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The Impact of Monetary Policy Through Production Networks—Empirical Evidence from Sectoral Electricity Consumption in China

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Abstract

This paper utilizes unique high-frequency, daily electricity consumption data across economic sectors to examine the impact of monetary policy shocks on economic output, with a particular focus on the network spillover effects and sectoral heterogeneity introduced by inter-sector linkages. The study finds that quantity-based monetary policy (e.g., M2) generates significant positive and cascading spillover effects within the production network. However, the total effects of monetary policy shocks are broadly similar across upstream, midstream, and downstream sectors, exhibiting only minor differences. Notably, the proportion of network (indirect) effects increases systematically from upstream to downstream sectors and displays marked sectoral heterogeneity. In contrast, interest-rate-based monetary policy displays insufficient spatial spillover through production networks. These findings offer important insights for policymakers to optimize structural policy design and promote coordinated sectoral chain development, which can guide the pursuit of sustainable economic strategies that balance growth, resource utilization and sectoral interdependencies.

Keywords: monetary policy; production networks; sectoral electricity consumption; sustainable economic strategies

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1. Introduction

The impact of monetary policy on sectoral output has become a focal point in macroeconomics, particularly as economic systems grow more complex and sectors become increasingly interconnected. Monetary policy refers to the set of actions taken by a central bank or monetary authority to control the money supply, interest rates, and other financial conditions in order to achieve macroeconomic objectives such as price stability, economic growth, and employment. Typical components of monetary policy include adjustments to policy interest rates, reserve requirements, and the supply of money (e.g., M2). "Monetary policy shocks" are unexpected changes or interventions in these monetary policy instruments that can influence the behavior of economic agents and sectoral output. While traditional theory emphasizes aggregate demand channels, recent advances in Production Network theory (Acemoglu et al., 2012; Basu, 1995) [1,2] suggest that inter-sector input–output linkages not only amplify or propagate these shocks but also shape the resilience and sustainability of the overall economic system. As global attention shifts toward sustainable

economic growth, a growing literature investigates the interactions among environmental, economic, and social systems. Achieving sustainability requires efficient resource allocation, green transformation, and synergistic upgrading across different sectors, which is crucial for driving high-quality economic growth, ecological civilization, and carbon neutrality (Ferraz et al., 2020; Frank, 2014) [3,4].

Since Leontief established the input–output framework, economists have investigated how sectors influence one another through supply and demand linkages. Acemoglu et al. (2012) [1] demonstrated that when key sectors serve as major input suppliers, micro-level shocks can be amplified through network connections, leading to significant aggregate fluctuations. This theory highlights the relevance not only to macro stability but also to the attainment of sustainability targets, such as reducing sectoral volatility and enhancing systemic resilience. Basu (1995) [2] further theorized that in the presence of production networks, strategic complementarities in pricing decisions amplify the effects of monetary policy. For instance, if upstream prices adjust with a lag due to price stickiness, downstream firms may delay their decisions until upstream prices respond, thereby transmitting upstream stickiness downstream and increasing short-run non-neutrality. This mechanism has been extended in many New Keynesian models (e.g., Nakamura & Steinsson, 2010; Pasten et al., 2020) [5,6], though empirical evidence remained scarce for some time.

Recent empirical research has started to fill this gap. For example, Ozdagli and Weber (2017) [7] used spatial econometric regressions with production networks modeled as spatial weights to measure the cross-sector transmission of monetary policy. Using stock market reactions around Federal Reserve announcements, they found that indirect network transmission accounted for 50% to 85% of the total effect of monetary tightening, as demand shocks propagated upstream from final demand sectors. Conversely, supply-side micro-shocks tend to propagate downstream. These findings underscore the critical role of production networks in monetary policy transmission, whereby macro shocks affect not only targeted sectors but also generate considerable spillover effects. Ghassibe (2021) [8] used monthly data to show that 20% to 45% of the aggregate demand response can be attributed to network amplification, which typically materializes after about 18 months. Clearly, incorporating network linkages is essential for a complete understanding of the macroeconomic effects of monetary policy shocks.

In China, monetary policy transmission exhibits unique complexities. On one hand, the dominance of credit-based indirect financing instruments and quantity-based monetary policy tools (such as M2, total social financing, and relending) play a critical role in optimizing resource allocation and building resilient green production networks in the context of nationwide sustainable transition (Shao, C. et al., 2021; Dikau, S. & Volz, U., 2021) [9,10]. On the other hand, China's vast and highly specialized sectoral system, with its vertically integrated supply chains, makes the amplification, transmission, and differentiation effects of monetary policy shocks across sectors particularly significant. As China shifts toward a high-quality development paradigm, assessing the effects of monetary policy on sectoral chain coordination, resource efficiency, and the resilience of sectoral ecosystems has become an essential issue for policy design and sustainable development agenda.

Building on this foundation, this paper systematically analyzes how monetary policy shocks transmit through production networks, and try discussing their implications for coordinated and high-quality development of China's sectoral chains. We adopt a Spatial Autoregressive Model (SAR) and construct downstream-to-upstream and upstream-to-downstream spatial weight matrices based on inter-sector input–output tables. These matrices measure the influence intensity of each sector as a downstream consumer or an upstream supplier. This approach captures the spillover effects of monetary policy shocks through network channels and distinguishes the roles of demand- and supply-

side networks in shock propagation. We further utilize high-frequency microdata to reflect real-time changes in sectoral production. Electricity consumption growth, often regarded as a "barometer" of sectoral activity and cited by policymakers to assess economic trends, provides a timely and accurate proxy for output growth. This research not only enhances our understanding of the transmission mechanisms of monetary policy but also offers empirical insights for improving policy effectiveness and promoting sustainable development and resilience within sectoral chains.

This study contributes to the literature in several key ways:

First, we incorporate high-frequency data to characterize the dynamic features of monetary policy effects. Traditional studies often rely on quarterly or annual data, which struggle to capture the immediate transmission paths of monetary policy shocks and the short-term dynamics of economic output. High-frequency data, however, can more precisely identify the "first-round effects" of policy shocks, avoiding estimation biases caused by temporal aggregation in low-frequency data (Nakamura & Steinsson, 2010) [5]. While high-frequency capital market data for listed companies are constrained by their qualification requirements, they cannot cover all economic entities within a sector. This paper innovatively employs monthly growth rates of sectoral electricity consumption as an output growth indicator. Electricity data, due to their "non-storability", possess real-time characteristics, instantly mapping the true state of economic activity. Hence, the electricity sector is regarded as an economic "barometer" and "precursor," capable of keenly capturing real-time fluctuations in economic activity. Compared to low-frequency indicators like GDP, high-frequency electricity consumption data are conducive to a more refined identification of dynamic response paths following monetary policy shocks.

Second, we integrate the production network structure into monetary policy transmission research, quantifying the spillover effects along the sectoral chain. Unlike previous models that assume sectors are independent of each other, this paper constructs a Spatial Autoregressive Model (SAR) that incorporates sectoral linkages, integrating inter-sector input–output relationships as spatial weight matrices into the model. Within this framework, a sector's output growth depends not only on its own lags and policy shocks but also on the growth of related sectors upstream and downstream in its sectoral chain. Based on input–output tables, we construct a downstream weight matrix D (reflecting the importance of downstream sectors to upstream ones) and an upstream weight matrix S (reflecting the importance of upstream sectors to downstream ones) to measure and compare the transmission effects of monetary policy shocks—arising from both quantity and interest rate rules. By comparing the estimation results of the model under different weight matrices, this paper quantifies the magnitude and differences in the transmission of monetary policy along the supply chain within the sectoral network. This analytical framework, combining network structure with spatial econometrics, expands the application of spatial econometric models in macro-financial fields.

Third, we further reveal that the total effects of monetary policy shocks do not differ significantly across upstream, midstream, and downstream sectors, while downstream sectors exhibit stronger network effect intensity. This finding provides a new perspective for understanding the structural impact of macroeconomic policy. We further examine the differential responses of various sectors within the network under monetary policy shocks, explore the possible mechanisms underlying these differences, identify the typical performance of selected sectors in the network, and explain how network position and sector attributes influence the policy transmission pathway. These efforts contribute to uncovering the micro-structural characteristics of heterogeneous monetary policy transmission across sectors, thereby informing the formulation of differentiated sectoral and structural monetary policy instruments.

The paper is organized as follows. Part II reviews the theoretical background and relevant literature of this paper; Part III details indicator construction and model specification; Part IV presents the empirical research results and analysis; and Part V concludes with findings and implications.

2. Theoretical Background and Relevant Literature

2.1. Theoretical Framework of Monetary Policy Shock Transmission and Dynamic Effects

Theoretical research paradigms on the impact of monetary policy on output are generally based on the New Keynesian framework. Existing studies typically incorporate features such as nominal rigidities (Christiano et al., 2005; Blanchard & Galí, 2007) [11,12] and financial frictions (Bernanke et al., 1996) [13] into models to depict real economies and expand the theoretical understanding of monetary policy transmission. Within this framework, researchers have found that monetary policy shocks can affect economic output through multiple channels. For example, monetary policy, by altering nominal interest rates, influences liquidity premia in financial markets. Lower nominal interest rates reduce the cost of holding liquid assets, encouraging banks to increase leverage, thereby lowering risk premia, raising asset prices, and increasing economic volatility, investment, and growth (Drechsler et al., 2017) [14]. Monetary policy also affects firms' financing capacity and investment decisions by influencing bank credit supply. The development of shadow banking and financial frictions (such as information asymmetry and collateral constraints) can also impact the effectiveness of the credit channel (Bernanke & Blinder, 1988; Bernanke et al., 1996) [13,15]. Furthermore, monetary policy can influence asset prices in capital markets, which then transmits to real economic output; contractionary monetary policy leads to stock price declines, prompting firms to reduce investment and curtail production, thereby affecting aggregate social output (Cassola & Morana, 2004) [16].

Regarding the research on the output effects of monetary policy, the academic community has long engaged in in-depth discussion from the perspectives of quantity rules and interest rate rules. Early theories, based on the quantity theory of money, emphasized that changes in money supply (such as M2) affect real economic output through the credit channel and liquidity effects (Friedman & Schwartz, 1963) [17]. Bernanke & Gertler (1995) [18] further proposed that monetary policy influences firms' investment and output via credit supply, with the quantity channel becoming a central research focus. In the context of China, the historical role of money supply as an intermediate target of monetary policy has led to numerous empirical works adopting aggregate variables such as M2 to analyze the impact of monetary expansion on economic growth and sector output. With financial market development, interest rate rules have gradually gained prominence. Bernanke & Blinder (1992) [19], using the federal funds rate as an example, systematically explained the core status of the interest rate channel in monetary policy transmission. Christiano et al. (2005) [11], within a New Keynesian framework, analyzed the dynamic effects of short-term interest rate shocks on output and prices. Interest rate indicators capture central bank policy intentions and market expectations more effectively, especially against the backdrop of ongoing interest rate liberalization and financial deepening, making market rates such as Shibor important variables for analyzing the effect of monetary policy in China.

2.2. Heterogeneous Sectoral Effects of Monetary Policy

Based on the classical IS-LM (Investment–Saving and Liquidity Preference–Money Supply) framework, monetary policy universally affects investment and consumption across sectors through the interest rate channel (The IS-LM framework, developed by John Hicks in 1937, is a standard macroeconomic model used to illustrate the interaction between the real economy (Investment–Saving, IS curve) and monetary equilibrium (Liquidity

Preference–Money Supply, LM curve). The IS curve represents the combinations of interest rates and output where the goods market is in equilibrium (i.e., saving equals investment), while the LM curve describes equilibrium in the money market (i.e., money demand equals money supply). Their intersection determines the equilibrium levels of income (output) and interest rate in the economy. The framework provides a foundation for analyzing how monetary and fiscal policy influence aggregate demand through the interest rate, investment, and consumption channels). However, empirical studies consistently reveal significant sector heterogeneity in its transmission. This divergence first arises from sector characteristics related to product attributes and financing structures: durable consumer goods and capital goods sectors, due to their strong cyclical demand and high sensitivity to financing costs, experience significantly larger output contractions during monetary tightening than non-durable goods sectors (e.g., necessities) (Dedola & Lippi, 2005) [20]. Concurrently, the credit channel further amplifies heterogeneous effects; sectors with vulnerable corporate balance sheets or high external financing dependence (e.g., small and medium-sized enterprise-intensive sectors, capital-intensive sectors) are more severely impacted by monetary tightening. The mechanism is that tight policy exacerbates information asymmetry in credit markets, raising external financing premia and amplifying the decline in real economic investment and output (Bernanke & Gertler, 1995) [18].

Beyond demand and financing attributes, the speed of sector price adjustment also contributes to the differential effects of monetary policy shocks across sectors: sectors with high price stickiness exhibit lagged output responses, while more flexible pricing sectors react faster but with limited amplitude (Boivin et al., 2009) [21]. Further research reveals that production network structures amplify heterogeneous transmission through two mechanisms: when key upstream suppliers possess high price stickiness, downstream sectors experience more persistent output contractions due to inter-sectoral pricing complementarities; sectors with a higher share of intermediate inputs exhibit significantly stronger volatility in output responses to monetary shocks (Pasten et al., 2020) [6]. Notably, the macroeconomic cycle state modulates the efficacy of the aforementioned transmission; for instance, policy effects during recessions are generally weaker than during expansions (Tenreyro & Thwaites, 2016) [22].

2.3. Production Networks and Macro Shock Transmission

Traditional macroeconomic models often assume an economy composed of numerous similar representative firms, neglecting the inter-sectoral input–output linkages. However, in the real economy, different sectors form complex production network structures through intermediate goods transactions. Fluctuations in one sector can be transmitted to other sectors via upstream and downstream relationships, thereby affecting overall economic volatility. To characterize this phenomenon, a macroeconomic research framework based on production networks has emerged in recent years, where micro shocks propagated through input–output chains have become a new key to understanding macroeconomic fluctuations (Carvalho, 2014) [23]. Acemoglu et al. (2012) [1] theoretically demonstrated that if the production network exhibits "heavy tails" in its linkage distribution, i.e., a few supplier or buyer nodes connect to numerous sectors, then micro-level shocks can be systematically amplified into macroeconomic fluctuations. For example, when a key upstream sector suffers a negative shock, its reduced supply affects the production of many downstream sectors, triggering a chain reaction that significantly fluctuates overall output; conversely, in a symmetrically dispersed network structure, individual shocks are more easily diversified and do not significantly impact the macroeconomy. Pasten et al. (2020) [6] constructed a model to compare the propagation of monetary policy shocks under different scenarios, finding that ignoring heterogeneous consumption shares and

input–output linkages underestimates the actual impact of monetary policy and misjudges key transmission sectors. Conversely, when detailed network structures are considered, the model can identify "key few" sectors crucial for policy transmission. These sectors, prominent in the network, can profoundly influence shock propagation. Ghassibe (2021) [8] directly measured network amplification effects using monthly sector data, showing that at least 30% of the total consumption change was due to the downstream price stickiness transmission in input–output chains, with a minority of sectors (accounting for only 17% of total consumption) contributing nearly 98% of the monetary shock amplification.

It is important to note, however, that the literature presents divergent views regarding the aggregate amplification effects of production networks. For example, Foerster et al. (2011) [24] find that idiosyncratic sectoral shocks account for only a small proportion of aggregate fluctuations, suggesting that the amplification role of production networks may be weaker or more context-dependent than originally hypothesized. This finding challenges the notion that production networks necessarily intensify aggregate volatility, and indicates that the nature and strength of spillover mechanisms may vary across economies and network structures. In the case of China, where production networks feature higher sectoral concentration and stronger upstream-downstream linkages, shocks to hub sectors are likely to be more robustly amplified throughout the network (Wang et al., 2023) [25], highlighting the theoretical and practical significance of studying China's production network effects.

In recent years, spatial econometric methods have been introduced into macro-finance to capture cross-sectoral spillover effects. The Spatial Autoregressive Model (SAR), by defining a spatial weight matrix, can measure the intensity of a unit's change on adjacent units. This idea can be applied to sectoral networks by treating input–output relationship matrices as "spatial weights," thereby quantifying the driving or dragging effect of a sector's output growth on "adjacent" sectors (e.g., upstream and downstream sectors in the supply chain). Ozdagli & Weber (2017) [7] first adopted this method, using weights constructed from U.S. input–output tables to decompose monetary policy shock effects, quantifying direct and network spillover effects. Caraiani et al. (2020) [26] applied a spatial regression model to study 24 OECD countries, finding that production network structures significantly influence the transmission of monetary policy to output, with differences in sectoral structures across countries leading to varied policy effects.

In a word, both theoretical and empirical research in existing literature indicate that monetary policy shocks, as demand-side shocks, diffuse across sectors through production networks. The magnitude of their impact depends on the network structure (the tightness of upstream and downstream linkages) and the inherent characteristics of each sector (scale, stickiness, financing constraints, etc.). However, systematic research on the subject of "monetary policy—production networks—sector output" in the Chinese context remains insufficient, especially in the measurement of monetary policy shocks. Most existing studies employ only a single policy tool indicator, with limited attention to the similarities and differences in the network transmission mechanisms and strengths between quantity-based and rate-based rules. This paper constructs two spatial weight matrices based on inter-sector input–output tables. By measuring each sector's dependence on upstream inputs as a downstream consumer and its influence on downstream sectors as an upstream supplier, we capture the differential roles of demand-side and supply-side networks in shock transmission. We then use the SAR model to verify the average effect of monetary policy shocks, quantify the contribution of network spillovers, compare the actual performance of different policy rules in network transmission, and delve into the underlying transmission mechanisms and sector differences.

3. Indicator Construction and Model Specification

3.1. Selection of Monetary Policy Variables

Given the multiple-tool and multi-objective nature of monetary policy in China, a variety of indicators can serve as policy proxies. In this study, both the quantity rule and interest rate rule approaches are adopted, with M2 (broad money supply) and Shibor (Shanghai Interbank Offered Rate) used as proxy variables for the monetary policy quantity rule and the interest rate rule, respectively. M2 serves as a core indicator reflecting liquidity provision by the banking system. According to the monetary quantity theory (Bernanke et al., 1996) [13] and the credit channel theory (Bernanke & Gertler, 1995; Kashyap & Stein, 2000) [18,27], M2 influences sector output through the following channels: (a) the credit channel, where expansion of M2 generally signals increased credit resources in the financial system. Banks can extend more loans to enterprises, lowering financing costs, facilitating investment and production expansion, and thereby promoting sector output growth; (b) the asset price channel, whereby monetary expansion boosts asset prices, improves firms' balance sheets, enhances their financing capacity and investment confidence, and thereby indirectly contributes to increased output.

Shibor, as a benchmark in the money market, directly reflects the funding cost in the interbank market and is a main tool for the central bank in regulating market liquidity. Based on the Taylor rule, a rise in interest rates directly raises the financing cost for firms and households, thereby dampening investment and consumption and suppressing sector output growth. Conversely, a decline in interest rates stimulates investment and consumption, supporting output growth (Mishkin, 1996; Bernanke & Blinder, 1992) [15,28]. Moreover, changes in money market rates can influence agents' expectations of future economic conditions, leading to adjustments in consumption and investment decisions, and thereby accelerating monetary policy transmission (Woodford, 2003) [29].

3.2. Measurement of Sectoral Output Based on Electricity Consumption

In empirical research, electricity consumption is commonly used as a proxy variable for sectoral economic output, based on the strong short-term correlation between electricity usage and production activity (Stern, 1993; Xie et al., 2020) [30,31]. Under relatively stable technological levels and industrial structures, fluctuations in sectoral electricity consumption can effectively reflect changes in production capacity (Lu, 2016) [32]. However, between 2019 and 2023, China vigorously promoted policies for green transformation and energy conservation, such as the "Action Plan for Carbon Peaking before 2030" (2021) and the "Guiding Opinions on Accelerating the Green Development of Industry" (2021), which advocate for improved energy efficiency and reduced electricity consumption. These measures may somewhat weaken the elasticity between electricity consumption and output.

Nevertheless, electricity consumption still possesses notable advantages as a real-time indicator of economic activity. Firstly, electricity is an indispensable foundation for modern economic activities, covering critical sectors such as manufacturing, services, and the digital economy. Its share in final energy consumption has increased to around 28% (https://www.cenews.com.cn/news.html?aid=1510193 25 September 2025). Secondly, because electricity cannot be stored on a large scale, its production and consumption occur almost simultaneously, making electricity consumption data capable of instantly reflecting economic fluctuations and avoiding signal delays caused by inventory adjustments. Moreover, electricity consumption statistics are available at high frequency (monthly) and with fine granularity (by sector and region), which strongly supports real-time monitoring. Although alternative energy sources such as natural gas have grown in certain areas, their share in primary energy consumption remains relatively low (about 8.5% (https://paper.people.com.cn/zgnybwap/html/2024-07/29/content_26072746.htm) in

25 September 2025), and they are mainly used for supplementary power generation and heating in specific contexts, making it difficult to broadly substitute electricity. Thus, the dominant position of electricity in the energy system and its data availability make it a superior indicator for monitoring economic activity.·

In summary, although improvement in energy efficiency may affect the intensity of the relationship between electricity consumption and output, a high correlation between the two persists in the short to medium term (Wang et al., 2021) [33]. Compared to other specific energy forms such as coal, electricity demonstrates a more robust and reliable relationship with economic growth (Kabeyi et al., 2021) [34], and continues to be a key driver of economic development (Laghari et al., 2023) [35]. Due to its real-time nature, broad coverage, and high data granularity, electricity consumption data can effectively capture the dynamic changes in economic activity and continue to serve as a key reference for evaluating sectoral business conditions by institutions such as the National Bureau of Statistics (https://www.nea.gov.cn/20250905/01765b89bbf84f6eb02f14ad229f1d60/c.html 25 September 2025). However, electricity consumption can also be influenced by numerous confounding factors. For example, many economic sectors reduce or suspend production during holidays, meaning daily electricity consumption changes may not reflect true output fluctuations. Some economic sectors, due to the inherent nature of their products and services, exhibit significant trends and seasonal effects in their electricity consumption. Additionally, temperature is a major influencing factor, as rising and sharply fluctuating temperatures can significantly affect socio-economic activities, especially electricity consumption and supply (Rosenthal et al., 1995; Auffhammer & Mansur, 2014) [36,37].

Based on the characteristics of electricity consumption data, this paper processes the raw electricity consumption data as follows: First, the year-on-year growth rate of daily electricity consumption for 30 sectors in Fujian Province, China, from 1 January 2019, to 31 August 2023, is selected as the raw variable to measure sector economic output growth. The specific algorithm involves taking the average daily electricity consumption of each sector in the same month of the previous year as the base, calculating the ratio of each sector's daily electricity consumption to this base, and then subtracting 1. This aims to eliminate the seasonal effects in the original electricity consumption data and exclude the influence of scale differences between sectors. Then, the time series of the daily sector electricity consumption growth rate is decomposed using the following model:

$$\widetilde{ELE}_{i,t} = \alpha_{0,i} + \alpha_{1,i}\boldsymbol{t} + \alpha_{2,i}Holiday_t + \alpha_{3,i}Weekend_t + \alpha_{4,i}Temp_t + \epsilon_{i,t} \quad (1)$$

where subscript i denotes the sector and subscript t denotes the date. $\widetilde{ELE}_{i,t}$ is the year-on-year growth rate of electricity consumption for sector i in Fujian Province on date t, obtained from the previous calculation step. $\boldsymbol{t}$ represents a time trend term, which mitigates the impact of technological change and sectoral upgrading. $Holiday_t$ is a dummy variable for statutory holidays, taking 1 if date t is a national statutory holiday and 0 otherwise. $Weekend_t$ is a dummy variable for weekends, taking 1 if date t is a weekend and 0 otherwise. The purpose of introducing these two dummy variables is to mitigate the interference of holiday factors. $Temp_t$ is the difference between Fujian Province's daily average temperature and the average temperature of the same month in the previous year, to mitigate the impact of concurrent temperature changes on production electricity consumption. Additionally, $\alpha_{0,i}$ is the intercept term, $\alpha_{k,i}$(k = 1,2. . .,4) are variable coefficients, and $\epsilon_{i,t}$ is the residual term.

Ultimately, this paper obtains the adjusted daily year-on-year electricity consumption growth rate for 30 sectors in Fujian Province $\Delta\widetilde{ELE}_{i,t}$, from 1 January 2019 to 31 August 2023, which is equal to the estimated residual $\hat{\epsilon}_{i,t}$ from model (1). Thus, this paper de-

composes the time trend effects, the seasonal effects, statutory holiday effects, weekend effects, temperature influences, and special public event influences from each sector's daily electricity consumption time series. The adjusted series can more accurately measure changes in the output growth of each sector.

In this study, the adjusted year-on-year growth rate of daily electricity consumption for industry i in month t, denoted as $\Delta\widetilde{ELE}_{i,t}$, is averaged for each month to define $\Delta\widetilde{Y}_{i,t}$, which serves as a measure of the output growth rate for industry i during month t. Figure 1 presents the series of year-on-year electricity consumption growth rates for the 30 sectors in Fujian. The horizontal axis represents time, and the vertical axis shows the year-on-year growth rates of electricity consumption and M2, together with the Shibor value. In comparison with series for monetary policy shocks, it is observed that the growth rate of output—as proxied by electricity consumption—lags behind both M2 and Shibor in terms of trend changes. This may be attributable to the existence of the financial accelerator mechanism, which induces a lagging effect in monetary policy transmission (Bernanke et al., 1996) [13]. This factor is accordingly incorporated into the empirical model in this study.

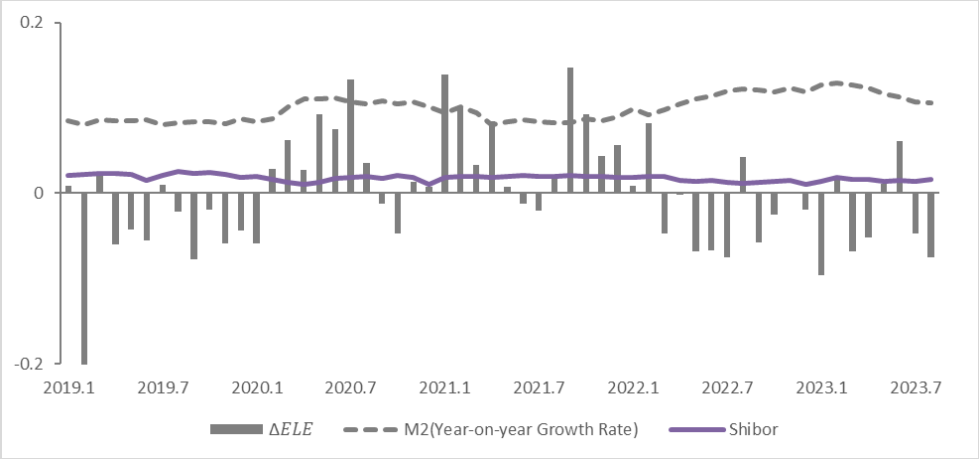


Figure 1. Comparison of Year-on-Year Electricity Consumption Growth Rate Series with Exogenous Monetary Policy Shock Series.

To validate the strong correlation between electricity consumption growth and industry output growth, we collected annual value-added data for major industries in Fujian Province (including Industry; Construction; Wholesale and retail; Transport, warehousing and post; Hotels, eating and drinking places) from 2019 to 2022. The growth rates of value-added for these five industries were calculated for the years 2020–2022. Simultaneously, the monthly $\Delta\widetilde{Y}_{i,t}$ values for 30 industries were grouped according to these five sectors, averaged within each group, and then further averaged by year to obtain the annual growth rates of electricity consumption for these main sectors from 2020 to 2022. It should be noted that only data from 2020–2022 are complete and included in the analysis, as sectoral electricity consumption data for 2023 only cover January to August, and those for January 2019 are excluded due to lack of lagged values required by the empirical model. Lastly, we calculated the Pearson correlation coefficients between the annual growth rates of value-added and the adjusted electricity consumption (for each sector). The results presented in Table 1 show that the Pearson correlation coefficients for all major industries are above 0.6. This finding confirms that, in the short term, sectoral electricity consumption and output are strongly correlated, thus supporting the validity of using electricity consumption as a proxy variable for industry output.

Table 1. Correlation Analysis between Industry Value-Added Growth Rate and Electricity Consumption Growth Rate in Fujian Province.

Sector	Index	2020	2021	2022	Person
Industry	value-added growth	−0.0099	0.1646	−0.0027	0.6048
	electricity consumption growth	−0.2257	0.0801	0.0500	
Construction	value-added growth	0.0184	0.0996	0.0158	0.7037
	electricity consumption growth	0.0346	0.0597	−0.0460	
Wholesale and retail trade	value-added growth	0.0793	0.2132	0.1371	0.8409
	electricity consumption growth	−0.0434	0.1225	−0.0698	
Transport, Warehousing and Post	value-added growth	−0.0308	0.1759	0.0517	0.9933
	electricity consumption growth	−0.1112	0.0767	−0.0557	
Hotels, Eating and drinking places	value-added growth	−0.0872	0.2094	0.0609	0.9035
	electricity consumption growth	−0.1197	0.1832	−0.0929	

To further strengthen the robustness of our findings, we conduct sensitivity analysis, comparing the official industry value-added growth with the corresponding annual electricity consumption growth from 2020 to 2022

3.3. Construction of Sectoral Linkage Network

To identify the position of each sector within the sector chain-based linkage network and the input–output relationships among them, this paper utilizes the Fujian Province input–output table from the "China Regional Input–Output Table-2017" published by the National Bureau of Statistics for analysis, which includes information on intermediate inputs and intermediate uses among various sectors. The central argument is that input–output tables primarily capture the medium- to long-term relationships among sectors, determined by production technology and capital structure, rather than short-term market fluctuations. Although the COVID-19 pandemic led to temporary supply chain interruptions and shocks, the underlying technical coefficients that define inter-sectoral purchase relationships generally remain stable and are unlikely to experience disruptive changes over the span of several years. This is because the input–output model reveals the interdependencies between industries, and these structural connections tend to be relatively stable over the medium and long term, mainly influenced by production technologies and capital composition. While technological progress and structural adjustments in modern economies may cause some changes in technical coefficients, these shifts are usually gradual in the short run and rarely sufficient to fundamentally alter the basic inter-sector dependencies (Miller & Blair, 2022; Mendoza, 2023; Michaelides, 2024) [38–40]. Consequently, utilizing the latest available input–output tables for empirical analysis is a well-established and widely accepted approach in the field of input–output analysis. Such tables continue to serve as essential tools for examining the fundamental structure and evolution of economic systems.

Firstly, to measure the input–output relationships between sectors, this paper draws on the methodologies of Nguyen et al. (2020) [41] and Yang et al. (2023) [42] to calculate an importance index for sector j relative to sector i within the sectoral chain structure, and further characterize the bidirectional transmission relationships along the sectoral chain. In a sectoral chain, sector i and sector j can be upstream and downstream to each other. Let w_{ij} be the (i,j)-th element in Quadrant I of the input–output table—the intermediate use section. Each element has a dual meaning: from a column perspective, it represents the consumption of sector i's products in the production of sector j's products; from a row perspective, it represents the allocation of sector i's products for use in the production of

sector j's products. Based on the meaning of the input–output table elements, this paper defines the following indicators:

$$demand_{ij} = \frac{consumption_{ij}}{output_i} \tag{2}$$

$$supply_{ij} = \frac{production_{ij}}{input_i} \tag{3}$$

In Equation (2), $demand_{ij}$ measures the importance of sector j as a downstream customer to upstream supplier sector i. Here, $consumption_{ij}$ represents the value of output from sector i directly consumed by sector j, corresponding to the element w_{ij} in the input–output table. $Output_i$ is the total intermediate use of sector i. If the proportion of $consumption_{ij}$ in $outputioutput_i$ is larger, it indicates that sector i's product sales are more dependent on downstream customer sector j. In Equation (3), $supply_{ij}$ measures the importance of sector j as an upstream supplier to downstream sector i. Here, $production_{ij}$ represents the value of inputs directly supplied by sector j in the production process of sector i, corresponding to the element w_{ji} in the input–output table. $Input_i$ is the total intermediate input of sector i. If the proportion of $production_{ij}$ in $input_i$ is larger, it indicates that sector i's production factor inputs are more dependent on upstream supplier sector j. Ultimately, this paper obtains a sector network matrix $D_{30\times30}$ reflecting the relative importance of customers (i.e., the importance of downstream sectors to upstream sectors), where the element $d_{ij} = demand_{ij}$; and a sector network matrix $S_{30\times30}$ reflecting the relative importance of suppliers (i.e., the importance of upstream sectors to downstream sectors), where the element $s_{ij} = supply_{ij}$.

Secondly, to identify the upstream, midstream, and downstream positions of each sector in the sectoral chain, this paper references Antràs et al. (2012) [43] to calculate the upstreamness coefficient (U_i) for each sector, defining a sector's position in the sectoral chain as its weighted average distance from final products:

$$U_i = 1 \times \frac{Final_i}{Output_i} + 2 \times \frac{\sum_{j=1}^{N} d_{ij} Final_j}{Output_i} + 3 \times \frac{\sum_{j=1}^{N}\sum_{k=1}^{N} d_{ik} d_{kj} Final_j}{Output_i} + \cdots \tag{4}$$

where subscript i denotes the sector, $Output_i$ is the total output of sector i, $Final_i$ is the portion of sector i's total output that goes to final consumption, and d_{ij} is the direct consumption coefficient of sector j for sector i, i.e., the output of sector i required for sector j to produce 1 unit of value product, which equals the value of sector i's output directly consumed by sector j divided by sector j's total output. Each term on the right side of the equation corresponds to a production stage in the value chain at varying distances from final consumption. The series of indices 1,2,3,... represents "distance," while the portion after the multiplication sign in each term represents the proportion of sector i's output used at the corresponding position, serving as a weight. The sum of these terms yields U_i, which represents the weighted average distance between sector i's output and final consumption, i.e., the concept of "upstreamness." A higher upstreamness indicates that the sector is closer to the intermediate input end of the value chain; conversely, a lower upstreamness indicates it is closer to the final product end. Although computing (4) might appear to require computing an infinite power series, notice that provided that $\sum_{i=1}^{N} d_{ij} < 1$ for all j (a natural assumption), the numerator of the above measure equals the i-th element of the $N \times 1$ matrix $[I - D]^{-2}F$, where D is an $N \times N$ matrix whose (i,j)-th element is dij, and F is a column matrix with $Final_i$ in row i (Antràs et al., 2012) [43]. This can be expressed in matrix form as: $U = \hat{Y}^{-1}[I - D]^{-1}Y$, where $\hat{Y}^{-1}$ is a diagonal matrix whose elements are the reciprocals of $Output_i$ and Y is a column matrix with $Output_i$ in row i.

After calculating the upstreamness for 30 sectors in Fujian Province, the resulting sector classification is presented in Table 2.

Table 2. Classification Results of Upstream, Midstream, and Downstream Sectors.

Classification	Sector	Upstreamness
Upstream Sector	Metal ore mining	27.54
	Non-metal minerals and other mining	14.75
	Coal mining and processing	11.16
Midstream Sector	Metal smelting and processing	4.65
	Chemical products	4.64
	Communication equipment, Electronic computer and Other computer devices	4.14
	Repair services for metal products, machinery, and equipment	4.02
	Petroleum refining and Coking	3.88
	Water production and supply	3.77
	Gas production and supply	3.75
	Products and Technical services for agriculture, forestry, livestock and fishing	3.11
Downstream Sector	Textile	2.93
	Metallic mineral products	2.80
	Furniture and products of wood	2.71
	Instruments	2.64
	Food and Tobacco products	2.61
	Printing and Cultural goods	2.46
	Telecommunication, Computing services and software	2.43
	Leasehold and Business services	2.38
	Wholesale and retail trade	2.13
	General sectoral machinery	2.12
	Non-metallic mineral products	2.12
	Transport, Warehousing and Post	2.10
	Transport equipment	1.99
	Special sectoral equipment	1.96
	Knitted mills, Wearing apparel, Leather, furs, down and related products	1.86
	Electric machinery and equipment	1.86
	Hotels, Eating and drinking places	1.62
	Real estate	1.51
	Construction	1.10

Table 2 reveals that Metal ore mining, Non-metal minerals and other mining, and Coal mining and processing have notably high upstreamness values (all greater than 10), indicating their clear position at the top of the production network. These sectors serve as primary suppliers of raw materials and exert fundamental influence on downstream segments, aligning with definitions of "upstream industries" in mainstream production network literature (e.g., Antràs et al., 2012; Carvalho, 2014) [23,43]. Following these are industries such as Metal smelting and processing and Chemical products. Most of these sectors provide intermediate industrial goods and essential services, with upstreamness values secondary to mining but still indicative of significant intermediary and processing roles within the supply chain. Agriculture, forestry, animal husbandry, and fishery, as fundamental sectors supplying raw materials to industrial manufacturing and other processing industries, are typically regarded as crucial nodes within the supply chain in input–output analyses. Therefore, in line with input–output theory, we designate these sectors as midstream industries. The remaining sectors—such as instruments, information

transmission and IT services, leasing and business services, wholesale and retail—display consistently lower upstreamness indices. These sectors predominantly occupy the end points of the production network, serving as final manufacturing or service providers and directly addressing ultimate consumption and terminal demand. Drawing on established economic principles and prior research (Acemoglu et al., 2012; Carvalho, 2014) [1,23], these industries are appropriately defined as downstream sectors.

Based on the above analysis, it is evident that the industry stratification derived from the upstreamness index aligns well with economic expectations and is convincing, thereby providing a solid foundation for the subsequent analysis in this paper.

3.4. Measuring Network Linkage Effects of Output Growth Under Monetary Policy Shocks

Referring to Ozdagli & Weber (2017) [7], this paper employs a Spatial Autoregressive Model (SAR) to capture the inter-sector spillover effects of monetary policy shocks. The basic form is as follows:

$$\Delta\widetilde{Y}_{i,t} = \alpha_i + \rho W \Delta\widetilde{Y}_{i,t} + \beta MP_{t-1} + \gamma_1 NX_{t-1} + \gamma_2 FAI_{t-1} + \gamma_3 IV_{t-1} + \varepsilon_{i,t} \quad (5)$$

where subscript i denotes the sector and t denotes the month. $\Delta\widetilde{Y}_{i,t}$ represents the output growth rate of sector i at time t, measured by the mean of the adjusted daily year-on-year electricity consumption growth rate $\Delta\widetilde{ELE}_{i,t}$ for sector i within month t. W is an $N \times N$ matrix representing the linkage network between N sectors. A larger value of w_{ij} indicates a stronger sector linkage. This paper uses $D_{30\times30}$ and $S_{30\times30}$ for measurement. The parameter ρ is the spatial autoregressive coefficient, which determines the overall strength of spillover effects. MP_t denotes the monetary policy shock at time t. Referring to Zhang & Liu (2011) [44], this paper selects the year-on-year growth rate of Fujian Province's exports NX_t, the year-on-year growth rate of Fujian Province government fixed asset investment FAI_t, and the year-on-year growth rate of the Sectoral Value Added IV_t at time t as control variables in the model, to control for other exogenous shocks. Given the potential time lag in monetary policy shock effects (Bernanke et al., 1996) [13], and to mitigate the possible endogeneity arising from causal relationships between explanatory and dependent variables, all explanatory variables in this study are lagged by one period. β, γ_1, γ_2, γ_3 are variable coefficients. The coefficient β represents the cumulative impact of the monetary policy shock on sector output growth after a month. α represents individual fixed effects. Following Di-Giovanni and Hale (2022) [45], the model specification does not control for time fixed effects because monetary policy shocks only vary in the time dimension; controlling for time fixed effects would absorb the effects of monetary policy shocks.

Furthermore, to study the network effects during monetary policy transmission, drawing on Ozdagli & Weber (2017) [7], this paper utilizes the SAR model regression results and the spatial weight matrix to decompose the total effect of monetary policy shocks into direct effects and network effects (indirect effects). Matrices $H(W)$ and $V(W)$ are defined as follows:

$$H(W) = (I_n - \rho W)^{-1} V(W) = H(W)\beta \quad (6)$$

Equation (5) can be rewritten in the following form:

$$\Delta\widetilde{Y}_{i,t} = V(W)MPS_{t-1} + H(W)\left(\alpha_i + \gamma_1 NX_{t-1} + \gamma_2 FAI_{t-1} + \gamma_3 IV_{t-1} + \varepsilon_{i,t}\right) \quad (7)$$

Based on Equation (7), three indicators are constructed to measure the total effect, direct effect, and indirect effect of monetary policy shocks. The sum of all elements in the *i-th* row of matrix $V(W)$ represents the total impact of the monetary policy shock in period $(t-1)$ on sector i. There are N sectors, and I_n is a column vector with N elements

all equal to 1. The total effect is defined as $I_n' V(W) I_n / n$. The direct effect is represented by $tr[V(W)]/n$, which is the average of the diagonal elements of the $V(W)$ matrix. The indirect effect is equal to the difference between the total effect and the direct effect. Furthermore, a decomposition can be performed for each sector individually: the total effect for sector i*i* is the sum of all elements in the *i-th* row of matrix $V(\mathrm{W})$; the direct effect is $V(W)_{i,i}$ (the diagonal element of the *i-th* row); and the sector indirect effect is the difference between the total and direct effects.

4. Empirical Results

4.1. Measurement of Network Effects of Monetary Policy Shocks

Table 3 presents the baseline regression results of this paper, illustrating the impact of different monetary policy rules on sector output in China and the corresponding network effects. First, an OLS regression model without accounting for sector network structure is employed to examine the direct impact of monetary policy quantity rules (represented by M2) and interest rate rules (represented by Shibor) on sector output. The results show that both M2 growth and Shibor rate changes have strong and statistically significant effects on sector output. Specifically, a 1-percentage-point increase in M2 growth is associated with an average increase of 6.46 percentage points in output, reflecting that expansionary quantity-based monetary policy can effectively release credit and liquidity, lower corporate financing constraints, and thus facilitate capacity expansion and investment in the real sector. Conversely, a 1-percentage-point increase in the Shibor rate—a tightening of monetary policy—results in an average decrease of 7 percentage points in output, suggesting that higher interest rates increase firms' financing costs and exert a pronounced restraining effect on the real economy. This pattern is consistent with the macroeconomic structure of China, where the banking system dominates and traditional finance plays a significant role in the real sector. These findings align with the common conclusions in the international literature regarding the monetary policy-real economy relationship (Bernanke & Gertler, 1995; Kuttner & Mosser, 2002) [18,46] and the dual-path framework of credit and interest rate policy in the Chinese context (Dai et al., 2005) [47].

Table 3. Empirical Regression Results for Sector Output and Monetary Policy Shocks.

Monetary Policy Rules	**The Quantity Rule**			**The Interest Rate Rule**		
	OLS	W = D	W = S	OLS	W = D	W = S
M2	0.0646 * (0.0343)	0.0662 *** (0.0216)	0.0202 ** (0.0095)			
Shibor				−0.0700 *** (0.0190)	−0.0723 (0.0741)	−0.0131 (0.0326)
IV	1.3660 ** (0.6452)	1.4352 (0.8909)	0.1595 (0.3889)	0.078 (1.4635)	0.1112 (0.7656)	−0.2715 (0.3361)
FAI	−0.3710 (0.3374)	−0.3946 (0.4796)	−0.0061 (0.2106)	0.3355 (0.7706)	0.3291 (0.4090)	0.2266 (0.1804)
NX	0.0869 (0.0619)	0.0885 (0.0955)	0.0183 (0.0421)	0.0748 (0.0482)	0.0760 (0.0957)	0.0132 (0.0422)
rho		−0.0422 (0.0772)	0.9138 *** (0.0110)		−0.0333 (0.0768)	0.9144 *** (0.0109)
standard error	Clustered on id	Clustered on id	Clustered on id	Clustered on id	Clustered on id	Clustered on id

Note: t-statistics in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

However, after introducing spatial weight matrices D (downstream dependence) and S (upstream dependence) based on input–output tables, the empirical results change

substantially. For monetary policy shocks measured by the interest rate rule (Shibor), the core explanatory variable in the model loses statistical significance once network weights are included, indicating that the interest rate policy tool fails to achieve strong cross-sector diffusion along the production network in China's current market environment. This result reflects the continued predominance of administrative and quantity-based controls in the Chinese financial system. Although interest rate liberalization has advanced (e.g., the development of Shibor), actual financing conditions—especially for SMEs and upstream manufacturing—have not become highly sensitive to short-term interest rates, which fundamentally differs from the market-driven transmission chains observed in advanced economies (Ghassibe, 2021; Dedola & Lippi, 2005) [8,20]. In sharp contrast, monetary policy shocks based on the quantity rule (M2 growth) remain highly statistically significant even after accounting for sectoral network structure. Notably, under the S matrix (upstream dependence network), the spatial autoregressive coefficient reaches as high as 0.9138 and is significant at the 1% level; the M2 variable is significant at the 5% level. The effects of quantity-based monetary policy shocks within the upstream-dependent network are decomposed as shown in Table 4. The total effect of the shock is 0.2429, and the indirect network effect (0.1975) is much larger than the direct effect (0.0454). This fully indicates that, under China's sectoral structure, quantity-based monetary policy can generate large-scale cross-sector diffusion and spatial spillovers via upstream channels in the production network. On one hand, capital-intensive upstream sectors, due to their higher share of fixed assets and longer investment cycles, generally face more prominent financing constraints. When monetary policy is expansionary and financing costs decrease, these upstream firms experience significantly increased motivation for capacity expansion and display strong sensitivity in investment and production activities to changes in credit conditions (Bernanke et al., 1996; Kiyotaki & Moore, 1997) [13,48]. On the other hand, within the production network, upstream sectors often serve as key "hubs", where changes in capacity can create multiplier amplification effects through technological dependencies in the supply chain—lifting not only their own output directly but also transmitting substantial effects downstream, thus spurring both demand and aggregate economic growth (Acemoglu et al., 2012; Carvalho, 2014) [1,23]. This "upstream-driven—chain amplification—terminal feedback" pattern verifies the core role of sectoral network hubs in macroeconomic cycles at a micro-level (Gabaix, 2011) [49] and closely matches empirical findings on supply chain shock propagation and amplification (Barrot & Sauvagnat, 2016) [50].

Table 4. Decomposition of Lagged Second-Period Monetary Policy Shock Effects.

	LR_Direct	LR_Indirect	LR_Total
W = S	0.0454 **	0.1975 **	0.2429 **
	(0.0215)	(0.0992)	(0.1201)

Note: t-statistics in parentheses. ** denotes significance at the 5% level.

Further analysis reveals that, under the D matrix (downstream dependence), the M2 variable remains significant, but the network spillover effect and spatial autoregressive parameter are not prominent, highlighting the marginal role of downstream demand-oriented networks in policy transmission. Specifically, while increased downstream procurement demand could promote upstream raw materials and intermediate production, factors such as fixed asset scale, technological constraints in upstream sectors, and inter-firm bargaining within the sectoral structure often led to dissipation and time lags in the client-chain transmission of policy shocks, making it difficult to achieve the cumulative amplification seen in upstream supply chains. This finding is consistent with Atalay (2017) [51], who observed the inherently limited spillovers of demand networks in the U.S. production system.

At present, China's economy remains characterized by credit dominance and vertical sectoral chain specialization. Large state-owned and leading private enterprises in upstream sectors (raw materials, energy, equipment manufacturing) control key assets and technological resources and are acutely sensitive to changes in market liquidity and credit conditions. Under quantity-based monetary policy environments, whether through central bank base money expansion or targeted relending and policy-directed loans, these upstream sectors are the primary beneficiaries, driving investment expansion and technological upgrading. Through transmission along the sectoral chain, these changes rapidly permeate midstream and downstream sectors, resulting in synchronized gains in overall output and employment and generating stronger indirect spatial spillovers than direct effects alone. This process closely resembles the "production network accelerator" effects noted in Japan, France, and other economies after credit crises (Aghion et al., 2012) [52], and it is directly in line with Acemoglu et al. (2012) [1], who established theoretically that the macroeconomic impact of monetary policy is fundamentally shaped by production network structure. For the interest rate rules, however, such "network transmission–spatial spillover" effects are not empirically supported. This outcome can be attributed to several factors: Firstly, China's credit pricing still has administrative elements, preventing full transmission of interest rate changes to the real sector; secondly, some sectors—especially downstream, service, and innovation sectors—are more concerned about overall liquidity rather than marginal financing costs; and in the end, deep structural reforms in financial markets and the capacity for autonomous rate bargaining remain incomplete, impeding the influence of interest rate changes on end-sector output. In sum, at the current stage, the macro-regulatory capacity released by quantity-based monetary policy through sectoral networks clearly exceeds that of interest rate-based policies.

4.2. Heterogeneity Analysis of Upstream, Midstream, and Downstream Sectors' Responses to Monetary Policy Shocks

Based on empirical analysis of quantity-based monetary policy shocks, this paper further classifies 30 sectors into upstream, midstream, and downstream groups. Using the upstream dependency weight matrix (S matrix), the total effect, direct effect, and network (indirect) effect at different hierarchical sector levels are measured, thereby providing a nuanced view of how quantity-based monetary policy diffuses through supply-side production networks, revealing distinct structural hierarchies and spatial heterogeneity in network spillovers. Table 5 reports the impact of quantity-based monetary policy shocks on upstream, midstream, and downstream sectors. The results show that the average total effect is 0.1074 for upstream sectors, 0.1018 for midstream sectors, and 0.1123 for downstream sectors. This outcome may be attributed to the fact that downstream industries, being closer to final demand, are more directly exposed to monetary policy-induced changes in aggregate consumption and investment, whereas midstream sectors, which mainly serve as intermediaries in the supply chain, are affected more diffusely by upstream and downstream adjustments, resulting in a somewhat dampened policy effect. While the effect is slightly higher for downstream industries and lowest for midstream sectors, the differences across the three groups are fairly minimal. This finding suggests that, from a macro-aggregate perspective, the ultimate impact of monetary policy shocks across different supply chain positions tends to be relatively even, without a pronounced hierarchical bias.

Table 5. Heterogeneity Analysis of Monetary Policy Shock Network Transmission.

Sector Classification	Total Effect	Direct Effect (Share)	Network Effect (Share)
Upstream	0.1074	0.0592 (55.20%)	0.0482 (44.80%)
Midstream	0.1014	0.0421 (41.00%)	0.0593 (59.00%)
Downstream	0.1123	0.0319 (28.74%)	0.0803 (71.26%)

However, further decomposition of the total effect reveals important differences in transmission mechanisms. Specifically, the proportion of the total effect attributable to network effects (i.e., indirect effects) systematically increases as one moves from upstream to downstream sectors. Further comparing network effect shares (i.e., the ratio of network spillover to total effect) between upstream and downstream sectors reveals that downstream sectors feature the most pronounced network spillovers, with an average share of 71.26%, followed by midstream and upstream sectors at 59.00% and 44.80%, respectively. This indicates that, despite the overarching uniformity in aggregate impacts, there is significant heterogeneity in the role that network channels and indirect spillovers play in mediating policy shocks at different supply chain tiers. Downstream sectors, in particular, rely more heavily on network-based transmission mechanisms. This observation uncovers the cumulative "terminal aggregation" and progressive summation characteristic of spillovers in production networks. Specifically, shocks originating in upstream sectors are transmitted through multiple layers of the network and tend to concentrate and further diffuse at downstream nodes (such as construction, wholesale and retail, and life-services sectors). Such mechanisms are theoretically and empirically corroborated by extensive international research. It has been shown that supply chain shocks, after sequentially propagating through upstream linkages, lead to accumulation and multiplier effects at the terminal sectors due to aggregation, feedback, and market demand adjustments (Carvalho et al., 2014) [23], with policy impacts on terminal sectors such as real estate, wholesale, and retail being especially pronounced in terms of final diffusion and stimulus effects (del Rio-Chanona et al., 2020) [53]. Barrot and Sauvagnat (2016) [50], through the study of natural disasters in production networks, noted that downstream sectors characterized by multiple inputs and high degrees of network embeddedness most efficiently absorb and propagate upstream shocks, resulting in increased spillover shares. The progressively enhanced network effect found in this study validates the phenomenon of "convergent polarization" in market competition. Notably, while upstream sectors exhibit higher total effects, their network effect shares are lower compared to midstream and downstream segments. This structural contrast is endogenous to the "vertical dependence" characteristic of China's sectoral chain: as the starting point of the supply chain, upstream sectors first benefit from the liquidity and financing ease brought by monetary expansion, with the most prominent direct capacity and investment responses; meanwhile, the outward propagation of their effects is primarily limited to immediate downstream sectors, so indirect network effects, though significant, rarely exceed direct reactions. Thus, it is typically in the first periods after policy stimulus that upstream sectors react first, with their driving effects subsequently and volatily transmitting to midstream and downstream, where significant diffusion and spillovers occur. This is closely aligned with Gabaix's (2011) [49] "granular theory" regarding node effects and endogenous diffusion in networks, as well as with Pasten et al. (2020) [6] on the amplification of heterogeneous production network monetary policy shocks.

Table 6 reports the sectors ranking highest and lowest in network effect share (i.e., the percentage of indirect effect within the total effect) under quantity-based monetary policy shocks along the upstream-dependent network. Construction (downstream), wholesale and retail (downstream), and general equipment manufacturing (downstream) have the top three rankings, highlighting the prominent roles of "terminal aggregation—horizontal diffusion—feedback stimulus" in these sectors. This is because construction and wholesale/retail, as terminal sectors in the broad national economy, not only absorb positive or negative shocks from the entire supply chain, but also transmit feedback into wider services and consumption demand sectors. In China, the deep coupling of construction with real estate consumption forms a critical engine for macroeconomic cycles and urbanization, and its high network effect share reflects the structural characteristics of China's "infrastructure—investment—consumption" economic linkage. Similarly, the wholesale and retail sector is highly responsive to upstream supply conditions (particularly raw materials and manufacturing) and directly interfaces with end-consumers, giving rise to "multi-round feedback—comprehensive diffusion" dynamics. General equipment manufacturing, as a core midstream sector, distributes upstream liquidity across diverse downstream sectors via its systemic position, forming a classic "technological spillover—supply diffusion" pattern. These high network effect shares reflect the profound restructuring of dynamic policy transmission mechanisms among sectors in China's deeply specialized and highly interconnected supply-side production network.

Table 6. Analysis of Monetary Policy Shock Sector Network Effect Intensity (Based on Network S).

Network Effect Intensity Rank	Sector Name	Group	Network Effect Intensity
TOP3	Construction	Downstream	81.31%
	Wholesale and retail trade	Downstream	79.84%
	General sectoral machinery	Downstream	78.74%
BOTTOM3	Non-metal minerals and other mining	Upstream	45.55%
	Metal ore mining	Upstream	39.97%
	Communication equipment, Electronic computer and Other computer devices	Midstream	30.37%

In contrast, sectors such as non-metallic mineral and other mining, metal mining, and the communication, computer, and other electronic equipment sectors exhibit the lowest network effect shares; their total effects are mainly driven by direct effects. This reveals that, while upstream extraction sectors are highly sensitive to monetary expansion, their indirect economic spillovers are constrained by sector structure and market characteristics. Extraction sectors tend to have specialized products, closed supply chains, and highly concentrated downstream customers, restricting their spillover capacity to the distribution and procurement stickiness of immediate partners. High-tech sectors at the middle-upstream, such as communication equipment and electronic computer, feature pronounced specialization and innovation, and their transmission efficiency is dampened by technical barriers and demand misalignment. Previous literature likewise notes that sector segments with high barriers and strong specificity display greater heterogeneity and local rigidity in spillover magnitudes within the monetary policy transmission network (Herskovic, 2018) [54], closely matching these observations for high-tech chains in China.

4.3. Robustness Checks

To assess the robustness of our findings with respect to the timeliness of the input–output table data, we conducted a series of supplementary analyses. Given that the most recent officially published input–output table for Fujian Province is from 2017, it does not directly reflect post-pandemic production relationships. To indirectly examine the stability and validity of the production network structure, we compared the structure of China's national input–output tables (Data source: Eora database) from 2017 and 2022, with a particular focus on the matrices describing inter-sector intermediate inputs across the main sectors examined in this study. Specifically, we constructed intermediate input matrices for 29 sectors matched to those used in our empirical analysis for both the 2017 and 2022 national input–output tables. Due to differences in statistical classifications—namely, the absence of the "Repair services for metal products, machinery, and equipment" sector in the national tables, and considering the unique characteristics of sectoral input–output relationships in Fujian Province—we did not perform robustness checks by directly substituting the Fujian provincial table with the national input–output tables. Subsequently, we conducted row-to-row, column-to-column, and QAP (Quadratic Assignment Procedure) correlation analyses on the national intermediate input matrices between 2017 and 2022. As reported in Table 7, all three Pearson correlation coefficients (r) exceeded 0.998, indicating a remarkably high degree of structural consistency among key industries and suggesting that the evolution of the production network has been notably gradual and stable in China. Therefore, employing the most recent input–output table is considered appropriate and valid for input–output-based analyses such as those conducted in this study (Miller & Blair, 2022; Mendoza, 2023; Michaelides, 2024) [38–40].

Table 7. Correlation Analysis of Intermediate Input Matrices for 2017 and 2022.

Pearson Correlation Coefficient	Row-to-Row Correlation Analysis	Column-to-Column Correlation Analysis	QAP Correlation Analysis
r	0.9997	0.9980	0.9993

Furthermore, we replaced the network connection matrices in our empirical model with the D and S matrices calculated from Fujian Province's 2012 input–output table and re-estimated the model. As shown in Table 8, the estimated coefficients of core explanatory variables were robust in both statistical significance and direction, further supporting the reliability of our main results.

Additionally, we analyzed the time series of annual value-added growth rates across major sectors in Fujian Province (data from the National Bureau of Statistics). As illustrated in Figure 2, where the solid lines represent value-added growth rates and the dashed lines indicate their trends, these sectors exhibited overall stable trends from 2017 to 2023, with most indicators rebounding rapidly and returning to their prior trajectories after the temporary shock of the COVID-19 pandemic in 2020–2021. This further affirms the validity and reliability of the network spillover analysis based on the 2017 input–output structure.

The results of these robustness checks indicate that, despite short-term disturbances such as the pandemic, the production network based on Fujian's 2017 input–output table remains a valid and reliable foundation for analyzing spillover effects in the current research period.

Table 8. Robustness Check: Empirical Regression Results Based on 2012 Input-Output Table.

Monetary Policy Rules	The Quantity Rule		The Interest Rate Rule	
	W = D	W = S	W = D	W = S
M2	0.0630 *** (0.0212)	0.0360 * (0.0192)		
Shibor			−0.0682 (0.0723)	−0.0545 (0.0645)
IV	1.3409 (0.8643)	1.1401 (0.7732)	0.0891 (0.7452)	0.4881 (0.6672)
FAI	−0.3657 (0.4676)	−0.3647 (0.4185)	0.3170 (0.4004)	−0.0047 (0.3594)
NX	0.0844 (0.0935)	0.0413 (0.0838)	0.0717 (0.0937)	0.0354 (0.0837)
rho	0.0230 (0.0424)	0.3157 *** (0.0411)	0.0345 (0.0420)	0.3280 *** (0.0401)
standard error	Clustered on id	Clustered on id	Clustered on id	Clustered on id

Note: t-statistics in parentheses. ***, * denote significance at the 1% and 10% levels, respectively.

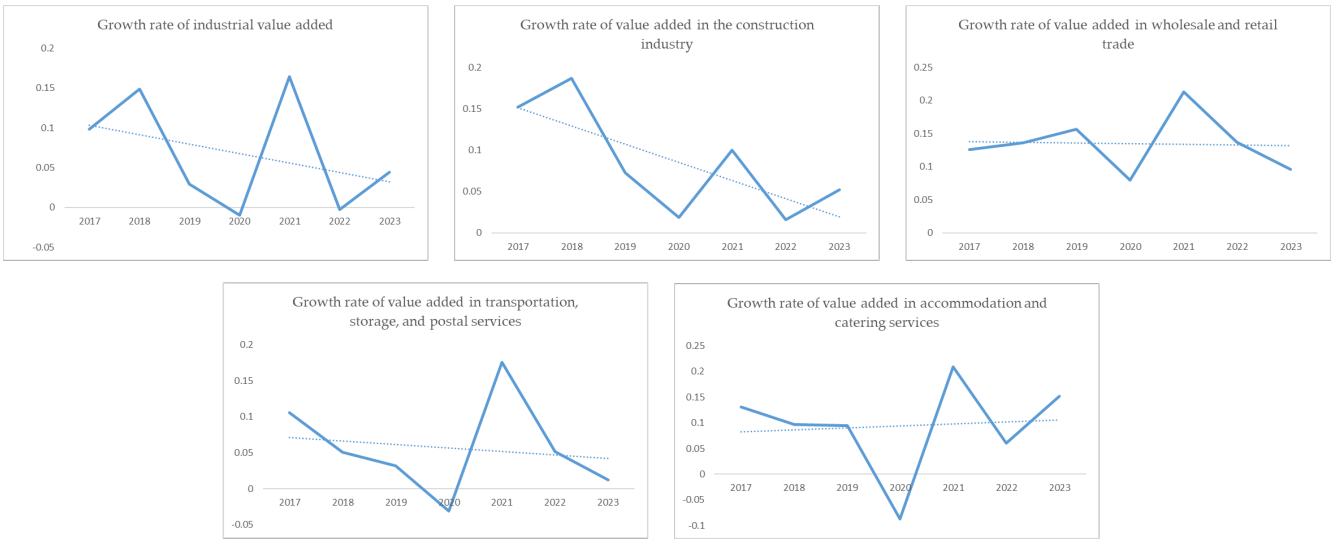


Figure 2. Growth Rate of Value Added in Major Sectors of Fujian Province.

5. Conclusions

This paper empirically investigates the dynamic effects of monetary policy shocks on output by leveraging high-frequency electricity consumption data at the sector level in China and employing a spatial econometric framework. By integrating sector linkage network matrices into the analysis, we capture both network spillover mechanisms and sector-level heterogeneity in monetary policy transmission. Particular attention is given to the differential responses between upstream and downstream sectors. The main conclusions are as follows:

(i) Quantity-based monetary policy shocks exhibit significant network spillover effects within upstream-dependent production networks. The results indicate that expansionary monetary policy not only directly stimulates upstream sectors' output, but also releases strong network (indirect) effects layer by layer through the vertical nesting of the production network. This network spillover is most pronounced under the spatial autoregressive model, wherein the majority of aggregate output gains are driven by network effects, and indirect effects far exceed direct effects, constructing a diffusion model of "upstream

driven—chain amplification—terminal feedback." Upstream sectors, due to their direct control over raw materials, energy, and equipment, display the most sensitive and immediate responses at the initial stages of policy expansion. Simultaneously, as China's banking credit resources are highly concentrated in upstream core sectors, credit easing first releases effectiveness in resource allocation, capacity expansion, and investment decisions, consistent with the network hub amplification mechanisms established in production network theory (Acemoglu et al., 2012; Carvalho, 2014) [1,23]. In contrast, interest rate-based monetary policy (represented by Shibor) does not exhibit significant spatial spillover effects within upstream-dependent production networks. This suggests that, under current structural conditions, China's sectoral system lacks the financial foundation necessary for large-scale cross-sector interactions under interest rate-based regulation. Short-term adjustments primarily impact individual firms' costs of financing, with limited ability to generate sectoral coordination and spatial diffusion. This is shaped by incomplete interest rate liberalization, segmentation within the financial system, and the predominance of quantity-based policy tools in real sector transmission (Ghassibe, 2021) [8].

(ii) The empirical analysis further reveals that the network (indirect) effects of quantity-based monetary policy shocks are heterogeneous across sectors and exhibit a systematic, monotonic increase from upstream to downstream along the production chain. Despite this, the aggregate (total) effects remain broadly uniform across different supply chain positions, indicating that while the contribution of network spillover channels increases for downstream sectors, this does not translate into significant differences in the overall response of each sector. Specifically, as the sectoral chain moves downstream, sectors such as construction, wholesale and retail have significantly higher network effect shares than midstream and upstream sectors. This reflects the role of downstream sectors as "aggregation points" in the chain, benefiting not only from direct policy stimuli but also from the accumulated passage of indirect effects, forming the archetypal "terminal aggregation effect". Within such networks, downstream sectors serve as "systemic diffusion nodes", amplifying overall policy spillovers through multi-level horizontal feedback and consumer market responses. This is especially typical in China's deeply specialized, strongly embedded sectoral ecosystem and aligns with "terminal aggregation" observations in international production networks (Gabaix, 2011; Carvalho et al., 2021) [49,55]. In contrast, upstream sectors' network effect shares are lower, as output gains are mainly driven by direct policy effects, with indirect diffusion curtailed by specialization, concentrated customer bases, and narrow channels. Some upstream sectors, such as mining and high-tech equipment, show limited policy spillovers due to market focus and strong specificity.

From a sustainability perspective, identifying the network positions and spillover capacities of different sectors provides useful guidance for designing monetary policy tools that not only stabilize short-term output but also steer long-term structural transformation. For instance, prioritizing sectors with high network diffusion potential —such as sectors with high network effect intensity—when channeling green credit or renewable energy investment could accelerate positive spillovers throughout the production chain. Likewise, safeguarding the resilience of upstream sectors, which act as critical hubs for capacity expansion, can enhance the economy's ability to absorb shocks while supporting sustainable industrial upgrading. By aligning monetary policy transmission mechanisms with environmental and social objectives, policymakers can better promote a balanced pathway toward sustainable economic growth.

Overall, the findings demonstrate the layered responses and structural constraints of monetary policy transmission in production networks, emphasizing the functional heterogeneity of sectoral nodes in spillover diffusion. These insights not only broaden traditional monetary policy analysis and enrich understanding of the Chinese economy but

also carry significant implications for the refinement of policy frameworks in the context of sustainability. It may be beneficial for policymakers to consider integrating sustainability objectives into monetary and industrial policy, drawing on frameworks such as Dikau & Volz (2021) [56] to guide concrete action. For instance, green credit could be strategically allocated to upstream hubs and key diffusion nodes identified through network centrality analysis, provided that this does not come at the expense of sectors critical to basic wellbeing and the achievement of fundamental SDGs, such as food producers and water suppliers. A balanced and context-aware approach is therefore necessary, in which resource allocation supports both network-centric spillover and direct social objectives. This can be achieved by combining network-based prioritization with targeted support for sectors that are pivotal to poverty reduction, food and water security, and sustainable production patterns, in line with the full spectrum of SDGs. Coupled with strict environmental impact assessments and "green eligibility" standards to avoid excessive resource use, as well as adaptive regulatory tools and monitoring mechanisms, such interventions can more effectively support the transition toward a resource-efficient, inclusive, and resilient industrial ecosystem. By aligning monetary policy tools with Sustainable Development Goals through empirically grounded mechanisms, monetary policy can promote not only economic growth but also meaningful progress toward long-term sustainable development.

At the same time, we fully recognize the lag in input-output table data as a limitation of our study. As more up-to-date input–output data become available, future research may further refine these empirical findings and provide deeper insights into the evolving dynamics of production networks. Continued updating and expansion of sector-level datasets will allow for more granular and timely assessments, advancing both the theoretical and practical applications of network-based policy analysis in the context of economic transformation and sustainability.

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