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Reexamining the Impact of Global Value Chain Participation on Regional Economic Growth: New Evidence Based on a Nonlinear Model and Spatial Spillover Effects with Panel Data from Chinese Cities

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Abstract: This study utilizes panel data drawn from 239 Chinese cities, and it employs fixed-effects models, mediation models, and spatial spillover models to reexamine the actual impact of the global value chain's (GVC) participation on regional economic growth. The findings reveal that this impact exhibits a U-shaped nonlinear pattern, with the turning point of GVC occurring at 0.45, which is higher than that of 222 cities. Most cities are on the left side of the U-shaped curve, which corresponds with the second stage of the "in-out-in-again" GVC participation pattern (i.e., the "out" stage). During this stage, a decline in foreign value-added ratio (FVAR), with regard to exports (accompanied by an increase in the domestic value-added ratio), promotes economic growth. Innovation capability acts as a mediator in the relationship between GVC participation and economic growth. Furthermore, GVC participation has significant spillover effects on neighboring cities, with siphon and spillover effects coexisting. Thus, China should focus on establishing domestic value chains and innovation systems, achieving relative independence from existing GVCs dominated by developed countries, enhancing indigenous innovation capabilities, and laying the foundation for the third stage (in-again) of reintegration into GVCs, at the high value-added end, to achieve a higher level of openness. This study explores the nonlinear impact of GVC participation on regional economic growth in China from both theoretical and empirical perspectives, focusing on the finest divisions that remain feasible-cities. This approach expands and supplements the relevant field of research in valuable ways, yielding more realistic research conclusions and policy recommendations.

Keywords: GVC participation; economic growth; nonlinear analysis; innovation capability; spatial spillover

1. Introduction

Trade liberalization has long been advocated as an important means of promoting sustainable economic growth and improving welfare levels. International trade helps countries exploit their comparative advantages and achieve specialization and large economies, thereby playing an increasingly important role in alleviating regional resource shortages, promoting the efficient use of global resources, stimulating economic growth, and improving social welfare [1]. In the new context of global value chains (GVCs), the nature of



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trade has undergone significant changes. The production process associated with GVCs crosses national borders multiple times, and it involves more than two countries [2]. Unlike traditional international trade, which only involves countries that import and export final products, GVC-related trade is dominated by multinational corporations in developed countries, wherein the production process is divided into sub-processes that are completed in different countries, and different production segments are traded between countries in the form of tasks or intermediate goods. The emergence of GVCs poses new challenges with regard to the study of the economic impact of globalization. In-depth analyses of the relationship between GVC participation and economic growth can help countries and regions understand their roles and positions in the global economy, they can provide important guidance for policymakers, formulate more effective policies in accordance with the characteristics of different stages of GVC participation, and use globalization trends to achieve sustainable economic growth and development.

China is one of the most important participants in international trade, and trade is considered to be a crucial driving force for China's economic growth [3,4]. Since the reform and opening up of the economy, China has seized the opportunity to join the GVC and it has rapidly achieved industrialization, becoming the world's second largest economy and the largest trading nation in terms of goods. As the largest developing country, China has played diverse roles at various production stages of the GVC. Different cities exhibit significant heterogeneities in terms of the degree and role of GVC participation, ranging from coastal cities in the east to inland cities in the central and western regions. China's experience of participation in GVCs is both universal and typical, thereby providing valuable insights for other countries, especially developing countries, concerning how to participate in GVCs and promote economic growth. Presently, China is undergoing a critical period of economic transformation and it is upgrading, which requires a focus on enhancing independent innovation capabilities. Investigating the impact of China's GVC participation on economic growth and exploring the mediating role of innovation capabilities in this context can provide insights and recommendations for sustainable development paths and strategies for China's economy in the era of technological empowerment.

Most previous studies have suggested that GVC participation has a positive effect on China's economic growth [5,6]. However, long-term empirical data have shown that the relationship between these factors may be more complex. This study calculated the foreign value-added ratio (FVAR) in exports, a critical indicator of GVC participation [7], and it found that China's level of GVC participation has not always been increasing; rather, it has exhibited significant stage disparities. From 2001 to 2004, when China was in the early stages of joining the World Trade Organization (WTO) [8], the FVAR continuously increased. After 2005, the FVAR exhibited a marked decline, with a slight rebound in 2010, followed by years of consolidation at a low level. Interestingly, during this period, China's per capita gross domestic product (GDP) continued to grow. This information gives rise to a rethinking of the situation, as follows: could the impact of GVC participation on China's economic growth be nonlinear? As a developing country that exhibits significant internal regional heterogeneity, is the impact of GVC participation on economic growth different at a more granular, regional level, namely, in cities? Does GVC participation have spatial spillover effects on neighboring cities? These are the questions this study attempts to investigate.

Clarifying the impact of GVC participation on economic growth is crucial for ensuring economic growth and sustainable development. Economic development is one of the three pillars of sustainable development [9]. The stage theories of development, offered by Smith, Mill, and Marx, provide rich historical and theoretical explanations for economic development, highlighting the fact that the division of labor, the advancement of knowledge, technological transformation, and innovation are key drivers for improvements in labor productivity and the achievement of sustainable economic development [10]. The GVC represents a type of labor division that extends across national borders within the production process, which has substantial influence on knowledge accumulation, technological

innovation, efficiency improvements, and economic development in participating countries. The implementation of effective strategies for GVC participation can help countries achieve sustainable growth [11].

Previous research has extensively explored the concepts, theories, governance, and influencing factors associated with GVCs; however, studies directly examining the macroeconomic impact of GVC participation remain limited (Kano, 2020) [12]. The extant literature on this topic has mainly discussed the impact of GVC participation on the economic growth of developing economies from the perspective of a linear relationship, and these reports present conflicting conclusions. Most studies have suggested that through GVC participation, developing countries can access the global market, specifically, certain production stages or components, without developing the entire product, thereby achieving economic growth. Conversely, other researchers have noted that GVC participation might hinder skill-biased technological transformations in developing countries, thus trapping them in low-value production activities and impeding long-term sustainable growth. The inconsistency of these conclusions may be due to the fact that the relationship between GVC participation and economic growth is nonlinear, and its impact varies across different stages. However, very few studies have examined the impact of GVC participation on economic growth from a nonlinear perspective, especially with regard to China. Recent works by Lee et al. (2018) and Mao (2022) have used cross-national data to explore this topic from a nonlinear perspective [13,14], which highlights this possibility. Their research also highlights the fact that emerging economies, represented by China, are following in the footsteps of successful economies that are 'catching-up', and they exhibit a similar nonlinear pattern, wherein the FVAR first rises and then falls. Drawing on empirical evidence from successful economies that are 'catching-up', China and other developing economies could potentially achieve economic growth through a nonlinear pattern of GVC participation. Therefore, it is necessary to reexamine the impact of GVC participation on China's economic growth from a nonlinear perspective, with the aim of precisely identifying optimal strategies for GVC participation at different stages. This endeavor could offer practical policy recommendations regarding technological progress and sustainable economic development in China and other developing countries.

Research in the relevant field is also limited in terms of its analysis at the subnational level, which is particularly important in light of China's deep and broad territory, which is characterized by obvious regional heterogeneity in terms of resource endowments and development levels [15]. Consequently, disparities in GVC participation could potentially lead to imbalances in regional economic growth [16]. In particular, the ability of major cities to absorb, innovate, complete specific production tasks, as well as respond to dynamic changes in GVCs, is key to regional economic development disparities [17]. Due to data limitations, research on the economic effects of China's GVC participation has mostly been conducted at the national, industrial, and entrepreneurial levels. Only a few studies have been conducted at the regional level, and these studies have mostly adopted a more macrolevel perspective (i.e., they have focused on provinces). Comprehensive research analyzing the economic impact of regional GVC participation at the city level remains scarce.

This study aims to address these research gaps by exploring the nonlinear impact of GVC participation on regional economic growth in China based on city-level panel data. This paper proposes a theoretical hypothesis regarding a nonlinear relationship between GVC participation and regional economic growth in China based on Lee's "inout-in-again" theory. Subsequently, empirical tests were conducted using panel data collected from 239 Chinese cities from 2001 to 2016. The study indicates a U-shaped nonlinear relationship between GVC participation and regional economic growth in China during the sample period. Most cities are currently on the left side of the U-shaped curve, indicating that China is generally in the second stage of the "in-out-in-again" process. Technological innovation is identified as an important mediating variable, through which, GVC participation affects regional economic growth. Furthermore, this study confirms the existence of the spatial spillover effects of GVC participation on economic growth in neighboring cities. These findings suggest important policy implications regarding ways in which China can effectively participate in GVCs to promote long-term sustainable economic growth; they also provide valuable lessons for other developing economies.

China is a country with a deep and broad territory which is characterized by obvious regional heterogeneity. Resource endowments of different cities and location conditions vary significantly, affecting their GVC participation and economic development [16]. Additionally, regional GVC participation may influence economic growth in other regions. Therefore, based on the "in-out-in-again" hypothesis, this study examines the actual impact of GVC participation on economic growth at a more granular and regional level, starting with cities. Panel data of 239 Chinese cities from 2001 to 2016 were used in the research sample, and fixed effects models, mediation models, and spatial spillover models were employed to investigate the relationship between GVC participation and regional economic growth.

The main contributions of this paper are as follows. First, it explores the nonlinear impact of GVC participation on regional economic growth from both theoretical and empirical perspectives. This approach extends and supplements related research on GVC and regional economic growth by accurately identifying optimal strategies for different stages of GVC participation, and this paper can thereby serve as a valuable reference for sustainable economic development in China and other developing countries. Second, it introduces a mediation model to empirically validate the mediating effect of technological innovation on the impact of GVC participation on regional economic growth. This contribution provides beneficial insights for enhancing technological innovation capabilities in various regions of China and other developing economies, with the goal of enabling such countries to take advantage of the economic benefits of GVC participation more effectively. Third, given that under the influence of factor mobility, technology spillovers, and backward and forward industrial linkages, regional GVC participation may have spatial spillover effects on neighboring regions, this paper employs appropriate spatial econometric models to reexamine the nonlinear relationship between GVC participation and regional economic growth after considering the spatial dimension, thereby unveiling the spatial spillover effects of GVC participation on regional economic growth. Fourth, unlike previous research, this paper extends the analysis of the impact of regional GVC participation on economic growth in China to the most granular and feasible level-the level of cities—thereby addressing the inadequacies of previous research with regard to these finer regional dimensions. China's internal administrative division levels include the provincial, prefectural, county, and township levels. Among these divisions, 34 provinciallevel administrative regions feature limited sample sizes, and they only provide limited information. There are 297 cities at the prefecture level or above [18], which represent the backbone of China's economic development. Different cities, even within the same province, exhibit significant variations in resource endowments and locational conditions, thus impacting their GVC participation and economic growth [16]. City-level samples have larger capacities, yielding more robust empirical evidence. They represent the most viable and detailed sample choice for current research on China's regional GVC participation. Regions are composed of different city-level geographical units. By selecting cities as the sample, this paper incorporates city heterogeneity into the analysis, effectively capturing the dynamic features of China's regional GVC participation at a more micro level, thus facilitating a more accurate examination of the nonlinear relationship between GVC participation and economic growth. The study thus yields more practically relevant research conclusions and policy recommendations.

The rest of this paper is organized as follows: Section 2 provides a literature review; Section 3 presents the theoretical mechanisms underlying the effects of GVC participation on regional economic growth, and it proposes the research hypotheses; Section 4 describes the empirical research methods and data; Section 5 reports the empirical results; and Section 6 concludes the paper by providing a summary, policy recommendations, and research limitations.

2. Literature Review

GVC specialization involves fragmented production processes and trade on a global scale, and it is thus different from traditional trade, although it fundamentally remains a type of trade. Different trade theories also offer various theoretical explanations for the economic effects of GVC participation. More specifically, the participation of developing countries in the GVC enables them to leverage their comparative advantages [19] and to take advantage of the benefits of the specialized division of labor, economies of scale [20], and optimized resource allocation [21], thereby promoting economic growth.

GVC theory suggests that cross-border production can lead to a more international division of labor and greater trade benefits [2]; it can thus serve as a crucial way in which developing countries can achieve industrialization and economic development, and catch up with leading countries [22]. Through improvements in information and communication technology (ICT) have been made, developing countries can easily join existing supply chains by taking responsibility for specific production stages in the GVC division of labor, thereby obtaining access to global markets [23], and opportunities to industrialize and catch up with leaders in terms of manufacturing productivity [24]. Most of the theoretical literature has suggested that GVC participation is beneficial for economic growth [25]. A country can obtain favorable economic effects through GVC participation [26] due to the specialization of production tasks [2], access to high-quality imported intermediates [27], knowledge spillovers from multinational corporations in developed countries [28,29], and resource optimization which will produce competitive effects [30].

Early empirical research focused mainly on developing new indicators to measure GVC participation [31]. Hummels, Ishii, and Yi (hereafter referred to as HIY) first proposed one of the most important indicators of GVC participation (i.e., foreign value-added (FVA) in exports or vertical specialization (VS)) in their seminal work [32]. Subsequent research based on HIY's work has diverted into two directions. On one hand, using cross-country input-output (IO) tables, total exports are decomposed into "domestic value-added (DVA) absorbed abroad" exports, "DVA exported and then returned domestically" exports, "FVA" exports, and "pure double-counting" exports [33]. Indicators of GVC participation and positioning are constructed based on the aforementioned decomposition [34]. Although this approach has been widely used, it is difficult to apply directly to the regional level due to issues with the availability of IO tables. On the other hand, Upward et al. (2013) merged China's industrial enterprise database with its customs trade database, addressing the temporal discontinuity in China's regional IO tables and using the distinction between processing trade and general trade to refine VS [35]. These authors introduced the concept of FVAR as an improved measure, which is also known as GVC backward linkages, and it is the most commonly used indicator to measure the degree of GVC participation [36]. This indicator can be applied at a subnational level, and it constitutes the core indicator employed in this study. A country or region's exports consist of both FVA and DVA, with the sum of the FVAR and domestic value-added ratio (DVAR) being one. An increase in the FVAR (which means a reduction in the DVAR) prompts an increase in GVC participation [14].

Surprisingly, few studies have directly addressed the macroeconomic impacts of GVC participation (Kano, 2020) [12]. With improvements in GVC measurement indicators and methods, some recent studies have attempted to empirically test the economic impact of GVC participation. Kummritz (2015) conducted an early empirical study that used cross-country IO tables to verify the positive impact of GVC participation on economic development in middle- and high-income countries [31]. Subsequent empirical research discovered that GVC participation has a significant positive effect on output growth in terms of manufacturing and services [37], per capita GDP, and environmentally friendly growth [11] in all countries. However, these studies mainly focused on developed and emerging economies, as the GVC participation data of many low-income economies are

unavailable [14]. Additionally, some studies have indicated that this linear relationship becomes less distinct after financial crises [38]. Certain empirical studies have also provided evidence indicating that GVC participation can facilitate economic growth in developing countries. Ajide (2023) reports a significant positive correlation between GVC participation and total factor productivity in the context of African economies [39]. Piermartini and Rubínová (2019) indicate that GVC-related trade, as opposed to conventional trade, can promote knowledge spillovers and economic growth more effectively [40]. Boffa et al. (2016) report a positive effect of GVC participation on per capita GDP, which weakens as per capita GDP increases, suggesting that low-income countries can benefit more from GVC participation with regard to economic growth [41]. Countries in the early stages of development are located far from the technological frontier, and they have more room to benefit from knowledge transfers or spillover effects via GVC participation. Thus, they are able to 'catch up' with the global efficiency frontier [42]. Using a panel estimation covering 47 countries and 13 manufacturing sectors from 1995 to 2011, Urata (2020) notes that developing countries benefit more from improved productivity when they source intermediate goods from advanced countries and engage in backward GVC participation [43].

In contrast to the optimistic attitude exhibited by the literature discussed above, considerable research has expressed concerns regarding the negative effects of GVC participation on developing countries. For example, some studies have suggested that GVC participation may hinder developing countries' skill-biased technological changes [44], leading to "low-end lock-in" [45,46] and "capture effects" [47,48], thus trapping those countries in lowvalue activities [49]. Baldwin claims that GVCs may boost productivity and employment during the early stages of an economy's development, but they may hinder long-term development [50]. Rodrik further argues that GVCs demand high levels of technical accuracy and quality standards, necessitating more automation. This situation could challenge the comparative advantage of abundant unskilled labor in developing countries, potentially leading to reshoring to advanced countries [51]. Humphrey and Schmitz [52] and Barrientos et al. [53] highlight a governance structure featuring asymmetric power relations between leading firms in developed countries and suppliers in developing countries, which often results in the latter becoming trapped in low-value activities. Kaplinsky and Farooki further note that GVC participation has had positive growth effects, but only for a limited number of emerging economies, whereas the majority of developing countries have not experienced such effects [54]. In terms of empirical research, Kummritz (2015) reports that the impact of an increase in FVAR on GDP in low-income countries is negative, but not significant, in contrast to the significant positive effects observed in the case of middle- and high-income countries [31]. Fagerberg et al. (2018) and Lotfi (2021) report that latecomer economies with increased GVC participation grew slower when controlling for other relevant factors [55,56]. Raei et al. (2019) also reports that the positive relationship between GVC participation and economic growth mainly pertains to middle- and high-income countries that feature a high degree of GVC participation, whereas the effect of GVC participation in latecomer countries is negative but not significant [36].

The existence of such conflicting conclusions suggests that the relationship between GVC and economic growth may not be linear, and the impact of increasing GVC participation on economic growth varies across different stages. Research in this area is still limited, and only a few recent studies have obtained relevant conclusions. Based on case studies in South Korea and Chinese Taipei, Lee et al. [13] and Mao [14] provide preliminary empirical evidence that indicates a U-shaped relationship between GVC participation and economic growth. Lee et al. propose the "in-out-in-again" hypothesis based on a theoretical framework of firms or industries progressing through the "Original Equipment Manufacture (OEM)—Original Design Manufacture (ODM)—Original Brand Manufacture (OBM)" stages within the GVC. This suggests that the N-shaped GVC participation pattern can lead to a more successful 'catch-up'. Using panel data across various countries, Mao empirically tests the nonlinear U-shaped relationship between GVC participation and economic growth at the macro level. Lema et al. identifies the "in-out-in-again" trajectory as a significant developmental path in the coevolution process of GVCs and local innovation systems [57]. Zhou et al. argue that the extant research has failed to focus on the second (i.e., the "out",) phase, and that it lacks policy guidance with regard to how firms in emerging economies can avoid capture during this phase [58]. Qu et al. used panel data from 17 manufacturing industries in China from 2000 to 2014 and found that when the GVC position is below a certain threshold, increasing the degree of GVC participation will have a negative impact on green economic growth. After the GVC position reaches a certain threshold value, the impact of the degree of GVC participation on green growth changes from negative to positive [59]. In addition, other studies have recognized that the impact of GVC participation on economic growth varies across different stages, with Mehta (2022) proposing a hypothesis based on 'upgrading within GVC in four stages' [60], similar to Lee's theory. However, the judgments of such studies, regarding the final stage of GVC participation, have differed, with Mehta arguing that GVC participation decreases during this stage and Lee et al. arguing that it increases and promotes economic growth. Recent data drawn from successful economies that are 'catching-up', such as South Korea and Singapore, show that these countries exhibit high levels of both GVC participation and per capita GDP, and this paper posits that Lee's "in-out-in-again" GVC participation model is more consistent with reality.

Empirical research on the impact of GVC participation on economic growth is increasing, but still limited [36]. Many studies have investigated the indirect effects of technology spillovers and productivity improvements instead of analyzing the relationship between GVC participation and economic growth directly. Some research has explored the role of GVC in the promotion of technological progress and upgrading at the business, industrial, and national levels in developing countries [61,62]. Such research has suggested that developing countries can acquire foreign knowledge (technology) from the GVC that can promote innovation [63], and thus, it can facilitate 'catch-up' through 'learning-by-doing' or 'learning-by-using approaches' [64]. Wang and Fritsch et al. propose that developing countries can benefit from GVC participation in terms of technological progress through three channels, as follows: exporting, importing, and pure knowledge technology spillover [65,66]. Antràs and Chor argues that GVC participation can enhance the productivity of enterprises in developing countries through "selection effects" and "resource reallocation effects" [67]. Timmer et al. indicate that GVC participation tends to increase the proportion of high-skilled labor [68]. Pietrobelli [45] notes that only when a good domestic innovation system provides sufficient opportunities for the absorption of new technologies can developing economies break free from the low-end lock-in of GVC participation and improve their productivity. However, these studies have not empirically tested the mediating effect of technological innovation on the relationship between GVC and regional economic growth.

Research on China's GVC participation has mainly focused on industry [69,70]. Despite the fact that differences in resource endowments and development between regions in China may lead to heterogeneity in terms of GVC participation [71], little relevant research has focused on the regional level. The few previous studies in this field have focused mostly on the provincial level [71,72], and research focusing on regional dimensions remains scarce. This lack of research may be due to data limitations. Cross-country research has generally used IO tables to calculate relevant indicators. Some studies have attempted to combine China's provincial IO tables with cross-country IO tables, but China's provincial IO tables are compiled every five years and they exhibit a large time gap. More importantly, the National Bureau of Statistics of China does not provide city-level IO tables. To capture the dynamic characteristics of regional GVC participation in China from a time series perspective, Shao and Su (2017) [73] employed the methods developed by Hummels et al. [32] and Upward et al. [35], and they used Chinese customs data from 2000 to 2007 to measure the degree of GVC participation in 30 provinces. This method is not limited by the availability of IO tables, and Shao and Su's research can serve as a valuable reference for the construction of time series indicators concerning GVC participation at more granular regional levels [72]; it can even be applied at the microenterprise level [74].

Cities are playing an increasingly important role in globalization and economic growth [75]. Different cities differ significantly in terms of their ability to complete GVC production tasks and their ability to innovate [17]; this is key to regional economic development differences. In China, cities at the prefecture level and above, which comprise finer administrative divisions than provinces, have become the backbone of China's economic development and the center of technological innovation [76]. Different cities exhibit significant differences in terms of resource endowments, economic development, and GVC participation [16], thus indicating that higher-level regional research may not be able to identify the impact of GVC participation on economic growth. Some research has suggested that city samples have a larger capacity and can provide more microlevel and reliable empirical estimates than provincial-level research [77,78]. However, studies focusing on the direct economic impact of China's GVC participation at the city level are extremely scarce. Some studies have used the methods developed by Upward et al. [35] and Shao and Su (2017) [73] to construct indicators of GVC participation in Chinese cities using customs data, thereby exploring the impacts of GVC participation on carbon emission intensity [16] and air pollution [78] at the city level.

Considering the close spatial linkages and interactions between different regions within a country, GVC participation in one region not only affects local economic growth, but it also promotes spatial linkages and interactions between regions, thereby influencing the economic growth of other regions through resource flows, technology spillovers, and industrial linkages. Research has indicated that the economic growth of Chinese cities is closely associated with the economic growth and production factors of neighboring cities [79]. However, few studies have investigated the spatial dimension of GVC participation. Men et al. analyze data drawn from 42 countries, and they found that a country's increased GVC participation and higher GVC positions effectively drive its economic development. Moreover, they have significant spillover effects on the economic development of neighboring countries [29]. Su et al. reports that GVC participation not only directly impacts the economic growth of the participating region, but it also indirectly affects the economic growth of other regions based on data from 30 Chinese provinces during 2001–2014 [80]. By analyzing Chinese provincial data, Shaol demonstrates that GVC participation has a spatial spillover effect on resource allocation efficiency and productivity in adjacent provinces [73]. Xiang et al. note that importing intermediate goods can have a spatial spillover effect on surrounding cities [81].

The extant literature has discussed the impact of GVC participation on the economic growth of developing economies, and it comprises preliminary explorations into the spillover effects of GVC. However, most of these studies have been conducted from the perspective of linear relationships, and they have reported inconsistent conclusions. This situation is likely due to the nonlinear nature of the relationship between GVC participation and economic growth, in which context, the effects of GVC involvement vary across different stages. Several recent studies using data drawn from advanced economies have revealed this possibility and noted that emerging economies, represented by China, also exhibit similar patterns. However, to date, no studies have empirically tested the nonlinear relationship between GVC participation and regional economic growth in China. This paper reexamines the relationship between these two factors with the goal of supplementing and expanding the extant research. Second, most studies have been conducted at the cross-national level [29], and regional heterogeneity and the economic effects of GVC participation within a country has received little attention. Several studies on China have focused on the provincial level, but very few of these studies have conducted an analysis at a more micro level—i.e., with a focus on cities. Chinese cities exhibit significant heterogeneity as well as strong spatial connections and interactions, and an analysis of the city level is expected to provide richer empirical evidence. Third, many studies have verified the impact of GVC on developing economies in terms of indirect effects such as

technological spillovers, but such studies have not empirically verified the mediating effect of technological innovation. Fourth, the spatial effects of regional GVC participation have received little attention from previous researchers. In light of these considerations, this paper attempts to address these research gaps by reexamining the relationship between GVC participation and regional economic growth in China from a nonlinear perspective, based on city panel data. Moreover, this paper also examines the mediating transmission mechanism of technological innovation capabilities, with the goal of obtaining richer and more realistic empirical evidence and proposing more practical policy recommendations.

3. Theoretical Analysis and Research Hypotheses

3.1. The "In-Out-In-Again" Pattern of GVC and Its Nonlinear Impact on Economic Growth

The "in-out-in-again" hypothesis proposed by Lee et al. (2018) [13] suggests that a country's GVC participation is divided into three stages (Figure 1). During the initial stage ("in"), developing countries mainly participate in GVC in terms of OEM production. Therefore, they are able to gain access to global markets and they can acquire knowledge and skill spillovers from developed countries' multinational corporations via "learning by doing." During this stage, increasing GVC participation (as measured by FVAR) and dependence on foreign imports are conducive to economic growth. The second stage is "out," in which context, developing countries establish and develop domestic production and innovation systems after obtaining a foothold in GVCs, thus transforming their production mode to ODM. This helps these countries to achieve upgrade industrially. During this stage, developing countries seek to separate and become independent from existing foreign-led GVCs, with the growth rate of DVA exceeding that of FVA; in addition, in this context, a decline in the FVAR (which means an increase in the DVAR) is more conducive to economic growth. The third stage is "in-again." After establishing their own domestic value chains (DVCs), developing countries reintegrate into the GVC based on the OBM production mode. During this stage, countries with enhanced innovation and internationalization capabilities reintegrate into the GVC. They can obtain more benefits from higher value-added positions, they ensure the global optimization of the supply chain layout, and they promote economic growth by increasing the FVAR once again.



Figure 1. The theoretical framework of GVC participation with regard to the "in-out-in-again" pattern. Source: Author's creation based on the relevant literature.

As shown in Figure 1, during the first stage of GVC participation ("in"), developing countries import many intermediate goods and they mainly engage in OEM production, with processing trade being the dominant trade mode. During this stage, the level of FVA in developing countries is high, and their DVC development is not fully formed. These countries are more integrated into the GVC, which allows them to acquire foreign knowledge and production skills via methods such as "learning-by-doing", and which includes the widespread adoption of OEM by East Asian countries during the early stages of GVC participation. During this stage, increasing the FVAR has a positive effect on economic growth.

During the second stage of GVC participation ("out"), developing countries seek to achieve industrial upgrades and sustained economic growth by decoupling, to a certain degree, from the value chains that are dominated by developed countries. Such countries strive for independence in areas such as marketing, brand building, and technological innovation. Production methods shift towards ODM and OBM, and the proportion of processing trade declines [82]. This independent process is challenging but necessary. The GVC, led by multinational enterprises in developed countries, pursues the maximization of profits for leading enterprises, thus essentially squeezing the profits of the lower-tier GVC divisions in which developing countries participate. In addition, developing economies face competition from subcontracting locations and subcontracting companies with lower labor costs. However, the purpose of this independent phase is not to disengage from the global market but to achieve industrial upgrades and economic growth, thus laying the foundation for future reintegration into the GVC. During this stage, reducing the FVAR (and increasing the DVAR) and strengthening independent technological innovations is conducive to economic growth [14], helping developing countries or regions break free from the dilemma of "low-end lock-in" and the "middle income trap" [83], and thus enabling a transition to the third stage.

The third stage involves reintegration into the GVC ("in-again"). After developing countries establish their DVCs and achieve industrial upgrades in the second stage, they reintegrate into the GVC via the high-value end. They gain more benefits and growth momentum through greater openness and global resource integration, and therefore they are the inevitable choice for economies in the high-income stage with enhanced innovation capabilities and internationalization. During this stage, an increase in the FVAR (which causes a reduction in the DVAR) is conducive to economic growth.

When using the "in-out-in-again" GVC participation pattern, the degree of GVC participation and economic growth exhibit a nonlinear relationship. Lee et al. suggest that GVC participation can promote economic growth using an N-shaped path [84], and they used long time series data drawn from successful 'catching-up' economies to demonstrate this pattern [19]. According to the OECD, China's national-level FVAR increased from 15% to a peak of 24% between 1995 and 2004 (the earliest data provided by the OECD are from 1995); then, the FVAR underwent a significant decline, dropping to 18% in 2009, rebounding slightly in 2010, and remaining at a low level for several years thereafter. Combined with previous research on other economies, this paper claims that China is still in the second stage of the "in-out-in-again" phase, and it has not yet entered the third stage. According to Lee et al. (2018) [13], South Korea's GVC participation and economic growth trajectory can serve as precursors for China, since the progress of that country precedes that of China by more than 20 years. Since the 'opening up' of the economy in the 1970s, via OEM exports of labor-intensive goods, South Korea's FVAR continued to increase until it reached a peak of 36% in 1980. Then, FVA began to decline, dropping to a low of 28% in 1993. During this period, South Korea rapidly 'caught up' in terms of technology, and it escaped the middle-income trap by increasing the DVAR in terms of exports. After 1993, South Korea's GVC participation rose once again, reaching a maximum of 41%).

Due to GVC participation, China has obtained substantial access in terms of highquality imported intermediate and capital goods, thus facilitating rapid industrialization. The country has emerged as a global manufacturing hub and the world's largest exporter of goods [85]. Beginning in 2005, China's GVC participation has consistently declined, indicating efforts to reduce reliance on imported intermediates and enhance the DVAR in exports (however, overall, China's manufacturing sector remains in a downstream position due to its limited autonomous technological innovation capacity [15]). China's regional economic growth increasingly depends on local production and the DVC, thus reducing dependence on GVCs. However, the development of China's DVC has not yet matured. Overall, China remains in the second stage of the "in-out-in-again" phase, and it has yet to cross the turning point. Notably, significant heterogeneity exists among the country's internal regions, with certain eastern cities making attempts to transition to the third stage.

Lee et al. (2018) and Mao's (2022) [13,14] cross-national empirical analyses reveal a U-shaped relationship between GVC participation and economic growth from the second stage to the third stage. However, due to a lack of early historical data, the positive impact of GVC on economic growth during the early stage cannot be verified. This study is also constrained by this limitation. Although China began to 'open up' in 1988, the Chinese customs database only provides data after 1995. Given the significant adjustments to China's urban administrative boundaries, which occurred in approximately 2001, this study selects 2001 as the starting point for research to ensure data consistency. At this point in time, China's GVC participation level had nearly reached its peak. Thus, this study primarily focuses on the second stage of China's GVC participation and beyond, based on the "in-out-in-again" framework.

Accordingly, two research hypotheses are proposed:

H1. Between 2001 and 2016, there is a U-shaped nonlinear relationship between the degree of GVC participation and China's regional economic growth. GVC participation does not always have a positive effect on economic growth.

H2. During the study period, most Chinese cities are located on the left side of the U-shaped curve, indicating that they are in the second stage of the "in-out-in-again" GVC participation pattern. At this stage, a decline in the FVAR (accompanied by an increase in the DVAR) promotes economic growth.

3.2. The Mediating Role of Technological Innovation

Based on the theoretical analysis in Section 3.1, creating a local innovation system, enhancing regional innovation capabilities, and achieving relative independence from the GVC, which is led by developed countries, are critical tasks for developing countries after entering the second stage of the "in-out-in-again" GVC participation pattern. These tasks determine whether a developing economy can successfully transition to the third stage ("in-again"), thus rejoining GVC from a more advantageous position, achieving greater openness, and optimizing global resource allocation. Therefore, this paper suggests that regional innovation capabilities may play a significant mediating role with regard to the impact of GVC participation on economic growth.

On the one hand, GVC participation is an important channel for improving regional innovation capabilities [44]. Developing countries like China, that are engaged in global production networks led by advanced nations, may employ two categories of mechanisms—"export-chain learning" and "import-chain learning" [86]—to facilitate knowledge spillovers and to foster technological advancement [87]. The former mechanism concerns export-oriented firms which have greater exposure to cutting-edge technologies, management, and marketing practices in the international market. They actively or passively improve their technical capacity in response to the requirements, guidance, and training of leading enterprises in developed countries. The latter mechanism suggests that developing countries can also derive technological spillovers by importing high-quality machinery and intermediate inputs. Through imitation, learning, and reverse engineering, they subsequently enhance their own technological capabilities [61].

On the other hand, GVC participation might hinder developing countries' skill-biased technological progress, leading to "low-end lock-in" [45] and capture effects [47], thus

trapping those countries in low-tech OEM or assembly stages and preventing them from successfully transitioning to higher stages of GVC participation.

Moreover, the innovation capability of developing countries affects the economic effects of GVC participation. Through the continuous improvement of the domestic innovation system and the enhancement of regional innovation capabilities, developing countries can effectively connect with the technological level of enterprises in developed countries, thereby fully leveraging the "learning-by-doing" process, and realizing the positive impact of the GVC on economic growth.

Therefore, the paper proposes the following third hypothesis:

H3. *Innovation capability is an important mediating channel for the impact of the GVC on regional economic growth.*

3.3. Spatial Spillover Effects of GVC Participation on Regional Economic Growth

The progression of socioeconomic activities depends on spatial units. In economic geography research, spatial correlation analysis is essential to improve the accuracy of statistical and quantitative analysis [88]. Krugman argued that there is no compelling reason for a geographic boundary to limit the spatial extent of spillover [89]. The spatial spillover mechanisms of GVC participation on regional economic growth may include the following aspects. First, we consider the knowledge and technology spillover effects of GVC participation. When a region gains knowledge spillover effects from GVC participation, it can facilitate the diffusion and spread of knowledge, technology, etc., among adjacent regions through unconscious spillover effects, demonstration effects, or the free flow of production factors, hence promoting economic growth in neighboring areas. Second, we consider competition effects. Adjacent regions, or regions at similar stages of economic development, are likely to engage in intense competition for production resources such as talent, technology imitation, labor, and capital. GVC participation in one region could potentially have a "siphon effect" on the economic resources of adjacent regions due to this competition, thereby negatively impacting other regions' economic growth. Third, industrial linkage effects. Through the input-output linkage mechanism along the industrial chain, regions participating directly in the GVC can transfer international advanced technology and management experience to other regions, leading to vertical spillover effects on these regions.

Based on this, the paper proposes the fourth hypothesis:

H4. Due to the combined effects of siphons and spillovers, GVC participation will have a nonlinear spatial effect on the economic growth of adjacent regions.

4. Empirical Modes and Data

4.1. Empirical Modes

4.1.1. Baseline Model

To capture the impact of GVC participation on China's urban economic growth, this study employs the following standard reduced-form fixed effects model; when discussing this approach, reference is made to Kummritz et al. [90] and Boffa et al. [41], as follows:

$$lnY_{it} = \alpha_0 + \alpha_1 GVC_{it} + \sum_{s=1}^m \gamma_s Z_{sit} + u_i + \varepsilon_{it}$$
(1)

where *i* represents the city, *t* represents the year, lnY_{it} represents economic growth measured as the logarithm of per capita real GDP, GVC_{it} denotes the degree of GVC participation measured as the FVAR in total exports, Z_{sit} represents a series of control variables, α_0 , α_1 , and γ_s represent model regression coefficients, u_i represents the city-fixed effect and ε_{it} represents the error term and m is the number of control variables. The indicators in the following formulas have the same meanings.

To test the nonlinear relationship between GVC and economic growth, this study adds the quadratic term of GVC to Equation (2), as follows [14]:

$$lnY_{it} = \alpha_0 + \alpha_1 GVC_{it} + \alpha_2 GVC_{it}^2 + \sum_{s=1}^m \gamma_s Z_{sit} + u_i + \varepsilon_{it}$$
(2)

4.1.2. Mediation Model

Next, this article uses an interactive effect model and a mediating effect model to test the mediating transmission effect of regional innovation on the impact of GVC on economic growth. First, this article introduces the interaction term between GVC and innovation capability ($GVC_{it} \times lnINNOV_{it}$) in Model 3. Suppose the estimated parameter of the interaction term is significant. In that case, it proves that innovation ability has a significant moderating effect on the relationship between GVC and economic growth, or that there is a significant interaction effect between GVC and innovation ability. The empirical model is set as follows:

$$lnY_{it} = \alpha_0 + \alpha_1 GVC_{it} + \alpha_2 GVC_{it}^2 + \alpha_3 GVC_{it} \times lnINNOV_{it} + \sum_{s=1}^m \gamma_s Z_{sit} + u_i + \varepsilon_{it}$$
(3)

where $lnINNOV_{it}$ denotes innovation capability, which is measured as the logarithm of the number of invention patents granted per ten thousand people.

Subsequently, this article refers to the three-step method developed by Wen et al. [91], and it constructs a mediation effect model to examine the mediating role of regional innovation capability in the relationship between GVC participation and economic growth. The complete mediation effect model is as follows:

$$lnY_{it} = \alpha_{10} + \alpha_{11}GVC_{it} + \alpha_{12}GVC_{it}^2 + \sum_{s=1}^{m} \gamma_{1s}Z_{sit} + u_{1i} + \varepsilon_{1it}$$
(4)

$$lnINNOV_{it} = \alpha_{20} + \alpha_{21}GVC_{it} + \alpha_{22}GVC_{it}^2 + \sum_{s=1}^{m} \gamma_{2s}Z_{sit} + u_{2i} + \varepsilon_{2it}$$
(5)

$$lnY_{it} = \alpha_{30} + \alpha_{31}GVC_{it} + \alpha_{32}GVC_{it}^{2} + \alpha_{33}lnINNOV_{it} + \sum_{s=1}^{m} \gamma_{3s}Z_{sit} + u_{3i} + \varepsilon_{3it}$$
(6)

where $\alpha_{.0}$, $\alpha_{.1}$, $\alpha_{.2}$, $\alpha_{.3}$ and $\gamma_{.s}$ represent model regression coefficients, u_{1i} , u_{2i} , and u_{3i} represent the city-fixed effect, and ε_{1it} , ε_{2it} , and ε_{3it} represent the error term. The definitions of the other variables are consistent with the definitions used in model (1) and model (3).

4.1.3. Spatial Econometric Model

This study attempts to construct a spatial econometric model to verify the spatial spillover effects of regional GVC participation and to understand how GVC participation affects regional economic growth from a spatial perspective.

There are three basic forms of spatial econometric models, as follows: the spatial autoregressive model (SAR), spatial error model (SEM), and spatial Durbin model (SDM) [92]. The expressions for the three basic models are as follows:

$$SAR: Y = \rho WY + X\beta + \varepsilon \tag{7}$$

SEM:
$$Y = X\beta + \delta Wu + \varepsilon$$
 (8)

$$SDM: Y = \rho WY + X\beta + WX\theta + \varepsilon$$
(9)

In the above expressions, Y is the matrix of dependent variables, X is the data matrix representing the explanatory and control variables in the model, W is the spatial weight matrix, β , θ are regression coefficient vectors, and u, ε are the random disturbance terms which are independent and identically distributed. These three models examine spatial effects from different perspectives. The coefficient ρ examines the impact of the neighbouring regions' dependent variables on the dependent variable of the local region. The coefficient δ in the SEM examines the impact of the neighbouring regions' error terms on the dependent variable of the local region. The SDM is a combined extended form of the

SAR and SEM, including the dependent and independent variables' spatial lag and spatial error terms [93]. In comparison, the use of the SDM can effectively reduce the problem of variable omission [94].

Therefore, this study first constructs the SDM, and then uses the LR and Wald tests to determine whether the spatial Durbin model can degenerate into the spatial autoregressive or spatial error model [95]. The SDM is formulated as follows:

$$lnY_{it} = \alpha_0 + \rho \sum_{j=1}^{n} w_{ij} lnY_{jt} + \alpha_1 GVC_{it} + \alpha_2 GVC_{it}^2 + \sum_{s=1}^{m} \gamma_s Z_{sit} + \theta_1 \sum_{j=1}^{n} w_{ij} GVC_{jt} + \theta_2 \sum_{j=1}^{n} w_{ij} GVC_{jt}^2 + \sum_{s=1}^{m} \sum_{j=1}^{n} \theta_{s+2} w_{ij} Z_{sit} + u_i + \varepsilon_{it}$$
(10)

where w_{ij} represents the spatial weight, and other indicators have the same meanings as previously described.

Considering the geographical proximity and the possible influence of economic connections between regions on GVC participation, this study introduces a 0–1 adjacent space weight matrix (W1), an economic spatial weight matrix (W2), and an inverse economic distance matrix, based on the combination of geographical distance and economic scale (W3) to reflect the different cities' spatial relationships. Based on general practice, the specific spatial weight matrix was calculated as follows [96,97]:

$$w_{ij}^{bin} = \begin{cases} 1, city \ i \ adjacent \ to \ city \ j \ i \neq j \\ 0, otherwise \ i = j \end{cases}$$
(11)

$$w_{ij}^{eco} = \begin{cases} \frac{1}{|PGDP_i - PGDP_j|} & i \neq j \\ 0 & i = j \end{cases}$$
(12)

$$w_{ij}^{inveco} = \begin{cases} \frac{1}{|PGDP_i - PGDP_j + 1|} & * exp(-beta * d_{ij}) \ i \neq j \\ 0 \ i = j \end{cases}$$
(13)

where d_{ij} denotes the distance between two places measured based on latitude and longitude, and *PGDP* denotes GDP per capita.

4.2. Variable Selection

Based on the theoretical analysis and research hypotheses in the previous section, to study the nonlinear relationship between GVC and China's regional economic growth, this paper intends to use the following key variables:

4.2.1. Dependent Variable

This paper uses the logarithm of real per capita real GDP (InY) as the dependent variable to measure the economic growth of 239 cities in China. Since some years lack city-level data on per capita GDP and per capita GDP deflators, the paper uses the GDP index to adjust the city-level GDP, it calculates the constant price GDP for 2001, and then divides it by the average population for that year to obtain city-level real per capita GDP data, which are then transformed logarithmically.

4.2.2. Core Explanatory Variable

The core explanatory variable is the GVC participation index (GVC). It is measured in terms of the FVAR in exports, with reference to the methods developed by Hummels et al. [32], Upward et al. [35], and Shao and Su [73]. This method is suitable for GVC participation analysis at the regional and city levels because it is not limited by the availability of input-output table data. The paper attempts to estimate the GVC participation level at the most detailed level—the city level—by fully considering issues such as processing trade and depreciation of imported capital goods. Using China's customs data from 2001 to 2016, the GVC participation level for 239 prefecture-level and above cities was calculated as follows: First, each city's actual imports and exports were determined [16]. City-level customs databases were used to directly identify and code the consumption and production in cities, noting each import and export trade activity, thus identifying each city's actual import and export activities and solving the problem of indirect imports. Second, considering the importance of processing trade in China's exports, processing trade and general trade were distinguished. Third, with the help of the HS-BEC conversion table, the trade of intermediate goods was identified, assuming that intermediate goods imported through general trade were proportionally used for domestic sales and general trade exports [98]. Finally, following the approach used by Zhang et al. [99], the cumulative depreciation of imported capital goods in the current year was calculated and included in production to compensate for the previous literature's neglect of capital depreciation, which led to an underestimation of GVC participation.

Taking the above into consideration, the measure of the GVC participation level for city *i* at time *t* is as follows:

$$GVC_{it} = \frac{M_{itp}|_{BEC} + (M_{ito}|_{BEC} + D_{it}) \cdot (\frac{X_{ito}|_{BEC}}{G_{it} - X_{itp}|_{BEC}})}{X_{ito}|_{BEC} + X_{itp}|_{BEC}}$$
(14)

77 |

where subscripts *p* and *o* represent processing trade and general trade, respectively. $M_{itn}|_{BEC}(n = p, o)$ represents the actual intermediate goods imported by city *i*, and $X_{itn}|_{BEC}(n = p, o)$ represents the actual exports of city *i*. $G_{it} - X_{itp}|_{BEC}$ represents the total output of city *i* minus the portion used for processing trade exports, which is the sum of domestic sales and general trade exports, estimated using the total industrial output value for city *i*. D_{it} represents the cumulative depreciation of imported capital goods for city *i* in period *t*. The larger this index is, the greater the FVA contribution contained in the exports, implying that the city is more inclined to accept intermediate goods and capital goods provided by other countries for production and operation in the GVC division of labor.

4.2.3. Control Variables

This study selects physical capital input, labor input, human capital, and technological innovation as control variables based on the economic growth model proposed by Mankiw et al. [100]. Additionally, trade openness is considered in light of Frankel and Romer's research [101], and government intervention and infrastructure are included in light of Su and Shao's research [73]. More specifically, physical capital input (INV) is measured as the proportion of fixed asset investment to GDP; labor input (LABOR) is represented by the proportion of total employment to the total population; human capital (HC) is proxied by the number of university students per ten thousand people; trade openness (OPEN) is measured as the proportion of total import and export volume to GDP; government intervention (GOV) is assessed using the proportion of the city government's financial expenditure to GDP; infrastructure (INFRA) is measured by the per capita road area in the city; and technological innovation (INNOV) is evaluated using patents granted per ten thousand people. In the empirical analysis, INV, LABOR, OPEN, and GOV are treated as relative numbers, without taking logarithms, whereas other variables are logarithmically transformed.

4.3. Data Description

This paper uses panel data from 239 prefecture-level and above cities in China, from 2001 to 2016, as the research sample. This choice is based on two considerations, as follows. (a) The first consideration takes data availability and consistency into account. The research requires matching balanced and consistent panel data from the China City Statistical Yearbook and China Customs Trade Database. Available public data can cover the period from 2001 to 2016, but not the years from 2017 to 2022. The development of the Chinese economy mainly relies on 297 prefecture-level and above cities, but some

cities with administrative changes were excluded, resulting in a final sample of 239 cities for the study. (b) The second consideration takes the incorporation of a crucial phase of China's GVC participation into account. The period from 2001 to 2016 was a stage of rapid economic and trade development in China. After China joined the WTO in 2001, it accelerated the development of the manufacturing sector, and it gradually emerged as the world's second-largest economy and the largest goods trading nation. During this period, China experienced the impacts of the SARS epidemic and the global financial crisis. GVC participation and the economic development of China's regions from 2001 to 2016 have particular significance, and an examination of these factors can provide reliable and rich empirical evidence.

In the empirical analysis, 3824 observations were obtained for the panel data. The main data used in this study are from two sources, as follows: trade data from China Customs trade statistics database, and production data at the city level from the China City Statistical Yearbook, China Regional Economic Statistical Yearbook, and various provincial and municipal statistical yearbooks. Moreover, GDP deflators were used to adjust per capita GDP, and several relative indicators were employed to eliminate the influence of price changes.

Descriptive statistics were computed for the variables before analyzing the nonlinear relationship between GVC and regional economic growth. The statistical analysis of each variable, and the regression analysis of each model, were processed using Stata/MP 18 software (2 cores). The results are shown in Table 1. The mean of the GVC is 0.16, indicating relatively low current GVC participation in Chinese cities, with a standard deviation of 0.18, indicating some variation in GVC participation among regions. Additionally, the maximum value of the variance inflation factor (VIF) for the variables is 2.96, and the minimum value is 1.47; both values are less than six, indicating no multicollinearity problem.

Variable	Variable Description	Obs	Mean	Std. Dev.	Min	Max
lnY	GDP per capital (log)	3824	9.83	0.83	7.73	12.67
GVC	FVAR in export	3824	0.16	0.18	0.00	1.00
INV	Proportion of fixed asset investment to GDP	3824	0.57	0.26	0.09	1.65
LABOR	Proportion of persons employed in various units to the total population	3824	0.12	0.11	0.03	1.53
lnINNOV	Invention patents granted per ten thousand people (log)	3824	-2.29	1.85	-9.21	3.91
lnHC	Students enrolled in general higher education per ten thousand people (log)	3824	4.36	1.37	-4.61	7.18
OPEN	Openness (%)	3824	22.32	39.94	0.14	564.89
GOV	Government intervention (%)	3824	13.36	6.07	2.79	67.50
InINFRA	Infrastructure (log)	3824	0.86	0.94	-3.87	4.29

Table 1. Description of variables and descriptive statistics.

5. Empirical Results

5.1. Unit Root and Cointegration Tests

Before conducting regression analysis, it is necessary to perform unit root tests on the panel data to ensure data stability and to avoid spurious regression. In this study, the IPS test [102] was used to test the unit root of GVC participation and related indicators to ensure data stationarity. The IPS test is suitable for heterogeneous unit root testing in panel data, allowing for different individual autoregressive coefficients [103]. The test results are presented in Table 2. With the exception of lnY, all other variables were stationary in this level. After first-order differencing, all variables, including lnY, were stationary at the 1% significance level. This finding indicates that all variables are first-order differenced stationary variables, thus meeting the prerequisite for cointegration testing.

		Le	vel		First Difference			
Variable	Intercept		Intercept and Trend		Intercept		Intercept and Trend	
	Statistic	<i>p</i> -Value	Statistic	<i>p</i> -Value	Statistic	<i>p</i> -Value	Statistic	<i>p</i> -Value
lnY	7.494	1.000	-7.818	0.000	7.494	1.000	-14.545	0.000
GVC	-15.086	0.000	-27.715	0.000	-15.086	0.000	-28.394	0.000
INV	-2.869	0.002	-21.515	0.000	-2.869	0.002	-24.354	0.000
LABOR	-11.211	0.000	-24.157	0.000	-11.211	0.000	-22.435	0.000
Intech	-20.686	0.000	-32.974	0.000	-20.686	0.000	-33.675	0.000
lnHC	-16.726	0.000	-29.148	0.000	-16.726	0.000	-29.002	0.000
OPEN	-14.508	0.000	-31.089	0.000	-14.508	0.000	-33.184	0.000
GOV	-8.706	0.000	-25.666	0.000	-8.706	0.000	-27.006	0.000
lnINFRA	-12.899	0.000	-27.406	0.000	-12.899	0.000	-28.523	0.000

Table 2. Results of the panel unit root test.

This study employs Pedroni's residual-based heterogeneous panel cointegration test [104] to examine the model, and the results are presented in Table 3. All test statistics reject the null hypothesis of no cointegration at the 1% significance level, indicating that the variables considered in this study are cointegrated, and supporting the examination of the long-term relationships between the variables. Consequently, the next step involved estimating the regression equations using econometric methods, and the results should be relatively efficient and accurate without spurious regression issues.

Table 3. Results of the cointegration test.

	Statistic	<i>p</i> -Value
Modified Phillips-Perron t	26.751	0.000
Phillips-Perron t	-12.250	0.000
Augmented Dickey-Fuller t	-10.565	0.000

5.2. Baseline Regression Results

Using the LSDV method with cluster-robust standard errors, this study conducted tests that showed that most of the virtual variables for cities were highly significant, indicating the presence of individual effects. Therefore, a fixed-effects model should be used. Table 4 reports the basic regression results. The coefficient of GVC is not significant in the linear model (column 1), indicating that it is difficult to infer that the impact of GVC on the economic growth of Chinese cities is linear. This finding is consistent with Mao's (2022) empirical analysis of 63 economies from 1995–2010 [14], and Kummritz's (2015) empirical analysis of low-income economies, including China from 1995–2008 [31]. Both studies show that the regression coefficient of GVC participation, as measured by the FVAR, with regard to the the economic growth of the selected economies, is negative and not significant. Yanikkaya et al.'s (2022) research shows that this coefficient is positive but also not significant [37], which may be due to the fact that the research sample referenced by those authors mainly includes developed countries. Raei et al.'s (2019) empirical analysis also shows that the regression coefficient of GVC participation on the per capita income of low-income economies is negative and not significant, whereas GVC participation has a significant positive effect on the economic growth of middle- and high-income countries [36]. The latter may have two reasons. First, developed economies have entered the third stage and can fully benefit from GVC participation by optimizing supply chains and improving resource allocation efficiency; second, Raei et al. used a different indicator, measuring GVC participation with reference to the sum of forward and backward linkages, in which context, backward linkages refer to FVAR and forward linkages refer to the DVA embodied in intermediate exports that are further reexported to third countries. This fact also indicates that the mechanism by which forward linkages affect economic growth may be different from that which is associated with backward linkages. However, given

18 of 31

that backward linkages (FVAR) are a more commonly used indicator for measuring GVC participation, and as data on forward linkages for Chinese cities cannot be obtained, this paper still uses the FVAR to measure GVC participation.

0	Table 4.	Baseline	regression.
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	Baseline Reg	ression Model	Separated Sam	ple Regression
	(1)	(2)	(3) GVC < 0.45	(4)
	lnY	lnY	lnY	lnY
GVC	-0.107	-0.558 ***	-0.341 ***	0.148
	(0.0675)	(0.137)	(0.102)	(0.141)
GVC ²		0.614 ***		
		(0.134)		
INV	0.513 ***	0.504 ***	0.521 ***	0.461 ***
	(0.0487)	(0.0482)	(0.0487)	(0.157)
LABOR	0.403 **	0.421 **	0.766 ***	0.153 *
	(0.178)	(0.177)	(0.257)	(0.0916)
InINNOV	0.138 ***	0.135 ***	0.121 ***	0.150 ***
	(0.0117)	(0.0116)	(0.0115)	(0.0262)
lnHC	0.0740 ***	0.0754 ***	0.107 ***	0.0215 *
	(0.0232)	(0.0227)	(0.0274)	(0.0119)
OPEN	0.000382	0.000142	0.0000594	0.000361
	(0.000325)	(0.000318)	(0.000787)	(0.000256)
GOV	0.0195 ***	0.0195 ***	0.0189 ***	0.0278 ***
	(0.00287)	(0.00282)	(0.00291)	(0.00533)
InINFRA	0.303 ***	0.304 ***	0.291 ***	0.424 ***
	(0.0374)	(0.0375)	(0.0389)	(0.0842)
_cons	8.971 ***	9.003 ***	8.774 ***	9.151 ***
	(0.112)	(0.112)	(0.117)	(0.215)
N	3824	3824	3518	306
R2	0.873	0.874	0.876	0.872

Note: Standard errors are in parentheses. * p < 0.1, ** p < 0.05, and *** p < 0.01.

After adding the quadratic term, the coefficient of the quadratic term in the fixedeffects nonlinear model (column 2) becomes significant and positive, whereas the coefficient of the linear term is significantly negative. The regression results in column (2) confirm that the effect of GVC participation on China's city-level economic growth exhibits a U-shaped nonlinear pattern, which is consistent with Mao's (2022) conclusion [14] and it supports Hypothesis H1. The degree of GVC participation (FVAR) and the DVAR of exports have a complementary relationship. This U-shaped relationship indicates that after obtaining a foothold and entering the second stage in the GVC, a decline in the FVAR (which is followed by an increase in the DVAR) is beneficial to China's economic growth. Increasing GVC participation (and thus, decreasing DVA share) can promote the economic growth of Chinese cities when they are in a better position in the GVC (i.e., after reaching the turning point of the U-shaped curve). This situation could be attributed to the fact that continuing to focus on OEM, processing trade, and relying excessively on imported intermediate goods for export production within GVCs, may lead to path dependence, thereby hindering independent innovation and resulting in a low-end lock-in. Developing countries passively accept the production tasks and prices that are allocated by multinational corporations in developed countries, thus remaining trapped in the lowvalue production phase of GVCs. The economic benefits of GVC participation are thus progressively compressed. At this juncture, an increase in the FVAR could impede longterm economic growth. Only after developing a certain independent innovation capability, and increasing GVC participation from a higher value-added position, can a fair share of economic benefits be obtained, can the supply chain layout be optimized, and can the resource allocation efficiency be improved. Increasing the FVAR in such circumstances can

then stimulate economic growth. Fagerberg et al. (2018), in their empirical study, also found that expanding GVC participation inhibits economic growth for countries that are located at the low-value-added end of GVCs and which possess lower development capabilities, whereas economies at the higher end of the value chain do not suffer such losses [56].

Furthermore, according to the regression results in column (2), the turning point of the GVC—from the negative to the positive effect—is calculated to be 0.45. In 2016, 222 cities had GVC values below 0.45, whereas only 17 cities had GVC values greater than or equal to 0.45, indicating that most cities are still on the left side of the U-shaped curve, which corresponds with the second stage of GVC participation, known as "out" in the "in-out-in-again" pattern. To achieve industrial upgrades and sustained economic growth, these cities need to seek a certain degree of separation and independence from the value chains led by developed countries. This entails attaining autonomy in marketing, brand building, technological innovation, and establishing local value chains and innovation systems. During the transition from the low to the high value-added end of the GVC, such as the shift from OEM to ODM and OBM, cities are likely to experience a decrease in FVAR and an increase in DVA share. As the DVCs and innovation systems mature, these cities will gradually enter the third stage of GVC participation, where GVC and economic growth exhibit a positive correlation. That is, after reaching a certain "threshold," deeper GVC involvement will foster economic growth. In this study, the value of GVC at the turning point is greater than the value reported by Mao (2022) (GVC = 0.32). A possible reason for this fact could be that the scope of the FVAR's numerator is broader in this study. First, China is responsible for a large proportion of processing trade, and this paper distinguishes between processing trade and general trade based on Upward et al.'s approach [35], according to which, all imports of processing trade are included in FVA. Second, following Zhang's methodology [99], this study considers the depreciation of imported capital goods, and includes it in the foreign components used in domestic production and exports, which also increases the numerator.

Following Mao's (2022) approach, this paper divides all samples into two groups, according to the turning point (GVC = 0.45), and it performs fixed-effects estimation separately. The estimation results are consistent with those reported by Mao (2022) [14]. As shown in column (3) of Table 4, in the low GVC participation group, the GVC coefficient is significantly negative, thus verifying that the samples are on the left side of the U-shaped curve. For these samples, an increase in the FVAR has a negative impact on economic growth, indicating that improving domestic value chains and increasing DVAR are important ways of promoting economic growth at this stage. This finding is consistent with Lotfi's (2021) case study of another developing country, Morocco, which shows that an increase in FVAR damages Morocco's economic growth, whereas an increase in DVAR has a significant positive effect on per capita GDP [55].

Column (4) of Table 4 shows that in the high GVC participation group, the GVC coefficient is positive but not significant, which may be due to the small sample size. This finding indicates that most cities in China are in the second stage of the "in-out-in-again" pattern and have not yet reached the third stage, thus verifying H2. Kummritz's (2016, 2017) empirical research indicates that high-income and middle-high-income countries exhibit greater GVC participation, which is correlated with a more pronounced positive effect of GVC participation on economic growth [90,105]. These studies also suggest that factors such as domestic market connectivity, innovation, and education can mediate the benefits offered by GVC participation. It can be expected that if China can improve its DVC further, achieve a substantial increase in independent innovation capabilities, transition from low-tech to high-tech manufacturing, increase the share of high-tech sectors in GVC exports, and reintegrate into the GVC from the high value-added end, then increasing GVC participation will have a positive effect on economic growth.

5.3. Robustness Tests

This study conducted robustness tests of the benchmark regression results using various methods, including replacing the dependent variable, replacing the explanatory variables, using instrumental variables (IV), and the system generalized method of moments (GMM). The results are presented in Table 5. More specifically, the tests occurred as follows: (1) the dependent variable was replaced. Per capita GDP was substituted with city GDP and the dependent variable (lnRGDP) was recalculated. The regression results are shown in column (1). (2) The independent variable was replaced. Following Hummels' method, without distinguishing between processing trade and general trade, this study directly aggregates the imported intermediate goods at the city level and replaces the GVC participation level with GVCnew. The regression results are presented in column (2). (3) Using instrumental variables (IVs), this study added several control variables and controlled for city-fixed effects to mitigate potential endogeneity issues caused by the omitted variables [106]. However, endogeneity issues resulting from bidirectional causality remain unavoidable. Therefore, the study used the lagged values of the independent variable, GVC, and its quadratic term as instrumental variables. Moreover, this study conducted two-stage least squares (2SLS) estimations to ensure the robustness of the benchmark test results, as shown in columns (3), (4), and (5). (4) The GMM system was adopted. This method was employed to handle endogeneity issues and it is more efficient than 2SLS when in the presence of heteroskedasticity. The results are presented in column (6).

Table S	5. R	obustne	ss Test	s.
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	Replacing t	he Variables		2SLS		GMM
Variables	(1) lnRGDP	(2) lnY	(3) First1 GVC	(4) First2 GVC ²	(5) Second lnY	(6) System GMM lnY
GVC	-0.566 *** (0.145)				-0.866 *** (0.210)	-0.187 ** (0.08)
GVC ²	0.669 *** (0.137)				0.968 *** (0.223)	0.120 *
GVCnew	()	-1.051 *** (0.267)			()	()
GVCnew ²		1.127 *** (0.247)				
L.GVC		(0.217)	0.701 ***	0.098 *		
L.GVC ²			-0.133 * (0.074)	(0.001) (0.449 *** (0.071)		
_cons	14.93 *** (0.109)	9.003 *** (0.111)	(0.07 1)	(0.071)		
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations R-squared	3824 0.878	3824 0.875	3585 0.457	3585 0.423	3585 0.872	3346
Number of cities	239	239	239	239	239	239

Note: Standard errors are in parentheses. * p < 0.1, ** p < 0.05, and *** p < 0.01. The completed table with all results of indicators can be provided upon request (these points also apply below).

Columns (1), (2), (5), and (6) show that using the methods mentioned above, the coefficient of the linear term of GVC is significantly negative. The coefficient of the quadratic term is significantly positive, indicating that GVC participation has a U-shaped nonlinear impact on regional economic growth in China. This further confirms the robustness of the conclusions drawn in this study.

5.4. Heterogeneity Test

Given the significant regional disparities in China's economic development and the differences in geographic locations and factor endowments among regions, the impact of GVC participation on regional economic growth varies across different regions. In this study, the sample of 239 cities is divided into four regions, Eastern, Central, Western, and Northeastern, to examine the differences in the effect of GVC participation on regional economic growth. The regression results are shown in Table 6. Columns (1), (2), and (3) indicate that the coefficients of the quadratic term of GVC participation are significantly positive in these three regions, suggesting a U-shaped relationship between GVC participation and regional economic growth, with the most pronounced effect observed in the eastern region. After the calculation, the obtained turning point of GVC participation in the eastern region is the highest, at 0.59, whereas for the central and western regions, it is 0.35 and 0.37, respectively. This indicates that in the relatively underdeveloped central and western regions, there is a higher likelihood of achieving positive economic effects due to "learning-by-doing" from GVC participation. Column (4) shows that GVC participation in the northeastern region does not have a significant impact on economic growth.

Tal	ble	6.	Н	leterog	enei	ity	anal	lysis.
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	Eastern	Central	Western	Northeastern
	(1)	(2)	(3)	(4)
GVC	-1.007 ***	-0.232	-0.419 *	-0.0811
	(0.313)	(0.176)	(0.222)	(0.270)
GVC ²	0.847 ***	0.327 *	0.559 **	0.158
	(0.257)	(0.173)	(0.271)	(0.324)
Cons	9.775 ***	8.597 ***	7.962 ***	7.853 ***
	(0.192)	(0.216)	(0.155)	(0.324)
Control variables	Yes	Yes	Yes	Yes
N	1204	1092	616	434
R-squared	0.897	0.891	0.903	0.862

Note: Standard errors are in parentheses. * p < 0.1, ** p < 0.05, and *** p < 0.01.

5.5. Mediation Mechanism Test

As shown in column (1) of Table 7, the coefficient of the linear term of GVC is significantly negative, and the coefficient of the quadratic term is significantly positive, indicating that even after introducing the interaction term between GVC and innovation capabilities, there is still a U-shaped relationship between GVC and economic growth. The coefficient of the interaction term is significantly positive, which is consistent with Kummritz's (2017) [90] suggestion regarding the presence of an interaction or moderating effect between GVC and innovation capabilities. Only when developing economies can fully utilize the technology embedded in FVA can they fully benefit from GVC participation. With the inclusion of the interaction term, the turning point of the U-shaped curve shifts to the left (from GVC = 0.45 to 0.32), indicating that enhancing innovation capabilities can accelerate the transition to the rising phase of the U-shaped curve. This effect could be attributed to the improved ability of the region to absorb the technology spillovers resulting from GVC participation. Cities, through methods such as "learning-by-doing," can better acquire knowledge and skills, thereby positively impacting economic growth.

	Moderating Effect		Mediation Effect	
	(1) lnY	(2) lnY	(3) lnINNOV	(4) lnY
GVC	-0.347 **	-0.830 ***	-2.022 ***	-0.558 ***
	(0.144)	(0.158)	(0.542)	(0.137)
GVC ²	0.544 ***	0.957***	2.550 ***	0.614 ***
	(0.146)	(0.154)	(0.758)	(0.134)
GVC × lnINNOV	0.0760 ***			
	(0.0262)			
lnINNOV	0.123 ***			0.135 ***
	(0.0122)			(0.0116)
_cons	8.980 ***	8.190 ***	-6.040 ***	9.003 ***
	(0.110)	(0.107)	(0.229)	(0.112)
Control variables	Yes	Yes	Yes	Yes
Ν	3824	3824	3824	3824
R2	0.876	0.835	0.668	0.874

Table	7.	M	edia	ting	effect	tests.
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Note: Standard errors are in parentheses. ** p < 0.05, and *** p < 0.01.

Columns (2), (3), and (4) present the results of the mediation analysis. As the mediating variables are the same as the control variables in this case, column (2) excludes the innovation capability, InINNOV, from the benchmark regression of GVC concerning economic growth, and thus, the U-shaped nonlinear impact of GVC on economic growth still stands. Column (3) reports the estimation results of the mediation model of GVC regarding innovation capabilities, with the coefficient of the quadratic term being significantly positive, indicating a significant U-shaped relationship between GVC and innovation capabilities. Column (4) shows the estimation results of the mediation effect model of GVC and innovation capabilities with regard to economic growth. The quadratic term of GVC is positive, indicating a U-shaped relationship between GVC and economic growth after introducing innovation capabilities. Moreover, innovation capabilities have a significant positive effect on economic growth at the 1% level. This suggests that innovation capabilities serve as a mediator between GVC and economic growth, confirming Hypothesis H3.

Simultaneously, column (4) of Table 7 indicates that when the GVC is below 0.45, it has a suppressive effect on economic growth; however, when GVC is above 0.45, it has a promotional effect on economic growth. In the mediation model of column (3), the turning point is 0.40, which is slightly lower than the former, suggesting that when the GVC participation index exceeds 0.40, it can indirectly promote economic growth by enhancing innovation capabilities. Nevertheless, before reaching the threshold, it exhibits a suppressive effect on regional innovation capabilities. Wang and Zheng's (2019) research also notes that when the FVAR is low, it has a suppressive effect on the technological content of exports, whereas a high degree of FVAR actively promotes the technological complexity of exports [107]. This situation may be due to the fact that long-term engagement in low value-added production links, such as simple processing and assembly, is not conducive to innovation. Only by breaking free from the predicament of low-end GVC, and reentering GVC from the high value-added end (thereby using a large number of foreign intermediate goods to achieve the global optimization of supply chain allocation), can the country benefit, as it is allowed to focus on core links and improving its technological innovation level.

These results show that building a domestic innovation system and improving technological innovation capabilities are important not only for economic development, but also for the possibility of benefiting from GVC participation. This finding is consistent with the conclusions of Fagerberg (2018) [56], and the task of achieving this goal is a major challenge faced by developing countries, as is the issue that is explored in further detail in the policy recommendations provided in the final section of this paper.

5.6. Spatial Spillover Effect Test

5.6.1. Spatial Autocorrelation

To test Hypothesis 4, this study employs spatial econometric models for subsequent empirical analysis. Before conducting the empirical analysis, it is necessary to examine whether spatial effects exist in the spatial series of GVC and lnY (i.e., by conducting spatial autocorrelation tests). This article calculates the spatial effects for each year using the adjacent 0–1 matrix (W1), inverse economic distance matrix (W3), and Moran's I method [97], as shown in Table 8. Moran's I index for both GVC and lnY is significantly correlated at the 1% level in most years, indicating the presence of a significant spatial positive correlation between GVC participation and economic growth. This confirms the existence of spatial dependence, and it supports the appropriateness of employing spatial econometric models.

Table 8. Moran's I index.

Nam	GVC(W1)		GVC(V	V3)	lnY(W	lnY(W1)		(3)
Year	Moran Index	z-Value						
2001	0.346 ***	7.785	0.311 ***	6.934	0.456 ***	10.210	0.655 ***	14.465
2002	0.380 ***	8.547	0.384 ***	8.527	0.456 ***	10.221	0.662 ***	14.623
2003	0.407 ***	9.126	0.419 ***	9.286	0.483 ***	10.803	0.687 ***	15.159
2004	0.330 ***	7.427	0.340 ***	7.547	0.496 ***	11.091	0.699 ***	15.415
2005	0.246 ***	5.567	0.239 ***	5.345	0.487 ***	10.879	0.692 ***	15.268
2006	0.288 ***	6.529	0.276 ***	6.180	0.499 ***	11.159	0.703 ***	15.487
2007	0.252 ***	5.711	0.264 ***	5.923	0.527 ***	11.781	0.727 ***	16.017
2008	0.236 ***	5.380	0.246 ***	5.534	0.532 ***	11.880	0.731 ***	16.107
2009	0.203 ***	4.645	0.281 ***	6.312	0.533 ***	11.903	0.733 ***	16.143
2010	0.217 ***	4.969	0.244 ***	5.500	0.535 ***	11.941	0.735 ***	16.185
2011	0.200 ***	4.586	0.225 ***	5.084	0.534 ***	11.909	0.734 ***	16.150
2012	0.156 ***	3.583	0.167 ***	3.800	0.530 ***	11.826	0.730 ***	16.080
2013	0.113 ***	2.622	0.119 ***	2.733	0.526 ***	11.736	0.728 ***	16.025
2014	0.093 **	2.186	0.090 **	2.078	0.519 ***	11.579	0.727 ***	16.001
2015	0.115 ***	2.668	0.119 ***	2.724	0.514 ***	11.467	0.725 ***	15.962
2016	0.111 ***	2.587	0.118 ***	2.705	0.511 ***	11.392	0.718 ***	15.794

Note: ** *p* < 0.05, and *** *p* < 0.01.

5.6.2. Spatial Estimation Results

To validate the suitability of spatial econometric models, this study conducted the LM, Hausman, LR, and Wald tests [108], which confirmed the presence of spatial correlation in the error and lagged terms. Consequently, this study chose the fixed-effects SDM for our regression analysis. The detailed regression results are shown in Table 9.

Based on Table 9, the small values of sigma2_e for each model indicate that the spatial econometric models are robust. The spatial spillover effect coefficient (ρ) is significantly positive, indicating that there may be a positive impact of economic growth in other regions with regard to the economic growth of the local area. Under the three spatial weight matrix models, the coefficient of the linear term of GVC is negative, and the coefficient of the quadratic term is positive; both pass the significance test at the 1% level. This indicates that the nonlinear U-shaped relationship between GVC participation and regional economic growth still stands when the spatial econometric model setting is used. This conclusion is consistent with the claims of Mao [14], thus verifying that the "in-out-in-again" GVC participation pattern can more accurately depict the relationship between GVC participation and economic growth.

Variable	W1 (1)	W2 (2)	W3 (3)	Variable	W1 (4)	W2 (5)	W3 (6)
GVC	-0.262 ***	-0.119 ***	-0.168 ***	$W \times GVC$	-0.106	-0.013	-0.142 **
	(-6.39)	(-3.89)	(-5.33)		(-1.34)	(-0.11)	(-2.30)
GVC ²	0.314 ***	0.130 ***	0.178 ***	$W \times GVC^2$	-0.002	-0.049	0.200 ***
	(6.34)	(3.52)	(4.69)		(-0.02)	(-0.34)	(2.78)
INV	0.201 ***	0.094 ***	0.113 ***	W imes INV	-0.098 ***	-0.093 ***	-0.054 ***
	(12.82)	(7.92)	(9.80)		(-4.33)	(-3.71)	(-3.16)
LABOR	0.196 ***	0.130 ***	0.163 ***	$W \times LABOR$	-0.197 ***	-0.101	-0.155 ***
	(4.98)	(4.45)	(5.56)		(-2.81)	(-1.50)	(-3.00)
InINNOV	0.044 ***	0.011 ***	0.015 ***	W × lnINNOV	-0.008 *	-0.012 **	0.007 **
	(15.82)	(5.20)	(7.18)		(-1.92)	(-2.48)	(2.28)
lnHC	0.032 ***	0.015 ***	0.025 ***	$W \times lnHC$	-0.006	-0.018 ***	-0.016 ***
	(11.27)	(6.80)	(11.09)		(-1.12)	(-3.17)	(-3.52)
OPEN	0.000	0.000 **	0.000	$W \times OPEN$	0.001 ***	0.001 **	0.000 *
	(0.12)	(2.50)	(1.62)		(3.08)	(2.15)	(1.84)
GOV	-0.000	-0.008 ***	-0.007 ***	W imes GOV	0.008 ***	0.014 ***	0.012 ***
	(-0.45)	(-14.03)	(-11.58)		(7.80)	(9.71)	(13.58)
InINFRA	0.113 ***	0.073 ***	0.079 ***	W × lnINFRA	0.023 *	0.023	0.063 ***
	(17.15)	(14.76)	(15.66)		(1.90)	(1.26)	(6.49)
ρ	0.700 ***	0.908 ***	0.779 ***	sigma2_e	0.011 ***	0.006 ***	0.006 ***
	(60.15)	(68.80)	(84.93)		(42.22)	(43.28)	(42.08)
Overall R2	0.677	0.636	0.801	Within R2	0.932	0.969	0.952
Ν	3824	3824	3824		3824	3824	3824

Table 9. Estimation results of the fixed-effect SDM.

Note: t statistics in parentheses. * p < 0.1, ** p < 0.05, and *** p < 0.01.

By comparing the results in Table 9 with those in Table 4, it can be observed that most of the fitted coefficients of explanatory variables in the nonspatial panel fixed-effects model are larger than those in the SDM. The main reason for this difference is that the traditional panel fixed-effects model neglects spatial effects in the data sample. The withingroup R-squares show that introducing spatial factors significantly improves the model fit. The coefficients of GVC participation and its quadratic term's spatial lag variables, $W \times GVC1_{it}$ and $W \times GVC1_{it}^2$, only pass the significance test when the inverse economic distance matrix setting is used. However, judging the presence of spatial spillover effects based on the significance of coefficients can lead to incorrect conclusions due to biased estimation coefficients, so further analysis should be combined with the results of spatial spillover effect decomposition [94].

5.6.3. Spatial Spillover Effect Analysis

This study uses the partial derivative method employed by LeSage and Pace [94] to decompose the SDM and obtain the results shown in Table 10. From the direct effects, as shown in columns (1), (2), and (3), the coefficient of the linear term of GVC is significantly negative, and the coefficient of the quadratic term is significantly negative, thus confirming the U-shaped nonlinear relationship between GVC and regional economic growth.

The indirect effect of GVC is significant, confirming Hypothesis H4. The coefficient of the linear term is negative, and the coefficient of the quadratic term is positive, indicating that the improvement in the level of GVC in this city will have a U-shaped impact on economic growth in neighboring cities or cities with similar economic development levels through spillover effects. A possible reason for this is that adjacent or economically similar cities are in a similar stage of GVC participation, leading to intense regional competition. Therefore, in the early stages, GVC participation will have a "siphoning effect" on the production resources of neighboring cities, which is detrimental to the economic growth of other cities. However, in the subsequent stages of GVC participation, with knowledge

and technology spillovers, backwards and forwards linkages, and factor mobility, GVC participation has positive spillover effects on the economic growth of other cities.

	Direct Effect			Indirect Effect			Total Effect		
Variable	W1	W2	W3	W1	W2	W3	W1	W2	W3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GVC	-0.336 ***	-0.132 ***	-0.261 ***	-0.852 ***	-1.096 ***	-1.119 ***	-1.188 ***	-1.290 ***	-1.380 ***
	(-6.52)	(-3.64)	(-6.13)	(-3.51)	(-4.25)	(-4.30)	(-4.29)	(-4.61)	(-4.75)
GVC ²	0.367 ***	0.135 ***	0.293 ***	0.632 **	1.176 ***	1.385 ***	1.000 ***	1.372 ***	1.678 ***
	(5.88)	(3.07)	(5.65)	(2.18)	(4.12)	(4.46)	(3.01)	(4.38)	(4.82)

Table 10. Decomposition results of the fixed-effect SDM.

Note: t statistics in parentheses. ** p < 0.05, and *** p < 0.01.

6. Conclusions and Implications

6.1. Conclusions

The extant literature has mainly discussed the impact of GVC participation on the economic growth of developing economies such as China from the perspective of linear relationships, but the conclusions drawn from such studies have been significantly inconsistent. This is likely due to the fact that the relationship between GVC participation and economic growth is nonlinear, and the impact of GVC participation on economic growth varies across different stages. However, no study has yet empirically tested the nonlinear relationship between China's GVC participation and economic growth. Furthermore, few studies have explored regional heterogeneity in terms of GVC participation and economic growth within China. Accordingly, this paper reexamines the relationship between GVC participation and china's economic growth. According to the relevant theories and authoritative data drawn from the OECD, this paper argues that during the period 2001–2016, China was in the second stage of the "in-out-in-again" model. It proposes a U-shaped nonlinear relationship between GVC participation and regional economic growth in China, and it presents foundational research hypotheses.

This study extends the FVAR index proposed by Hummels et al. and Upward et al. so that it is able to measure the degree of GVC participation in Chinese cities. Based on the "in-out-in-again" GVC participation pattern, this study tests the research hypotheses proposed above using fixed-effects, mediating-effects, and spatial-effects models, and it explores the nonlinear relationship between GVC and economic growth in China. It is one of the first papers to investigate the nonlinear relationship between GVC and regional economic growth in China.

This paper finds that the linear regression coefficient of GVC participation on regional economic growth in China is negative and not significant, thus indicating that it is impossible to infer a linear relationship between these two factors. This finding is consistent with the conclusions of the empirical analyses of middle- and low-income economies, as shown by Kummritz (2015) [31] and Raei et al. (2019) [36]. However, the extant literature on empirical analysis of middle- and high-income economies has shown that GVC participation has a significant positive effect on economic growth. This situation is likely due to the fact that developing economies such as China are in the second stage of "in-out-in-again" GVC participation, they have not yet escaped low-end lock-in, and they cannot derive economic growth benefits from increased FVAR. In contrast, developed economies have progressed to the third stage, thus enabling them to capitalize on the advantages that come with full GVC participation.

Further research confirms that from 2001 to 2016, the actual impact of GVC participation on China's regional economic growth may have exhibited a U-shaped nonlinear pattern, which is consistent with the conclusions of Mao's (2022) cross-national research on 63 economies. This finding indicates that after obtaining a foothold in the GVC, a reduction in the FVAR and an increase in the DVAR benefit China's economic growth. When in a better position within the GVC (reaching the turning point), increasing GVC participation (via a reduction in DVA share) can promote economic growth. Most Chinese cities are on the left side of the U-shaped curve, and the impact of GVC participation on city economic growth is moving from, but has not yet crossed the turning point, inhibition to promotion. The robustness tests used in various methods support the baseline regression results. Heterogeneity analysis reveals that GVC has a U-shaped nonlinear effect on economic growth in China's eastern, central, and western regions, with the turning point moving to the left in economically less developed central and western regions, indicating that these regions are more likely to obtain positive economic effects through imitation and learning.

The research suggests that China is currently in the second stage of the "in-out-inagain" pattern, and that it is focusing on enhancing DVA, building DVCs, and fostering regional innovation systems. Achieving independence from the existing GVCs that are dominated by developed countries is challenging but inevitable for developing economies in the second stage; this is because, in the long run, they will face competition with lowerwage economies at the lower end of the GVC. The departure of many manufacturing companies from China, and their relocation to Southeast Asian countries with lower labor costs, confirm this point. However, the goal of this independence is not to decouple from the global market but to lay the foundation for reintegration into GVCs at the high value-added end and to further open markets and engage in globalization in the third stage.

The mediation mechanism analysis shows an interaction or moderating effect between GVC and innovation capacity. Improving regional innovation capacity can better leverage the positive promotional effect of GVC participation on economic growth. At the same time, regional innovation capacity serves as a mediator in the relationship between GVC and China's city economic growth, and there is a U-shaped relationship between innovation capacity and GVC. When GVC participation reaches a certain threshold, it can indirectly promote economic growth by enhancing innovation capacity.

Spatial effects analysis reveals the presence of spatial spillover effects on regional economic growth. GVC participation and economic growth in China still exhibit a nonlinear U-shaped relationship when placed in a spatial econometric model setting. The results of the partial derivative decomposition show that the improvement in the level of GVC in this city will have a U-shaped impact on economic growth in neighboring cities or cities with similar economic development levels through spillover effects. In the earlier stages, under the dominance of competitive effects, GVC participation will have a "siphoning effect" on the production resources of neighboring cities, which is detrimental to the economic growth of other cities. In the subsequent stage, with knowledge and technology spillovers, backwards and forwards linkages, and factor mobility, GVC participation has positive spillover effects on the economic growth of other cities.

6.2. Implications

Based on the above conclusions, to help China and other developing economies achieve an upgrade with regard to the "in-out-in-again" GVC pattern and smoothly enter the third stage, the following policy suggestions are proposed.

First, the regional innovation system should be improved, and the independent innovation capability should be enhanced. Creating a local innovation system is the key to rejoining GVCs at the high value-added end, and this plays a crucial role in leveraging the technological spillover effects of GVCs and promoting their positive economic effects [13]. Efforts should be made to strengthen local education and training systems, increase research and development investments, build industrial innovation platforms, improve the business environment, and create conditions for domestic enterprises to achieve technological independence and stimulate innovation vitality.

Second, to enhance the domestic value chain and increase the DVA in exports. The empirical analysis shows that most regions in China are in the second stage of the "in-out-in-again" GVC participation pattern, which focuses on building local value chains and regional innovation systems [58]. Efforts should be made to enhance inward-sourcing

capabilities, implement a dynamic transition to local from foreign sourcing in GVCs, and to cultivate and strengthen DVCs.

Third, effective industrial policies should be formulated to help domestic enterprises seek independence. The establishment of industrial academic research platforms should be promoted, and collaboration between enterprises and other institutions for research and development should be facilitated. Legal assistance and commercial insurance should be provided for enterprises in intellectual property disputes, and comprehensive consultation and investigation services should be offered for small and medium-sized enterprises with intellectual property to deal with disputes with foreign enterprises.

Fourth, factor and product flow between regions should be promoted to fully leverage the positive spillover effects of GVC participation on neighboring regions. Regional market barriers should be broken down, obstacles for factor and product flows between regions should be removed, resource allocation efficiency should be improved, and the dissemination and diffusion of knowledge and technology among adjacent regions should be promoted in order to fully leverage the positive spillover effects of GVC participation.

6.3. Limitations and Directions for Future Research

The limitations of this study are as follows. First, the empirical evidence required to analyze the economic effects of the first stage of the "in-out-in-again" GVC pattern is lacking. This study requires matching balanced panel data from the China City Statistical Yearbook and China Customs Trade Database, and currently, available public data can fully cover 239 cities from 2001 to 2016, but earlier data are limited due to data availability and consistency in statistical methods. In the future, efforts will be made to obtain improved data featuring longer time series to support more comprehensive testing, especially for the purposes of verifying the economic effects of GVC during the first stage and obtaining empirical evidence regarding the potential N-shaped relationship. Second, this study employs the FVAR to assess the extent of GVC participation in Chinese cities, focusing solely on the influence of backward participation on regional economic growth. Although forward participation may have distinct impact mechanisms, information at the city level is currently not available. Future research will attempt to contribute to the analysis of the economic effects of city-level GVC forward participation. Third, the question of whether GVC participation can reduce regional disparities in China and promote regional economic equality represents an important direction for future research. Finally, since 2016, there have been significant changes in geopolitics, which have brought new challenges to GVCs. However, due to data limitations, this study cannot cover this period under the existing methodological framework. Previous studies using trade data or IO tables to study China's regional GVC participation have sample periods that extend only as far as 2016 or even earlier (such as Pan, 2022; Li and Zhang, 2023) [16,72]. Future research can try to capture the impacts of these changes with improved data availability or new methodological frameworks.

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References

- 1. Xu, Z.; Li, Y.; Chau, S.N.; Dietz, T.; Li, C.; Wan, L.; Zhang, J.; Zhang, L.; Li, Y.; Chung, M.G. Impacts of international trade on global sustainable development. *Nat. Sustain.* **2020**, *3*, 964–971. [CrossRef]
- 2. Antràs, P. Conceptual aspects of global value chains. World Bank Econ. Rev. 2020, 34, 551–574. [CrossRef]
- 3. Kandil, M.; Shahbaz, M.; Mahalik, M.K.; Nguyen, D.K. The drivers of economic growth in China and India: Globalization or financial development? *Int. J. Dev. Issues* 2017, *16*, 54–84. [CrossRef]
- 4. Sheng, B.; Mao, Q. Trade openness, domestic market integration and inter-provincial economic growth in China: 1985–2008. *World Econ.* **2011**, *399*, 44–66. (In Chinese) [CrossRef]
- 5. Shahid, R.; Shahid, H.; Shijie, L.; Yifan, N. Developing Time-Series Nexus between Economic Opening-Up and Industrial Upgrading in Gvc Of China-New Insight From Wavelet Approach. *Multicult. Educ.* **2023**, *9*, 65–82.
- Yan, H.; Li, X.; Meng, S. Global Value Chain Participation and Sustainable Growth: Evidence from China. *Rom. J. Econ. Forecast.* 2023, 26, 5.
- Los, B.; Timmer, M.P.; de Vries, G.J. How global are global value chains? A new approach to measure international fragmentation. J. Reg. Sci. 2015, 55, 66–92. [CrossRef]
- 8. Jin, G.; Guo, B.; Deng, X. Is there a decoupling relationship between CO2 emission reduction and poverty alleviation in China? *Technol. Forecast. Soc. Change* 2020, 151, 119856. [CrossRef]
- 9. Tomislav, K. The concept of sustainable development: From its beginning to the contemporary issues. *Zagreb Int. Rev. Econ. Bus.* **2018**, *21*, 67–94. [CrossRef]
- 10. Manioudis, M.; Meramveliotakis, G. Broad strokes towards a grand theory in the analysis of sustainable development: A return to the classical political economy. *New Polit. Econ.* **2022**, *27*, 866–878. [CrossRef]
- 11. Wang, J.; Rickman, D.S.; Yu, Y. Dynamics between global value chain participation, CO2 emissions, and economic growth: Evidence from a panel vector autoregression model. *Energy Econ.* **2022**, *109*, 105965. [CrossRef]
- 12. Kano, L.; Tsang, E.W.; Yeung, H.W.-C. Global value chains: A review of the multi-disciplinary literature. *J. Int. Bus. Stud.* 2020, 51, 577–622. [CrossRef]
- 13. Lee, K.; Szapiro, M.; Mao, Z. From global value chains (GVC) to innovation systems for local value chains and knowledge creation. *Eur. J. Dev. Res.* **2018**, *30*, 424–441. [CrossRef]
- 14. Mao, Z. Global value chains (gvcs) and economic growth: A nonlinear analysis. Singap. Econ. Rev. 2022, 67, 985–1004. [CrossRef]
- 15. Liu, R.; Fan, J.; Dai, F. Comparison and Measurement of Economic Growth in Coastal Areas and Inland Provinces of China. *China Financ. Econ. Rev.* **2020**, *9*, 73–94. [CrossRef]
- Li, G.; Zhang, X. Does GVC embedding reduce carbon emissions? Empirical evidence from 218 Chinese cities. *Struct. Change Econ. Dynam.* 2023, 66, 253–263. [CrossRef]
- Thangavelu, S.M.; Kimura, F.; Narjoko, D. Global Value Chain, Cities and Urban Amenities: Case Study of ASEAN and East Asia. In *The Comprehensive Asia Development Plan (CADP) 3.0: Towards an Integrated, Innovative, Inclusive, and Sustainable Economy;* Economic Research Institute for ASEAN and East Asia (ERIA): Senayan, Indonesia, 2022; pp. 294–321.
- 18. National Bureau of Statistics of China. China City Statistical Yearbook 2021; China Statistic Press: Beijing, China, 2022. (In Chinese)
- 19. Sposi, M.; Yi, K.-M.; Zhang, J. Trade integration, global value chains, and capital accumulation. *IMF Econ. Rev.* **2021**, *69*, 505–539. [CrossRef]
- 20. Zhang, G.; Liu, G. Does Global Value Chain Embedment Contribute to Environmental Pollution in Emerging Economies? *Sustainability* **2023**, *15*, 1031. [CrossRef]
- Tian, K.; Dietzenbacher, E.; Jong-A-Pin, R. Global value chain participation and its impact on industrial upgrading. *World Econ.* 2022, 45, 1362–1385. [CrossRef]
- 22. Taglioni, D.; Winkler, D. Making Global Value Chains Work for Development; World Bank Publications: Washington, DC, USA, 2016. [CrossRef]
- 23. Baldwin, R. Trade and industrialization after globalization's second unbundling: How building and joining a supply chain are different and why it matters. In *Globalization in an Age of Crisis: Multilateral Economic Cooperation in the Twenty-First Century;* University of Chicago Press: Chicago, IL, USA, 2013; pp. 165–212. [CrossRef]
- 24. Rodrik, D. Unconditional convergence in manufacturing. Q. J. Econ. 2012, 128, 165–204. [CrossRef]
- 25. WTO; IDE-JETRO; OECD; RCGVC-UIBE; World Bank Group. Global Value Chain Development Report 2019: Technological Innovation, Supply Chain Trade, and Workers in Globalized World; WTO: Geneva, Switzerland, 2019.

- 26. Criscuolo, C.; Timmis, J. The relationship between global value chains and productivity. Int. Product. Monit. 2017, 32, 61–83.
- 27. Halpern, L.; Koren, M.; Szeidl, A. Imported inputs and productivity. *Amer. Econ. Rev.* 2015, 105, 3660–3703. [CrossRef]
- Pahl, S.; Timmer, M.P. Do global value chains enhance economic upgrading? A long view. J. Dev. Stud. 2020, 56, 1683–1705. [CrossRef]
- Men, K.; Sun, H.; Kou, M. Global Value Chains and Spatial Spillovers of Economic Growth—Based on the Perspective of Participation and Status Index in Global Value Chain. *Sustainability* 2022, 14, 15518. [CrossRef]
- Kee, H.L.; Tang, H. Domestic value added in exports: Theory and firm evidence from China. Amer. Econ. Rev. 2016, 106, 1402–1436. [CrossRef]
- Kummritz, V. Global Value Chains: Benefiting the Domestic Economy? IHEID Working Papers No: 02/2015; The Graduate Institute of International and Development Studies: Geneva, Switzerland, 2015.
- 32. Hummels, D.; Ishii, J.; Yi, K.-M. The nature and growth of vertical specialization in world trade. *J. Int. Econ.* **2001**, *54*, 75–96. [CrossRef]
- Koopman, R.; Wang, Z.; Wei, S.-J. Tracing value-added and double counting in gross exports. *Amer. Econ. Rev.* 2014, 104, 459–494. [CrossRef]
- Wang, Z.; Wei, S.-J.; Zhu, K. Quantifying International Production Sharing at the Bilateral and Sector Levels; National Bureau of Economic Research: Cambridge, MA, USA, 2013. [CrossRef]
- 35. Upward, R.; Wang, Z.; Zheng, J. Weighing China's export basket: The domestic content and technology intensity of Chinese exports. J. Compar. Econ. 2013, 41, 527–543. [CrossRef]
- Raei, M.F.; Ignatenko, A.; Mircheva, M. Global Value Chains: What Are the Benefits and Why do Countries Participate? Working Paper No. 2019/018; International Monetary Fund: Washington, DC, USA, 2019. [CrossRef]
- 37. Yanikkaya, H.; Altun, A.; Tat, P. Does the Complexity of GVC Participation Matter for Productivity and Output Growth? *Eur. J. Dev. Res.* 2022, *34*, 2038–2068. [CrossRef]
- 38. Wang, Z.; Wei, S.-J.; Yu, X.; Zhu, K. Global value chains over business cycles. J. Int. Money Financ. 2022, 126, 102643. [CrossRef]
- 39. Ajide, F.M. Global Value Chain and Total Factor Productivity in Africa. *Organ. Mark. Emerg. Econ.* **2023**, *14*, 26–55. [CrossRef]
- 40. Piermartini, R.; Rubínová, S. *Knowledge Spillovers through International Supply Chains*; The Graduate Institute of International and Development Studies: Cambridge, UK, 2014. [CrossRef]
- 41. Boffa, M.; Kumritz, V.; Santoni, G.; Taglioni, D.; Winkler, D. Overcoming the Middle-Income Trap: The Role of GVC Integration for *Climbing-Up the Income Ladder*; The University of Geneva: Geneva, Switzerland, 2016.
- 42. Ndubuisi, G.; Owusu, S. Trade for catch-up: Examining how global value chains participation affects productive efficiency. J. Productiv. Anal. 2023, 59, 195–215. [CrossRef]
- 43. Urata, S.; Baek, Y. Does participation in global value chains increase productivity? An analysis of trade in value added data. *Thail. World Econ.* **2020**, *38*, 1–28.
- 44. Shen, C.; Zheng, J. Does global value chains participation really promote skill-biased technological change? Theory and evidence from China. *Econ. Model.* **2020**, *86*, 10–18. [CrossRef]
- 45. Pietrobelli, C.; Rabellotti, R. Global Value Chains Meet Innovation Systems: Are There Learning Opportunities for Developing Countries? *World Devel.* 2011, *39*, 1261–1269. [CrossRef]
- 46. Li, Y.; Sun, H.; Huang, J.; Huang, Q. Low-end lock-in of Chinese equipment manufacturing industry and the global value chain. *Sustainability* **2020**, *12*, 2981. [CrossRef]
- 47. Zhang, J.; Zheng, W. The Innovative Effect of Chinese Domestic Firms under the Global Value Chain. *Econ. Res. J.* **2017**, *52*, 151–165.
- 48. Li, Y.; Zhang, H.; Liu, Y.; Huang, Q. Impact of embedded global value chain on technical complexity of industry export—An empirical study based on China's equipment manufacturing industry panel. *Sustainability* **2020**, *12*, 2694. [CrossRef]
- 49. Dünhaupt, P.; Herr, H. Global value chains–A ladder for development? In *Capitalism: An Unsustainable Future*? Routledge: London, UK, 2022; pp. 126–144. [CrossRef]
- 50. Baldwin, R. *The Great Convergence: Information Technology and the New Globalization;* Harvard University Press: Cambridge, MA, USA, 2016. [CrossRef]
- Rodrik, D. New Technologies, Global Value Chains, and Developing Economies; National Bureau of Economic Research: Cambridge, MA, USA, 2018. [CrossRef]
- 52. Humphrey, J.; Schmitz, H. How does insertion in global value chains affect upgrading in industrial clusters? *Reg. Stud.* 2002, *36*, 1017–1027. [CrossRef]
- 53. Barrientos, S.; Knorringa, P.; Evers, B.; Visser, M.; Opondo, M. Shifting regional dynamics of global value chains: Implications for economic and social upgrading in African horticulture. *Environ. Plan. A Econ. Space* **2016**, *48*, 1266–1283. [CrossRef]
- Kaplinsky, R.; Farooki, M. What are the Implications for Global Value Chains when the Market Shifts from the North to the South? Int. J. Technol. Learn. Innov. Dev. 2011, 4, 13–38. [CrossRef]
- Lotfi, I.; Lotfi, B. Global value chains and economic development: What impact on the Moroccan economy? *Rev. Econ. Financ.* 2021, 19, 227–236. [CrossRef]
- Fagerberg, J.; Lundvall, B.-Å.; Srholec, M. Global Value Chains, National Innovation Systems and Economic Development. *Eur. J. Dev. Res.* 2018, *30*, 533–556. [CrossRef]

- 57. Lema, R.; Rabellotti, R.; Gehl Sampath, P. Innovation trajectories in developing countries: Co-evolution of global value chains and innovation systems. *Eur. J. Dev. Res.* 2018, *30*, 345–363. [CrossRef]
- Zhou, W.C.; Yan, D.; Sun, S.L. Climbing the ladder: Inward sourcing as an upgrading capability in global value chains. *Res. Pol.* 2022, *51*, 104439. [CrossRef]
- 59. Qu, C.; Shao, J.; Cheng, Z. Can embedding in global value chain drive green growth in China's manufacturing industry? *J. Clean. Prod.* **2020**, *268*, 121962. [CrossRef]
- 60. Mehta, S. Upgrading within global value chains: Backward linkages, forward linkages and technological capabilities. *Asian J. Technol. Innov.* **2022**, *30*, 581–600. [CrossRef]
- 61. Gereffi, G.; Lee, J. Why the world suddenly cares about global supply chains. J. Supply Chain. Manag. 2012, 48, 24–32. [CrossRef]
- 62. Baldwin, J.R.; Yan, B. *Global Value Chains and the Productivity of Canadian Manufacturing Firms*; Statistics Canada: Ottawa, ON, Canada, 2014.
- De Marchi, V.; Giuliani, E.; Rabellotti, R. Do global value chains offer developing countries learning and innovation opportunities? *Eur. J. Dev. Res.* 2018, 30, 389–407. [CrossRef]
- 64. Lee, K. Schumpeterian Analysis of Economic Catch-Up: Knowledge, Path-Creation, and the Middle-Income Trap; Cambridge University Press: Cambridge, UK, 2013. [CrossRef]
- 65. Wang, J. Technology Spillovers in the Transnational Outsourcing System and the Technological Innovation of the Receiving Country. *Soc. Sci. China* **2013**, 108–125+206–207.
- 66. Fritsch, U.; Görg, H. Outsourcing, importing and innovation: Evidence from firm-level data for emerging economies. *Rev. Int. Econ.* **2015**, *23*, 687–714. [CrossRef]
- 67. Antràs, P.; Chor, D. Organizing the global value chain. Econometrica 2013, 81, 2127–2204. [CrossRef]
- Timmer, M.P.; Erumban, A.A.; Los, B.; Stehrer, R.; de Vries, G.J. Slicing Up Global Value Chains. J. Econ. Perspect. 2014, 28, 99–118. [CrossRef]
- 69. Wang, S.; Wang, H. Can global value chain participation drive green upgrade in China's manufacturing industry? *Int. J. Environ. Res. Public Health* **2022**, *19*, 12013. [CrossRef]
- 70. Yang, B.; Liu, B.; Peng, J.; Liu, X. The impact of the embedded global value chain position on energy-biased technology progress: Evidence from chinas manufacturing. *Technol. Soc.* **2022**, *71*, 102065. [CrossRef]
- 71. Li, J.; Meng, G.; Liu, J.; Li, Z. Value chain specialization and green economy performance: China's regional evidence. *Environ. Impact Assess. Rev.* **2023**, *103*, 107217. [CrossRef]
- 72. Pan, H.; Yang, J.; Zhou, H.; Zheng, X.; Hu, F. Global value chain embeddedness, digital economy and green innovation—Evidence from provincial-level regions in China. *Front. Environ. Sci.* 2022, *10*, 1027130. [CrossRef]
- 73. Shao, C.D.; Su, D.N. The Spatial Spillover Effect of Global Value Chain on Productivity. *Chin. Ind. Econ.* 2017, 34, 94–114. (In Chinese) [CrossRef]
- Meng, S.; Yan, H.; Yu, J. Global Value Chain participation and green innovation: Evidence from Chinese listed firms. *Int. J. Environ. Res. Public Health* 2022, 19, 8403. [CrossRef]
- 75. Seo, B.K.; Joo, Y.-M. Innovation or episodes? Multi-scalar analysis of governance change in urban regeneration policy in South Korea. *Cities* **2019**, *92*, 27–35. [CrossRef]
- Fan, F.; Lian, H.; Wang, S. Can regional collaborative innovation improve innovation efficiency? An empirical study of Chinese cities. *Growth Change* 2020, *51*, 440–463. [CrossRef]
- 77. Chen, Y.; Fang, Z. Industrial electricity consumption, human capital investment and economic growth in Chinese cities. *Econ. Modelling* **2018**, *69*, 205–219. [CrossRef]
- Tang, H.; Zhang, J.; Yu, H.; Fan, F. Global Value Chain Embedment and Air Pollution: City-Level Evidence from China. SSRN 2022, 4060755. [CrossRef]
- 79. Li, F.; Li, G. Agglomeration and spatial spillover effects of regional economic growth in China. *Sustainability* **2018**, *10*, 4695. [CrossRef]
- Su, D.; Shao, C. Global Value Chain, Regional Economic Growth and Spatial Spillover. J. Int. Trade 2017, 11, 48–59. (In Chinese) [CrossRef]
- Xiang, Y.; Zheng, J.; Tu, X. The Impact of Intermediate Goods Imports on Energy Efficiency: Empirical Evidence from Chinese Cities. Int. J. Environ. Res. Public Health 2022, 19, 13007. [CrossRef]
- 82. Wang, W.; Thangavelu, S.; Lin, F. Global value chains, firms, and wage inequality: Evidence from China. *China Econ. Rev.* 2021, 66, 101585. [CrossRef]
- 83. Andreoni, A.; Lee, K.; Torreggiani, S. Global value chains, 'in-out-in'industrialization, and the global patterns of sectoral value addition. In *Structural Transformation in South Africa*; Oxford University Press: New York, NY, USA, 2021. [CrossRef]
- 84. Lee, K.; Malerba, F. Catch-up cycles and changes in industrial leadership: Windows of opportunity and responses of firms and countries in the evolution of sectoral systems. *Res. Pol.* **2017**, *46*, 338–351. [CrossRef]
- 85. Yang, N.; Hong, J.; Wang, H.; Liu, Q. Global value chain, industrial agglomeration and innovation performance in developing countries: Insights from China's manufacturing industries. *Technol. Anal. Strateg. Manag.* **2020**, *32*, 1307–1321. [CrossRef]
- Hu, D.; Jiao, J.; Tang, Y.; Xu, Y.; Zha, J. How global value chain participation affects green technology innovation processes: A moderated mediation model. *Technol. Soc.* 2022, 68, 101916. [CrossRef]

- 87. Bank, W. World Development Report 2020: Trading for Development in the Age of Global Value Chains; World Bank: Washington, DC, USA, 2019. [CrossRef]
- 88. Anselin, L. Spatial Econometrics: Methods and Models; Kluwer Academic Publishers: Dordrecht, The Netherlands, 1988.
- 89. Krugman, P. Geography and Trade; MIT Press: Cambridge, MA, USA, 1992.
- 90. Kummritz, V.; Taglioni, D.; Winkler, D.E. *Economic Upgrading through Global Value Chain Participation: Which Policies Increase the Value Added Gains?* World Bank Policy Research Working Paper 8007; World Bank: Washington, DC, USA, 2017. [CrossRef]
- 91. Wen, Z.; Chang, L.; HauKit, T.; Liu, H. Testing and Application of the Mediating Effects. *Acta Psychol. Sin.* 2004, *5*, 614–620. (In Chinese)
- 92. LeSage, J.P.; Pace, R.K. Spatial econometric models. In *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications;* Fischer, M., Getis, A., Eds.; Springer: Berlin/Heidelberg, Germanny, 2010; pp. 355–376. [CrossRef]
- 93. Zhang, Q.; Tang, D.; Boamah, V. Exploring the role of forest resources abundance on economic development in the Yangtze River delta region: Application of spatial Durbin SDM model. *Forests* **2022**, *13*, 1605. [CrossRef]
- 94. LeSage, J.; Pace, R.K. Introduction to Spatial Econometrics; Chapman and Hall/CRC: New York, NY, USA, 2009. [CrossRef]
- 95. Xu, P.; Jin, Z.; Tang, H. Influence paths and spillover effects of agricultural agglomeration on agricultural green development. *Sustainability* **2022**, *14*, 6185. [CrossRef]
- 96. Jeanty, P.W. Spwmatrix: Stata Module to Generate, Import, and Export Spatial Weights; Statistical Software Components S457111; Boston College Department of Economics: Chestnut Hill, MA, USA, 2010.
- 97. Yang, Z. The Impact of Green Finance on High-Quality Economic Development in China: Vertical Fiscal Imbalance as the Moderating Effect. *Sustainability* 2023, *15*, 9350. [CrossRef]
- Yu, Y.; Duan, S. Global Value Chain Embedding and Environmental Pollution: An Examination from 230 Prefecture-level Cities. Econ. Rev. 2022, 2, 87–103. (In Chinese) [CrossRef]
- 99. Zhang, J.; Chen, Z.; Liu, Y. Measuring the Domestic Value Added in China's Exports and the Mechanism of Change. *Econ. Res. J.* **2013**, *48*, 124–137.
- 100. Mankiw, N.G.; Romer, D.; Weil, D.N. A contribution to the empirics of economic growth. Q. J. Econ. 1992, 107, 407–437. [CrossRef]
- Frankel, J.A.; Romer, D. Does trade cause growth. In *Global Trade*; Kirton, J., Trebilcock, M., Eds.; Routledge: Oxford, UK, 2017; pp. 255–276. [CrossRef]
- 102. Im, K.S.; Pesaran, M.H.; Shin, Y. Testing for unit roots in heterogeneous panels. J. Econom. 2003, 115, 53–74. [CrossRef]
- Afjal, M.; Kathiravan, C.; Dana, L.P.; Nagarajan, C.D. The Dynamic Impact of Financial Technology and Energy Consumption on Environmental Sustainability. Sustainability 2023, 15, 9327. [CrossRef]
- 104. Pedroni, P. Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econom. Theory* **2004**, *20*, 597–625. [CrossRef]
- 105. Kummritz, V. *Do Global Value Chains Cause Industrial Development?* CTEI Working Papers series 01-2016; Centre for Trade and Economic Integration, The Graduate Institute: Geneva, Switzerland, 2016.
- 106. Peng, Y.-C.; Han, X.; Li, J.-J. Economic Policy Uncertainty and Corporate Financialization. *China Ind. Econ.* **2018**, *82*, 137–155. (In Chinese) [CrossRef]
- 107. Wang, S.; Zheng, L. Impact of Embeddedness in Global Value Chains on the Differentiation of Technological Sophistication of Exports. *China Financ. Econ. Rev.* 2019, *8*, 22–39. [CrossRef]
- 108. Yu, Y.; Zhang, Q.; Song, F. Non-Linear Impacts and Spatial Spillover of Digital Finance on Green Total Factor Productivity: An Empirical Study of Smart Cities in China. *Sustainability* **2023**, *15*, 9260. [CrossRef]

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