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MONETARY POLICY, INNOVATION EFFICIENCY, AND TOTAL FACTOR PRODUCTIVITY

Hao-Chang Yang¹, Chun-Ping Chang², Sahminan³, Arnita Rishanty⁴

Abstract
This research explores the impact of monetary policy on the growth rate of total factor productivity (TFPG) and innovation efficiency (IE) through panel data of 30 countries from 1983 to 2018 by the bias-corrected fixed-effect dynamic (BCFE) model. We find that tight monetary policy negatively impacts the growth rate of total factor productivity (TFPG) and innovation efficiency (IE), which is still valid after replacing the independent variables and empirical methods. We then perform sub-sample regressions, and the results show that countries with higher government efficiency, higher financial development, and stricter environmental policy can reduce the negative impact of tightening monetary policy on total factor productivity and innovation efficiency. Our research illustrates that a tightening monetary policy not only adversely impacts total factor productivity, but also influences the main driving force of its growth-innovation efficiency.

Keywords: Monetary Policy; Innovation Efficiency; TFP; Government Efficiency

JEL Classifications: E22; D24; O31
1. Introduction

There has been a large amount of literature in recent years focusing on total factor productivity (TFP), which aims to measure the efficiency of production activities in a certain period - that is, the ratio of total output to total factor inputs (Y. Feng, Zhong, Li, Zhao, & Dong, 2019; Moran & Queralto, 2018). Existing studies mostly have discussed TFP from the macro-level (Song, Du, & Tan, 2018; Yang, Lu, & Tan, 2021) and micro-level perspectives (Liu, Yin, Yin, & Sheng, 2021; Mattsson, 2019). Rath and Jangam (2020) explored the impact of labor capital on total factor productivity by comparing the average wage levels of companies in developed and developing countries and finding a long-term relationship between the labor capital ratio, corporate wages, and TFP. Based on financial data of Chinese listed companies, Zhang and Liu (2017) presented for companies of different attributes that the financing constraints they face have differential impacts on TFP. From a macro-level perspective, most existing literature also has focused on the effect of foreign direct investment (Papaioannou & Dimelis, 2019; Rath & Jangam, 2020), technology spillovers (Madsen, 2007), government subsidies (Hong, Feng, Wu, & Wang, 2016; Wu, Li, Nie, & Chen, 2017), and trade openness (Miller & Upadhyay, 2000) on TFP. However, there is no literature exploring the impact of macro-monetary policy on TFP, which is the main purpose of this paper.

The monetary policy adopted by the central bank includes various measures to control and regulate the money supply and the amount of credit to achieve its specific economic objectives. It has an impact on private capital investment and aggregate demand, which in turn affect the overall macroeconomy (Cecchetti & Krause, 2002; Habib, Abbas, & Noman, 2019). However, it is still an unknown mystery whether TFP can be effectively improved when the central bank implements a loose monetary policy with an increase of money in circulation, reduction of credit constraints, and enterprises having more working capital for production and investment. Zhang, Guo, Wang, and Chen (2020) find that as economic globalization deepens further, the monetary policy of interest rate hikes by the U.S. authorities will have a significant positive impact on Chinese firms' innovative R&D activities, and this impact is more pronounced when economic policy uncertainty increases. Annicchiarico and Pelloni (2021) explored whether the economic growth model with innovation as the main driving force would influence monetary policy. de la Horra, Perote, and de la Fuente (2021) used data of U.S. listed companies from 2000 to 2019 to present that enterprises with high irreversibility of investment, low cash flow, and poor innovation ability find it difficult to effectively and timely change their investment strategies when facing monetary policy changes, and the effectiveness of monetary policy cannot be guaranteed. Therefore, the authorities should intervene in time to ensure the reduction of uncertainty and lower business risks.

The improvement of innovation efficiency has always been regarded as an important reason for the increase in TFP (Kim & Park, 2018; Tello, 2015; Wen, Zhao, & Chang, 2021). Ranasinghe (2014) stated that resource misallocation caused by policy distortion is the direct cause of a decline in enterprise productivity. Enterprises can compensate for this decline caused by resource misallocation by investing in innovative R&D activities, and government subsidies can also help inhibit the decline of TFP. However, innovation and R&D activities require a long period and high uncertainty, and so enterprises will consider the future benefits brought by innovation and R&D when facing investment decisions (Chu, Cozzi, Lai, & Liao, 2015; Edquist & Henrekson, 2017; Wang, Feng, Wang, & Chang, 2021). Therefore, based on the discussion of monetary policy’s effect on TFP, we further explore the impact of monetary policy on innovation efficiency.

This paper contributes to the existing literature mainly from the following aspects. First, we adopt the bias-corrected fixed-effect dynamic (BCFE) model as a tool to estimate the influence of monetary policy on the growth rate of total factor productivity and innovation efficiency based on balanced panel data of 30 countries from 1983 to 2018. Second, this paper shows that a tight monetary policy will negatively impact the growth rate of total factor productivity and innovation efficiency. This conclusion is still valid after replacing the independent variables and empirical methods. The reason for this conclusion may be that the tightening monetary policy may lead to a reduction in R&D funding for firms, which in turn leads to a decrease in innovation efficiency and a drop in the growth rate of total factor productivity. Finally, we perform
sub-sample regressions based on government efficiency, financial development, and environmental policy stringency and observe whether monetary policy has different effects on total factor productivity and innovation efficiency. The results show that countries with higher government efficiency, higher financial development, and stricter environmental policies can reduce the negative impact of external tightening monetary policies on total factor productivity and innovation efficiency.

The remainder of this paper is as follows: Section 2 deals with data and economic methodology. Section 3 presents the empirical results and discussion. The last part is the conclusion and policy recommendations.

2. Data and Economic Methodology

2.1. Data and Variables

2.1.1. Dependent Variables

This paper mainly investigates the impact of monetary policy on TFP and innovation efficiency. Most of the existing literature focuses on total factor production at the enterprise level (Shen, Lin, & Wu, 2019; Wu et al., 2017), while only a part of it targets research at the national level (Baltabaev, 2014; Gao & Chou, 2015). Compared to corporate micro-level data, we believe that cross-border panel data can better reflect the impact of different monetary policies on TFP and innovation efficiency. Therefore, this paper draws on the practice of Ramzan, Sheng, Shahbaz, Song, and Jiao (2019) and uses TFP data from the 10.0 version of the Penn World Tables (Feenstra, Inklaar, & Timmer, 2015; Fu, Chen, Jang, & Chang, 2020) to calculate its growth rate as the dependent variable. Figure 1 shows the growth rate of total factor productivity in the sample countries from 1983 to 2018. The equation for the growth rate of total factor productivity (TFPG) runs as follows:

\[
TFPG_{i,t} = \frac{(TFP_{i,t} - TFP_{i,t-1})}{TFP_{i,t-1}}
\]  

(1)

Figure 1: Total factor productivity growth rate (TFPG) of the sample countries

The variable of innovation efficiency (IE) mostly refers to the ratio of a country’s R&D investment to innovation output. Graham and Hancock (2014) believed that compared to patent data, trademark data cover a wider range of innovative R&D activities. In addition to manufacturing innovation, it also covers business
models and service innovation. At the same time, the data recorded by various countries on trademarks have been regularly and systematically continued for decades (Duygun, Sena, & Shaban, 2016), and so this paper uses trademark data to measure innovation efficiency. Figure 2 shows the difference between trademarks and patent applications in sample countries in 2018.

The specific equation of IE is:

\[
IE = \frac{\text{Trademark}_{i,t}}{R \& D_{i,t} + 0.8R \& D_{i,t-1} + 0.6R \& D_{i,t-2}}
\]

For Eq. (2), \( \text{Trademark}_{i,t} \) represents the number of trademarks in country \( i \) at year \( t \), and \( R \& D_{i,t} \) is the R&D expenditure of country \( i \) in year \( t \). We also take Hirshleifer, Hsu, and Li (2013)’s approach and apply 20% depreciation to incorporate the three-year cumulative R&D expenses into the equation for measurement.

![Fig. 2: Differences between trademark and patent applications for the sample countries in 2018](image)

### 2.1.2. Independent Variables

Numerous studies have focused on the assessment of climate vulnerability and its economic consequences. IPCC (2001) defines climate vulnerability as the degree to which an economy is susceptible to and having trouble coping with climate change and its corresponding hazards. Accordingly, subsequent studies assess climate vulnerability mainly from the following three dimensions (Feindouno et al., 2020; Ishtiaque et al., 2022). The first is exposure or more precisely physical exposure to climate hazards in the geophysical sense. The second is sensitivity, which measures the likelihood and extent to which a socioeconomic system is affected by climate change events. A higher sensitivity level indicates that a country is more vulnerable to climate shocks, thus resulting in a higher CVI. The third is adaptive capacity or the ability to adapt to and deal with climate-induced impacts. In most cases, exposure captures risks arising from geophysical factors that are independent of an economy’s socioeconomic status and relevant policies, whereas sensitivity and adaptive capacity involve socioeconomic factors to a large extent.

Among the existing climate vulnerability indicators, ND-GAIN’s CVI is the most commonly used one (Kling et al., 2021). It covers not only the above three vulnerability components, but also six sectoral dimensions, as well as the economic, social, and governance readiness of countries to take adaptation actions (Chen et al., 2015). Existing studies have utilized this index to explore the impacts of climate vulnerability on human migration (Grecequet et al., 2017), bond yields (Kling et al., 2018), the distribution equity and
efficiency of global climate finance (Chen et al., 2018; Islam, 2022), a firm’s cost of capital (Kling et al.,
2021), bank liquidity creation (Lee et al., 2022), etc. They generally confirm the negative economic
consequences of climate vulnerability and its positive role in promoting the equitable allocation of global
climate finance. These findings are consistent with studies using other climate vulnerability indicators, such
as the climate risk index compiled by Germanwatch (Huang et al., 2017), physical climate vulnerability
(Weiler et al., 2018), changes in temperature and precipitation (Kahn et al., 2021), and climate-related
disasters (Zhao et al., 2022).

Combing the macroeconomic consequences of climate vulnerability helps to analyze its potential
impacts on country-level green investment. Nordhaus (1994) is among the first to pay attention to the
macroeconomics of climate change and the estimation of its aggregate damages. Subsequent studies
investigate the macro-level risks and damages of climate change from multiple perspectives, including mainly
economic growth, agriculture, coastal communities, energy systems, and so on (Nordhaus and Moffat, 2017).
Rezai et al. (2018) build a theoretical model and deduce that climate change reduces profitability, investment,
and output of private sectors in both the short term and long term. Batten et al. (2020) suggest that climate
change events usually relate to financial loss and gross domestic product (GDP) decline, and relevant
mitigation policies may also lead to negative macroeconomic shocks. Acevedo et al. (2020) argue that
weather shocks cause economic output by reducing investment and labor productivity and undermining
human health and agricultural and industrial development.

Based on cross-country analyses, Kahn et al. (2021) indicate that deviations of temperature from its
historical norms reduce real GDP per capita. They further illustrate that the negative impacts of climate shocks
are more pronounced in poor countries. According to Sahin (2022), the macroeconomic influences of climate
change lie mainly in its negative roles in economic growth, labor productivity, and political stability. Lee et
al. (2022) find that climate vulnerability has negative impacts on bank liquidity creation, which is important
for economic growth and financial stability. They also show that climate vulnerability has greater negative
impacts on developing countries. These studies all conclude that climate vulnerability may depress investment
directly or through its adverse impacts on other macroeconomic factors, which is more pronounced in less
developed countries, but a few studies provide evidence for the positive influences of natural disasters on
economic growth through accelerating capital replacement (Skidmore and Toya, 2002; Cunado and Ferreira,
2011).

There is limited literature on the green investment effect of climate vulnerability, especially at the
transnational level. Existing studies pay more attention to the influencing factors of corporate green
investment, such as public environment concern (Gu et al., 2021) and firm size and import business
(Siedschlag and Yan, 2021), as well as the positive influences of green investment within a single country
(Chen and Ma, 2021; Zhang et al., 2022). Mielenke and Steudle (2018) define green investment as that going
toward green infrastructure and technologies and explore the dilemma of strengthening green investment
coordination at the micro-level. These studies mainly adopt green bonds and capital expenditure on green
infrastructure and technologies to measure green investment.

A few studies have discussed green investment at the cross-country level. Using cross-country panel
data, Eyraud et al. (2013) define green investment as financial investment in renewable and energy-efficient
technologies and R&D in green technologies and confirm that its determinants mainly include economic
growth, financial system, and fuel prices. Based on panel data of global multinational enterprises,
Amendolagine et al. (2021) find that green foreign direct investment in renewable energy has positive impacts
on green technology innovation. Sun et al. (2022) employ R&D expenditure as a proxy for green investment
and explore its role in ecologically sustainable development in OECD countries. By formulating the
Stackelberg models, Li et al. (2021) confirm the positive effects of government subsidies on manufacturers’
green technology investment and the heterogeneous effects of different subsidy policies. The above literature
shows that investment in green technologies is an important content and measure of green investment, both
at the firm level and at the national level. As for the green investment effect of climate vulnerability, Marshall
et al. (2021) and Zhao et al. (2022) provide evidence on the role of climate disasters in raising investors’ attention to green issues and impeding green innovation, respectively.

The definition and composition of climate vulnerability suggest that its impact on country-level green investment requires careful investigation. On the whole, climate vulnerability has negative impacts on macroeconomic factors, such as economic growth, financial stability, labor productivity, investment, technology innovation, etc. These macroeconomic consequences stem not only from climate change itself and related hazards, but also from the process of CCM (Kober et al., 2016). A country will suffer output shocks when it transitions to a green economy characterized by low carbon and resource efficient (Lee et al., 2022). As green investment needs certain economic, financial, and technical accumulation (Eyraud et al., 2013), climate vulnerability may be adversely associated with the foundation and capacity of green technology investment. Even if climate change shocks may promote capital replacement and new technology adoption to some extent, they do cause non-negligible damages and thereby inhibit innovation activities, especially in counties with poor economic and innovation performance (Hallegatte and Dumas, 2009; Nyiwul, 2021).

As for the potential role of climate vulnerability in raising investors’ green awareness and promoting equitable distribution of global climate finance, it relates more to physical vulnerability. Physical vulnerability objectively reflects a country’s exposure to climate hazards and the need for green investment. The dimensions of sensitivity and adaptive capacity closely relate to a country’s ability to mitigate and adapt to climate change events and to integrate and utilize climate funds. Since climate funds tend to flow more into countries with better CCA capacity, the most climate-vulnerable countries will not receive more funds (Chen et al., 2018). Therefore, when socioeconomic factors are not taken into account, climate-vulnerable countries may invest more in green technologies and infrastructure and receive more climate funds; otherwise, climate vulnerability might depress green investment. In sum, climate vulnerability negatively correlates to green investment, whereas physical vulnerability may promote more green investment.

The negative consequences of climate vulnerability are disproportionately borne by certain countries. Some studies focus on geographic differences, noting that African countries, south Asia, and small island developing states (SIDS) generally have more vulnerable climates and suffer more from climate change (Edmonds et al., 2020; Feindouno et al., 2020). Some studies pay attention to socioeconomic differences and come to similar conclusions. Using the vulnerability indices and readiness indices from ND-GAIN, Amegavi et al. (2021) show that adaptation readiness and its three dimensions (i.e., economic, social, and governance readiness) reduce climate vulnerability in African countries. Kahn et al. (2021), Lee et al. (2022), and Zhao et al. (2022) argue that countries with a higher level of economic development are generally less affected by climate change and related disasters. Technological innovation is critical to CCM and CCA and belongs to primary areas of green investment, thereby helping to mitigate the adverse effects of climate vulnerability on green investment. Green investment in countries with higher levels of adaptation readiness, economic development, and technological innovation is hence less susceptible to climate vulnerability.

Based on the above literature review and theoretical analysis, we put forward the following three hypotheses.

H1: Climate vulnerability has a negative impact on green investment.
H2: Physical climate vulnerability may promote more green investment.
H3: Adaptation readiness, economic development, and technological innovation moderate the adverse effects of climate vulnerability on green investment.

For the core independent variables of monetary policy, most of the existing literature chooses deposit interest rate, loan interest rate, M2, and other indicators as proxy variables. Therefore, this paper selects the deposit interest rate (DIR) as an independent variable to measure monetary policy. For ensuring the robustness of the results of this paper, we additionally choose the loan interest rate (LIR) as a proxy variable for robustness testing.
2.1.3. Other independent variables

For the remaining control variables, this paper selects GDP per capita (GDP), net foreign direct investment inflow (FDI), total imports and exports as a percentage of GDP (Trade), urbanization rate (Urbanization), industrial value-added (IS), energy consumption structure (ECR), and human capital (HC). The detailed information of all control variables goes as follows.

**Per capita real GDP (GDP):** The degree of economic development represents the efficiency of resource allocation. Many research papers have explored the relationship between the level of economic development and TFP. Ramzan et al. (2019) pointed out a certain complementary relationship between a country’s trade development level and TFP. When TFP increases as an intervention variable, it can promote a positive impact of trade openness on GDP.

**Net foreign direct investment inflow as a percentage of GDP (FDI):** Numerous studies have shown that foreign direct investment has an impact on a country’s economic growth. Alfaro, Kalemli-Ozcan, and Sayek (2009) found that foreign direct investment in countries with advanced financial development has a positive impact on total factor productivity. The reason for this growth is not from capital accumulation, but increased efficiency. Therefore, this paper chooses net foreign direct investment inflow as a percentage of GDP (FDI) as the control variable.

**Total imports and exports as a percentage of GDP (Trade):** The development of a country’s import and export trade is one of the important ways to stimulate economic growth, which is bound to have an impact on TFP (Chen, 2018; Ramzan et al., 2019). Therefore, this paper selects total imports and exports as a percentage of GDP as independent variables to observe the impact of trade development on TFP.

**Urbanization rate (Urbanization):** The degree of urbanization development can reflect the level of development of agglomeration economies. An agglomeration economy has a certain positive impact on industrial structure upgrading and technological innovation (Dai, Li, & Lu, 2017; Zheng, Feng, Jang, & Chang, 2021). Therefore, we choose the urbanization rate as a proxy variable for the agglomeration economy to control its impact on TFP.

**Industrial value-added (IS):** The innovation and upgrading of production technology mainly depend on the optimization and adjustment of the industrial production structure. Based on China’s provincial panel, Lu, Jiang, and Gong (2020) found a positive dynamic adjustment between the upgrading of industrial structure and green total factor productivity, and the upgrading and optimization of industrial structure can positively influence green total factor productivity. Thus, this paper selects industrial added value to control the impact of industrial structure upgrading on total factor productivity.

**Primary energy consumption from renewables (ECR):** A voluminous amount of studies has explored the relationship between energy consumption and economic growth. Rath, Akram, Bal, and Mahalik (2019) showed that an increase in the proportion of renewable energy consumption positively affects the growth of total factor productivity, and the corresponding increase in the proportion of fossil energy consumption inhibits the increase in total factor productivity. Therefore, we adopt primary energy consumption from renewables as a control variable to measure the energy consumption structure.

**Human capital (HC):** Human capital has a significant impact on the efficiency of enterprise innovation and technological growth. Miller and Upadhyay (2000) pointed out that it has a certain positive impact on the growth rate of factors, but this effect is influenced by economic development. The impact of human capital growth on total factor growth rates is more pronounced in economically developed countries than in poor countries. Hence, we collect data of human capital from PWT 10.0 as an independent variable.

To explore the impact of monetary policy on TFP, this research selects panel data of 30 countries from 1983 to 2018 for empirical testing. Figure 2 shows the natural logarithm of the number of trademarks in the sample countries in 2018. The data of GDP, ESC, Trade, IS, and FDI are all transformed into natural logarithm values. A description of the independent variables, dependent variables, and data sources is presented in Table 1.

Table 1: Data sources and descriptive statistics
<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFPG</td>
<td>Total factor productivity growth rate of the sample countries</td>
<td>PWT 10.0</td>
</tr>
<tr>
<td>IE</td>
<td>Trademark ( i,t ) / ( (Rd_{i,t} + 0.8RD_{i,t-1} + 0.6RD_{i,t-2}) )</td>
<td>(Hirshleifer et al., 2013)</td>
</tr>
<tr>
<td>DIR</td>
<td>Deposit interest rate is the interest rate paid by commercial banks or similar banks for demand, time, or savings deposits</td>
<td>International Monetary Fund</td>
</tr>
<tr>
<td>GDP</td>
<td>GDP per capita is gross domestic product divided by the mid-year population; the data are based on the constant price of the local currency</td>
<td>World Bank</td>
</tr>
<tr>
<td>FDI</td>
<td>Net foreign direct investment inflow (% of GDP)</td>
<td>International Monetary Fund</td>
</tr>
<tr>
<td>Trade</td>
<td>The proportion of merchandise trade in GDP is the sum of merchandise exports and imports divided by the value of GDP</td>
<td>World Bank</td>
</tr>
<tr>
<td>Urbanization</td>
<td>Urban population (proportion to total population)</td>
<td>World Bank</td>
</tr>
<tr>
<td>IS</td>
<td>Industrial value added (% of GDP)</td>
<td>World Bank</td>
</tr>
<tr>
<td>ECR</td>
<td>Primary energy consumption from renewables</td>
<td>BP Statistical</td>
</tr>
<tr>
<td>HC</td>
<td>Human capital index, based on years of schooling and returns to education</td>
<td>PWT 10.0</td>
</tr>
</tbody>
</table>

2.2. Estimation Method

To test the effect of monetary policy on TFP, we construct the following economic model.

\[
y_{i,t} = \theta_1 y_{i,t-1} + \beta_1 DIR_{i,t} + \beta' X + \mu_i + \mu_t + \epsilon_{i,t}
\]  

(3)

Here, \( y_{i,t} \) represents the explained variable corresponding to the growth rate of total factor productivity (TFPG) and innovation efficiency (IE); \( \theta_1 \) expresses the lagging period of the dependent variable; \( \beta_1 \) is the core independent variable of monetary policy - that is, country i’s deposit interest rate in year t; X corresponds to the remaining series of control variables; \( \mu_i \) is unobservable country-level fixed effects; \( \mu_t \) measures the time fixed effect; \( \mu_t \) represents the estimation error term; and \( \epsilon_{i,t} \) represents country and time, respectively.

Since the independent variable regression in equation (3) includes a lag of the dependent variable by one period, the regression is a typical dynamic panel regression. The least squares dummy variable (LSDV) estimator was been proposed to eliminate the bias caused by fixed effect estimation (Kiviet, 1995). For dynamic long panels with individual N greater than year Y, most studies of the existing literature have used the biased-corrected LSDV (LSDVC) method. However, the homoscedasticity assumption of the LSDV method is relatively strict, and it is difficult to guarantee the validity of this assumption in practice, which requires more relaxed assumptions to estimate the regression. Everaert and Pozzi (2007) proposed the bootstrap method to correct the deviation caused by the fixed effect in the dynamic panel regression (BCFE). Thus, this paper adopts the BCFE approach to estimate equation (3) and applies the biased-corrected LSDV (LSDVC) method to conduct a robustness test.

3. Empirical Result

3.1. Data Description

Table 2 displays the descriptive information of the variables used in this research. We see in Table 2 that the standard deviation of the deposit interest rate (DIR) is 11.359, with a maximum value of 94.959 and a minimum value of 0.000, indicating that there is some variation in the deposit interest rates of the sample countries. The standard deviation of total factor productivity growth rate (TFPG) and innovation efficiency (IE) is 0.022 and 1.586, respectively. For the minimum value, the value of TFPG is -0.125, and the value of IE is 0. The maximum value for TFPG is 0.096, and the maximum value for IE is 13.074. For the remaining control variables, the variable with the largest standard deviation is urbanization at 12.930, which indicates
that the levels of urbanization and agglomeration economic capacity among countries have their strengths and weaknesses. The standard deviation of foreign direct investment (FDI) is 6.538, the minimum is -40.330, and the maximum is 86.589. This statistical information shows that there are large differences in technology spillovers across countries.

Table 2: Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFPG</td>
<td>1080</td>
<td>0.005</td>
<td>0.022</td>
<td>-0.125</td>
<td>0.096</td>
</tr>
<tr>
<td>IE</td>
<td>980</td>
<td>0.625</td>
<td>1.586</td>
<td>0.000</td>
<td>13.074</td>
</tr>
<tr>
<td>DIR</td>
<td>1038</td>
<td>4.465</td>
<td>11.359</td>
<td>0.000</td>
<td>94.959</td>
</tr>
<tr>
<td>GDP</td>
<td>1007</td>
<td>11.442</td>
<td>1.912</td>
<td>8.091</td>
<td>17.374</td>
</tr>
<tr>
<td>FDI</td>
<td>1076</td>
<td>2.967</td>
<td>6.538</td>
<td>-40.330</td>
<td>86.589</td>
</tr>
<tr>
<td>Trade</td>
<td>1076</td>
<td>3.750</td>
<td>0.950</td>
<td>0.000</td>
<td>5.842</td>
</tr>
<tr>
<td>Urbanization</td>
<td>1080</td>
<td>75.025</td>
<td>12.930</td>
<td>21.545</td>
<td>100</td>
</tr>
<tr>
<td>IS</td>
<td>916</td>
<td>3.191</td>
<td>0.571</td>
<td>1.139</td>
<td>3.883</td>
</tr>
<tr>
<td>ECR</td>
<td>1075</td>
<td>3.809</td>
<td>2.240</td>
<td>-5.809</td>
<td>8.432</td>
</tr>
<tr>
<td>HC</td>
<td>1080</td>
<td>2.993</td>
<td>0.581</td>
<td>0.000</td>
<td>4.154</td>
</tr>
</tbody>
</table>

3.2. The impact of monetary policy on total factor productivity

Before performing the regression estimation, we first test the stationarity of panel data. This paper uses the IPS test and ADF test to perform unit root tests on regression variables. The test results appear in Table 3. The null hypothesis of IPS and ADF tests is that the variables contain unit roots. From the test results in Table 3, we see that all variables reject the null hypothesis, indicating that the variables are stable.

Table 3 shows the impact of monetary policy on the growth rate of total factor productivity. Among them, columns (1)-(2) correspond to the BCFE estimation result. Columns (3)-(4) show the regression results of the LSDVC method, and in the last columns (5)-(6) we provide fixed-effect estimation results for comparison. In Table 3 the independent variable corresponding to column (1), column (3), and column (5) is the deposit interest rate (DIR). The regression coefficients of the three are all negative and significant at the 1% level, indicating that a tight monetary policy hurts the growth rate of total factor productivity. The reason for this conclusion may be that rising deposit interest rates make households more willing to deposit, which will cause market investors to be more inclined to reduce investment, leading to a weakening of the liquidity of funds in the trading market, a tightening of corporate production capacity, and a decline in total factor productivity. To ensure the soundness of the underlying regression results, we also perform robustness tests using the lending rate as a proxy variable for monetary policy. The regression results are shown in columns (2), (4), and (6). The regression coefficient of loan interest rate (LIR) is also negative 0.001 and significant at the 10% and 5% levels, respectively. The results of the robustness test are consistent with the original findings, and both prove that a tightening monetary policy has a negative impact on the TFPG.

Table 3: Panel unit root test

<table>
<thead>
<tr>
<th>Variable</th>
<th>IPS</th>
<th>ADF</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFPG</td>
<td>-17.167***</td>
<td>163.187***</td>
</tr>
<tr>
<td>IE</td>
<td>-9.299***</td>
<td>94.701***</td>
</tr>
<tr>
<td>DIR</td>
<td>-6.296***</td>
<td>139.232***</td>
</tr>
<tr>
<td>GDP</td>
<td>-1.934**</td>
<td>230.780***</td>
</tr>
<tr>
<td>FDI</td>
<td>-7.552***</td>
<td>159.713**</td>
</tr>
<tr>
<td>TRADE</td>
<td>-7.985***</td>
<td>176.527***</td>
</tr>
<tr>
<td>Urbanization</td>
<td>-5.279***</td>
<td>148.158**</td>
</tr>
<tr>
<td>IS</td>
<td>-8.798***</td>
<td>124.367***</td>
</tr>
<tr>
<td>ECR</td>
<td>-4.781***</td>
<td>83.668**</td>
</tr>
<tr>
<td>HC</td>
<td>-7.135***</td>
<td>154.788**</td>
</tr>
</tbody>
</table>
3.3. The impact of monetary policy on innovation efficiency

Table 5 shows the effects of monetary policy on innovation efficiency. Columns (1)-(2) in the table show the estimation results based on BCFE. Columns (3)-(4) correspond to the robustness test results of the LSDVC method. Finally, columns (5)-(6) provide the regression results of fixed effects for comparison.

The coefficients of DIR and LIR in columns (1) and (2) of Table 5 are respectively -0.010 and -0.029 and significant at the 10% and 1% levels. The results suggest that a tight monetary policy also has a negative impact on innovation efficiency. This paper also adopts LSDVC method for the estimate again to ensure the reliability of the conclusion. Columns (3) and (4) illustrate the regression results based on the LSDVC method, where the regression coefficients of DIR and LIR are -0.012 and -0.030, respectively, are significant at the 10% and 1% levels, and are consistent with the results estimated by the BCFE approach.

The reason for the above conclusion maybe when the government finds that the market has overheated investment that it will implement a tightening monetary policy to prevent the generation of economic bubbles, which will lead to the weakening of market liquidity. After receiving this signal, companies and investors will reduce investment, especially in risky activities such as innovation, to avoid investment losses, which will inevitably have a negative impact on innovation efficiency. Moran and Queralto (2018) found through the construction of a new Keynesian model that a tightening monetary policy implemented by the government has a negative impact on technology investment and in turn affects the innovation and total factor productivity of enterprises, which is consistent with our conclusions.

For comparison, we also use fixed effects for estimation, and the regression results are shown in columns (5) and (6). The coefficients of DIR and LIR are -0.027 and -0.069, respectively, are significant at the 1% level, which also proves that a tight fiscal policy has a negative impact on innovation efficiency. Furthermore, we observe that the lag period of dependent variables in columns (1)-(4) is also significant at the 1% level. This demonstrates that the efficiency of innovation in the current period is also affected by the previous period, thus justifying the use of dynamic panels.

Table 4: Impact of monetary policy on total factor productivity growth rate (TFPG)

<table>
<thead>
<tr>
<th></th>
<th>BCFE</th>
<th>LSDVC</th>
<th>FE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>L. Dependent variable</td>
<td>0.172***</td>
<td>0.190***</td>
<td>0.415***</td>
</tr>
<tr>
<td></td>
<td>(5.12)</td>
<td>(5.04)</td>
<td>(7.57)</td>
</tr>
<tr>
<td>DIR</td>
<td>-0.001***</td>
<td>-0.001***</td>
<td>-0.001***</td>
</tr>
<tr>
<td></td>
<td>(-4.85)</td>
<td>(-4.41)</td>
<td>(-12.43)</td>
</tr>
<tr>
<td>LIR</td>
<td>-0.001*</td>
<td>-0.001*</td>
<td>-0.001*</td>
</tr>
<tr>
<td></td>
<td>(-1.71)</td>
<td>(-1.67)</td>
<td>(-2.34)</td>
</tr>
<tr>
<td>GDP</td>
<td>0.006</td>
<td>0.003</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(1.20)</td>
<td>(0.69)</td>
<td>(1.44)</td>
</tr>
<tr>
<td>FDI</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.70)</td>
<td>(0.55)</td>
<td>(0.67)</td>
</tr>
<tr>
<td>TRADE</td>
<td>0.013***</td>
<td>0.012***</td>
<td>0.010***</td>
</tr>
<tr>
<td></td>
<td>(4.39)</td>
<td>(4.36)</td>
<td>(4.62)</td>
</tr>
<tr>
<td>Urbanization</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(-1.59)</td>
<td>(-0.73)</td>
<td>(-1.53)</td>
</tr>
<tr>
<td>IS</td>
<td>-0.002*</td>
<td>-0.002</td>
<td>-0.002**</td>
</tr>
<tr>
<td></td>
<td>(-1.66)</td>
<td>(-1.25)</td>
<td>(-1.98)</td>
</tr>
<tr>
<td>ECR</td>
<td>0.001</td>
<td>0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.39)</td>
<td>(-0.31)</td>
</tr>
<tr>
<td>HC</td>
<td>-0.011**</td>
<td>-0.009*</td>
<td>-0.010**</td>
</tr>
</tbody>
</table>
3.4. The impact of monetary policy on innovation efficiency

To explore the overall impact of monetary policy on the growth rate of total factor productivity and innovation efficiency, this paper conducts a sub-sample regression from the three perspectives of government efficiency (GE), financial development (FD), and strictness of environmental policy (ES). The results of the sub-sample regression are shown in Table 6. The dependent variables corresponding to panels 6A and 6B in Table 6 are total factor productivity growth rate (TFPG) and innovation efficiency (IE).

3.4.1. Government efficiency

Chang, Wen, Zheng, Dong, and Hao (2018) found that a more efficient government can effectively reduce energy intensity and increase energy efficiency. An efficient government can issue various regulations and policies to ensure the sustainable development of its economy. Therefore, we incorporate the intersection of government efficiency and monetary policy to explore how government efficiency alters the impact of monetary policy on TFP. The data of government efficiency (GE) come from The Worldwide Governance Indicators, which estimate government efficiency through multiple dimensions such as the quality of public services, the quality of the civil service system, and the effectiveness of policy formulation and implementation. The value of GE ranges from -2.5 (weak) to 2.5 (strong). The larger the value is, the higher is the government efficiency (Kaufmann, Kraay, & Mastruzzi, 2011). Therefore, we divide the sample at the value of 0. Samples with a value higher than 0 are set as high-efficiency government samples (HGE), and samples with a value lower than 0 are set as low-efficiency government samples (LGE)

Columns (1) and (2) in Panel 6A are the regression results of sub-samples of high government efficiency (HGE) and low government efficiency (LGE). The coefficient of DIR in column (1) is -0.001, but is not significant, while the coefficient of DIR in column (2) is -0.001 and significant at the 10% level. This result shows that tightening monetary policies in countries with high government efficiency have no significant impact on TFPG, while tightening monetary policies in countries with low government efficiency still have a negative impact on TFPG. For the dependent variable of innovation efficiency (IE), columns (1) and (2) in Panel 6B show the regression results of sub-samples of government efficiency. For the high government efficiency sample (HGE) the coefficient of DIR is 0.041 and is not significant, while for the low government efficiency sample (LGE) the coefficient of DIR is -0.024 and is significant at the 10% level. The sub-sample regression results show that government efficiency affects the impact of monetary policy on total factor productivity and innovation efficiency and that the dynamic changes of monetary policy in countries with higher government efficiency do not affect production and innovation activities.

3.4.2. Financial development

The financial system has played an increasingly important role in economic development in the past two decades. At the same time, as an effective transmission tool for monetary policy, the financial system affects not only the effectiveness of the monetary policy, but also the allocation of resources, firm production, and thus total factor productivity. Based on provincial data of China from 1990 to 2009, Han and Shen (2015) found that an improvement of China’s financial development level has a positive impact on TFP. The faster the level of financial development is, the more time is the correction of resource mismatch, thus improving production capacity. Therefore, this paper adopts the approach of Ma and Lin (2016) who used (Domestic Credit + Stock Market Capitalization)/GDP to measure the level of financial development (FD). After calculating the financial development index, we set those samples above the average value as the high
financial development samples (HFD) and those samples below the average value as the low financial development samples (LFD) and perform sub-sample regression.

For TFPG columns (3) and (4) in Panel 6A respectively display the regression outcomes of high financial development (HFD) and low financial development (LFD). The regression coefficients of DIR are -0.002 and -0.001 and are significant at the 10% and 1% levels, respectively. The results show that a tightening monetary policy has a negative impact on TFPG in both samples of high financial development (HFD) and low financial development (LFD). However, the significance of this negative impact in the sample with high financial development (HFD) is lower than that in the sample with low financial development (LFD).

For innovation efficiency (IE) the regression coefficient of the sample with high financial development (HFD) corresponding to column (3) in Panel 6B is -0.009 and is not significant. For the low financial development (LFD) sample in column (4) the DIR regression coefficient is -0.015 and is significant at the 10% level. Countries with higher level of financial development can mitigate the impact of monetary policy changes on total factor productivity and innovation efficiency through a more complete financial system and risk prevention mechanism. Hsu, Tian, and Xu (2014) found that the innovation of high-tech enterprises is more dependent on the development of the external stock market and credit market. A higher level of financial development effectively improves the R&D investment of enterprises and increases innovation efficiency.

3.4.3. Environmental policy stringency

A large amount of literature has examined the impact of environmental policy stringency on innovative R&D activities and TFP. As an external supervision mechanism, environmental policy can effectively solve problems such as market failures and regulate unreasonable business behaviors of enterprises (Porter & van der Linde, 1995). Generally speaking, when a company’s operations face strict environmental policy supervision, it usually results in damage to the company’s operating interests. However, Martínez-Zarzoso, Bengochea-Moranco, and Morales-Lage (2019) found through panel data of 14 OECD countries from 1990 to 2011 that countries with strong innovation capabilities are not affected by strict supervision, but can have a certain positive effect on TFP. Thus, this paper conducts a sub-sample regression based on the environmental policy stringency index (EPS) from OECD statistics. We collect EPS data of the sample countries, and the mean value is set as the sub-sample standard. Those above the mean value are set as high environmental policy stringency samples, and those below the mean value are set as low environmental policy stringency samples.

Columns (5) and (6) in Panels 6A and 6B respectively show the impact of monetary policy on the growth rate of total factor productivity (TFPG) and innovation efficiency (IE) after sub-sample regression. From the results we see that the regression coefficients of DIR in column (5) of Panel 6A and 6B are -0.001 and -0.002 respectively, both of which are not significant, indicating under the sample of high environmental policy stringency (HES) that monetary policy has no significant impact on the growth rate of total factor productivity (TFPG) and innovation efficiency (IE). However, for the sample with low environmental policy stringency (LES) the regression coefficients in column (6) are -0.001 and -0.008, respectively, and are significant at the 1% and 5% levels. When a country implements stricter environmental policies, enterprises will face increased production costs, and to maintain profitability they will be forced to increase productivity to compensate for the increased costs. Stricter environmental policies also represent more perfect laws and regulations, which reduce the negative impact of external monetary policies on enterprise production and innovation (Morales-Lage, Bengochea Moranco, & Martínez-Zarzoso, 2016).

Table 5: Impact of monetary policy on innovation efficiency (IE)

<table>
<thead>
<tr>
<th>L. Dependent variable</th>
<th>BCFE (1)</th>
<th>BCFE (2)</th>
<th>LSDVC (3)</th>
<th>LSDVC (4)</th>
<th>FE (5)</th>
<th>FE (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L. Dependent variable</td>
<td>0.698***</td>
<td>0.581***</td>
<td>0.680***</td>
<td>0.583***</td>
<td>(23.53)</td>
<td>(18.96)</td>
</tr>
<tr>
<td></td>
<td>(23.53)</td>
<td>(18.93)</td>
<td>(23.64)</td>
<td>(18.93)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variable</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>----------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td>HGE</td>
<td>0.224***</td>
<td>0.139**</td>
<td>0.267***</td>
<td>0.098*</td>
<td>0.225***</td>
<td>0.144***</td>
</tr>
<tr>
<td>LGE</td>
<td>(4.89)</td>
<td>(1.98)</td>
<td>(3.39)</td>
<td>(1.95)</td>
<td>(2.88)</td>
<td>(3.62)</td>
</tr>
<tr>
<td>DIR</td>
<td>-0.001</td>
<td>-0.0001*</td>
<td>-0.002*</td>
<td>-0.001***</td>
<td>-0.001</td>
<td>-0.001***</td>
</tr>
<tr>
<td></td>
<td>(-0.61)</td>
<td>(-1.73)</td>
<td>(-1.87)</td>
<td>(-4.40)</td>
<td>(-0.01)</td>
<td>(-3.73)</td>
</tr>
<tr>
<td>Observations</td>
<td>437</td>
<td>246</td>
<td>201</td>
<td>523</td>
<td>235</td>
<td>500</td>
</tr>
</tbody>
</table>

Notes: In the table, HGE and LGE respectively represent high government efficiency and low government efficiency. HFD and LFD indicate high financial development and low financial development. HES and LES respectively state high-strict environmental policies and low-level environmental policy samples. t-statistics are in parentheses. *** p<0.01, ** p<0.05, and * p<0.1. Due to limited space, regression results of control variables are not shown. Please contact the author if necessary.
4. Conclusion and Policy Implication

Total factor productivity and innovation efficiency play a vital role in industrial upgrading and sustained economic growth. We use balanced panel data from 30 countries from 1983 to 2018 to test the impact of monetary policy on the growth rate of total factor productivity (TFPG) and innovation efficiency (IE). First, we use a bias-corrected fixed-effect dynamic (BCFE) model that can correct the deviation caused by the fixed effect in the dynamic panel regression as a tool to estimate the influence of monetary policy on the growth rate of total factor productivity and innovation efficiency. Second, we find that a tightening monetary policy has a significantly negative impact on the growth rate of total factor productivity (TFPG) and innovation efficiency (IE), and this conclusion remains consistent after changing the independent variable and using different estimations methods to conduct robustness tests. Third, we conduct sub-sample regression according to government efficiency, financial development, and environmental policy stringency respectively to observe whether monetary policy has different effects on total factor productivity and innovation efficiency. The sub-sample regression results show that countries with higher government efficiency, higher financial development, and stricter environmental policies are able to reduce the negative impact of external tightening monetary policies on total factor productivity and innovation efficiency.

Our research provides some enlightenment for the existing literature on monetary policy, TFP, and innovation efficiency. Specifically, when the government observes excessive investment in the market in order to introduce a tightening monetary policy, then it should consider the impact of a tightening policy on production and innovation activities. A tightening monetary policy inevitably leads to a reduction in market investment, which may affect the R&D funds of enterprises, resulting in lower innovation efficiency (Yang et al., 2021). Moreover, governments should focus on improving government efficiency, perfecting credit allocation, improving the financial level, and formulating reasonable and strict environmental policies to ensure that enterprises can make correct investment choices when facing tightening monetary policies (G.-F. Feng, Yang, Gong, & Chang, 2021). For enterprises, when the external financing environment deteriorates and their cash flow decreases, their management team should undertake sustainable management and green development as ambitious goals and continuously increase investment in R&D activities, instead of only pursuing short-term profits.
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