic variables, such as shadow banking (sb), the growth rate of the social entrusted loan scale, the money stock (M2), and economic growth (GDP). η_i denotes the bank fixed effect. Considering the accessibility of bank data, we select 343 banks, containing 6 state-owned banks, 12 joint-stock commercial banks, 111 city commercial banks, and 214 rural commercial banks, spanning from 2004Q2 to 2021Q4. We obtain bank characteristics and economic data from the WIND database.

Table 3 displays the estimation results for Equations (3)–(5). The standard errors are clustered at the bank level. In Columns (1), (4), and (7), the coefficient estimates for temperature shocks in Equation (3) are significantly negative at the 10% or 5% level, indicating that increases in temperature shocks impede bank lending. For example, the

Table 3. Mechanism test for credit channel.

	(1) loan	(2) npl	(3) loan	(4) loan	(5) npl	(6) loan	(7) loan	(8) npl	(9) loan
tempv_30	−0.007*	0.104***	−0.001						
	(−1.906)	(7.168)	(−0.298)						
tempv_25				−0.007**	0.124***	−0.000			
				(−1.978)	(8.069)	(−0.160)			
tempv_20							−0.008**	0.109***	−0.002
							(−2.175)	(7.325)	(−0.705)
npl			−0.040***			−0.040***			−0.039***
			(−5.651)			(−5.635)			(−5.638)
liq	0.105***	−1.119***	0.041	0.103**	−1.086***	0.041	0.103**	−1.111***	0.040
	(2.618)	(−3.596)	(1.009)	(2.571)	(−3.539)	(1.014)	(2.569)	(−3.580)	(0.978)
cap	0.153	−6.110***	0.085	0.150	−6.040***	0.085	0.153	−6.116***	0.085
	(0.651)	(−3.860)	(0.368)	(0.638)	(−3.801)	(0.368)	(0.649)	(−3.862)	(0.367)
lnsize	−0.033*	−0.428***	−0.031**	−0.033*	−0.418***	−0.031**	−0.033*	−0.430***	−0.031**
	(−1.888)	(−3.644)	(−2.008)	(−1.902)	(−3.560)	(−2.006)	(−1.891)	(−3.664)	(−2.017)
sb	−0.059***	−0.626***	−0.077***	−0.058***	−0.645***	−0.078***	−0.058***	−0.623***	−0.076***
	(−2.831)	(−5.581)	(−3.516)	(−2.785)	(−5.753)	(−3.515)	(−2.808)	(−5.561)	(−3.480)
M2	0.645***	−1.628***	0.670***	0.640***	−1.472***	0.672***	0.638***	−1.603***	0.664***
	(5.629)	(−3.537)	(6.258)	(5.558)	(−3.197)	(6.240)	(5.591)	(−3.496)	(6.227)
gdp	−0.012	0.268*	0.053	−0.013	0.285*	0.053	−0.016	0.299*	0.051
	(−0.228)	(1.677)	(1.533)	(−0.239)	(1.781)	(1.547)	(−0.289)	(1.852)	(1.478)
cons	0.171***	−2.028***	0.010	0.173***	−2.084***	0.010	0.172***	−2.016***	0.012
	(2.836)	(−5.514)	(0.183)	(2.857)	(−5.686)	(0.170)	(2.857)	(−5.502)	(0.220)
obs	4759	5451	4500	4759	5451	4500	4759	5451	4500
R^2	0.106	0.124	0.151	0.106	0.128	0.151	0.106	0.124	0.151

This table reports the estimation results for Equations (4)–(6).The key variables are the growth rate of loan size (loan), log non-performing loan ratio (npl) and tempv_H (H = 30/25/20), which reflects quarterly temperatures that deviate from the historical H-year moving average. Control variables include liquidity ratio (liq), capital ratio (cap), log total assets (lnsize), shadow banking (sb), money stock (M2) and the economic growth rate (GDP). Numbers in parentheses are t-statistics based on robust standard errors clustered on bank levels. ***, ** and * denote 1%, 5% and 10% significance levels, respectively.

estimated $\hat{\beta}_1$ for *tempv*_30 is −0.007 with a robust t-statistic of −1.906, which is significant at the 10% level. In Columns (2), (5), and (8), the estimates for temperature shocks in Equation (4) are significantly positive at the 1% level, suggesting that temperature shocks increase the non-performing loan ratio of commercial banks. In Columns (3), (6), and (9), the estimated coefficients for temperature shocks in Equation (5) are all insignificant, while the coefficients $\hat{\gamma}_3$ for the non-performing loan ratio are significantly negative at the 1% level. The significant $\hat{\beta}_1$s and $\hat{\gamma}_3$s and the insignificant $\hat{\beta}_3$s indicate that the non-performing loan ratio of banks has a complete mediating effect in explaining the influence of temperature shocks on monetary policies. Hypothesis H2 is confirmed.

6. Concluding remarks

In this paper, we investigate whether climate change affects the efficiency of monetary policy. We use temperature shocks, calculated as temperature deviations from historical average temperatures, to proxy climate change, and utilize TVAR models and GIRFs to reveal the effects of expansionary and tight monetary policies on economic output under high- and low-temperature regimes.

Our results suggest that there is a climate change regime dependency in monetary policy. Increases in temperature weaken the efficiency of monetary expansions and worsen the negative effects of monetary tightening. Consistent with previous findings,

we also find that there are asymmetric effects for expansionary and tight monetary policy, in which tight monetary policy has stronger effects in both high- and low-temperature regimes. The asymmetries are more obvious under high-temperature regimes. We explain our results by empirically confirming the climate-induced credit constraint of commercial banks argued by previous theoretical studies. Temperature shocks can decrease labor productivity and TFP growth and increase firm operation costs, which impairs firm profitability associated with loan repayment, corresponding to an increase in the non-performing loan ratio of banks. Increases in non-performing loan ratios lead to credit constraints induced by climate change and thus weaken the credit channel of monetary policy transmissions.

In the era of global warming, our study has meaningful implications for climate risk management and mitigation for central banks and financial institutions. First, central banks should incorporate climate change into their monetary policy framework to formulate optimal monetary policies. For example, central banks should implement more aggressive expansionary monetary policy and weaker tight monetary policy when climate change is severe. Second, it is critical for banks to manage climate risk. As climate conditions deteriorate, commercial banks should take precautions to increase their risk-taking ability to avoid capital losses and perform climate stress tests to frequently evaluate climate change risk.

There are several limitations of our work. First, we highlight the channel through which banks engage in risk-taking in monetary policy transmission because the banking sector dominates the Chinese financial system. In developed economies, the capital market is more important than the banking sector, and new channels through which climate change affects the influence of monetary policy should also be investigated. Second, climate change variables of daily frequency may be available, but macroeconomic variables are usually quarterly. When including both daily and quarterly variables in a TVAR model, we must transform the frequency of climate change variables from daily to quarterly. This results in a loss of information of climate change fluctuations. To address this issue, we may rely on a mixed-frequency data sampling model that accommodates variables of different frequencies (Ghysels et al., 2006, 2007). Third, other proxies of climate change and natural disasters, such as precipitation, drought, and floods, may also affect the transmission of monetary policy. We may use the TVAR or other models to provide additional evidence. We leave them for future research.

Disclosure statement

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Data availability statement

Available upon request.

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