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The correlation between the automotive industry output cycle and the business cycle in the Czech Republic

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Abstract

This paper aims to investigate the correlation between the output cycle and the business cycle of the Czech Republic's core industry, the automotive industry. The paper begins by analysing the volatility of each variable, and finds that the trends of the automotive industry output cycle and the business cycle align, while the automotive industry output cycle keeps lagging behind the business cycle. Secondly, this paper adopts the VAR model to examine the relationship between the Czech automotive output and its macroeconomic indicators, using the real GDP and the Gross Value added (GVA) to represent the macroeconomic situation. The results show that there is a correlation between Czech automotive industry output and the macroeconomy, but the correlation is asymmetric, which means the automotive industry is more sensitive to macroeconomic shocks but has weaker impact on the macroeconomy. Finally, this paper also measures the correlation between the automotive industry and monetary policy (M2) and finds that the monetary policy shows strong stability and independence, which can affect the progress of the automotive industry, but no reverse effect has been observed.

Abstrakt

Cílem tohoto článku je prozkoumat korelaci mezi produkčním cyklem a hospodářským cyklem klíčového odvětví České republiky, automobilového průmyslu. Článek začíná analýzou volatility jednotlivých proměnných a zjišťuje, že trendy výstupního cyklu automobilového průmyslu a hospodářského cyklu se vyrovnávají, zatímco výstupní cyklus automobilového průmyslu stále zaostává za hospodářským cyklem. Za druhé, tento článek používá VAR model ke zkoumání vztahu mezi českou produkcí automobilového průmyslu a jeho makroekonomickými ukazateli, přičemž k reprezentaci makroekonomické situace používá reálný HDP a hrubou přidanou hodnotu (HPH). Výsledky ukazují, že mezi produkcí českého automobilového průmyslu a makroekonomikou existuje korelace, která je však asymetrická, což znamená, že automobilový průmysl je citlivější na makroekonomické šoky, ale má slabší dopad na makroekonomiku. V neposlední řadě tento článek měří také korelaci mezi automobilovým průmyslem a měnovou politikou (M2) a zjišťuje, že měnová politika vykazuje silnou stabilitu a nezávislost, což může ovlivnit pokrok automobilového průmyslu, ale nebyl pozorován žádný opačný efekt.

Keywords

Automotive industry; business cycle; monetary policy; correlation; the Czech Republic, CEE countries

Klíčová slova

Automobilový průmysl; hospodářský cyklus; měnová politika; korelace; Česká republika, země střední a východní Evropy

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Declaration of Authorship

1. The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

2. The author hereby declares that all the sources and literature used have been properly cited.

3. The author hereby declares that the thesis has not been used to obtain a different or the same degree.

Prague 30.07.2023 Shiqi Yin Shiqi Yin

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Introduction

After World War I, advances in technology and production methods made it possible to manufacture cars on a mass scale, which led to a rapid increase in the number of cars on the roads and a corresponding growth in the automotive industry. At the beginning of 1909, the Model T automobile produced by the Ford Motor Company of the United States ushered in a new era of automotive manufacturing. In 1913, Ford Motor Company created the world's first automotive assembly production line, which greatly improved the efficiency of automotive manufacturing and reduced production costs, which also laid the groundwork for the popularity of the automobile. After more than a century of development and technological progress, the impact of the vehicle industry on the world economy is obvious to all. According to the UNCTAD (2022) database's statistics of global and major countries and regions, the global automobile product trade volume has reached 2.9 trillion U.S. dollars in 2017, which shows an increase of 2.58 times compared with 2001.

Currently, the automotive industry has become a cornerstone industry in many countries, playing a crucial role in driving their national economies. One significant automotive powerhouse is Germany, where the automotive industry was considered a guarantee of economic growth before the pandemic. The automotive industry contributes 10% to Germany's industrial value-added and supports many other industries, such as metal manufacturing, electrical equipment, machinery manufacturing, glass, ceramics, and telecommunications. According to the German VDA (Verband der Automobilindustrie) statistics, around 800,000 people were directly or indirectly employed in the auto industry in 2020. Japan is another example. In Japan, the automotive and related industries provide approximately 5.3 million jobs, accounting for 8.3% of the total employment population, according to data from Statista. Among Japan's top 500 industrial companies, half of the profits come from the automotive sector, making it the true backbone of Japanese industry. Moreover, the automotive industry also occupies a necessary position in the economies of the United States, China, and other countries. These important automotive nations have also contributed numerous well-known automotive brands to the global automotive industry.

The automotive industry not only holds significant importance for the economies of various countries but is also susceptible to the influence of the business cycle. Being a cyclical industry, it experiences periodic fluctuations, and its prosperity is highly correlated with external conditions. The industry's demand, prices, and production capacity all exhibit cyclical fluctuations (Qu, 2011). When demand rises, prices increase, leading to an expansion of production capacity to meet the demand, resulting in industry prosperity. Conversely, a decline in demand signifies an industry recession. Such industries are highly sensitive to changes in the macroeconomic environment. In recent years, the global economy has been unstable with continuous fluctuations, witnessing major crises worldwide. The two most impactful crises on the economy and most industries in this century were the 2008 financial crisis and the 2020 pandemic. Both of these crises caused significant turbulence in the automotive industry. Crises pose enormous challenges for the automotive industry. As a result, there are still important subjects remaining to be addressed on how to respond to macroeconomic changes, to adjust industry structures, and to minimize the impact of shocks on the industry and businesses.

Europe is one of the most traditional and crucial regions for the global automotive industry. However, the progress of the auto industry across Europe is uneven. The development of the European automotive industry can be traced back to the end of the 1980s. In the early 1990s, the entire industry began to flourish and countries such as France and Italy started to establish their own automobile manufacturers. After World War II, the automotive industry in Germany also began to thrive. As a result, in the early years, the European auto industry was predominantly concentrated in Western Europe. Due to factors such as historical background and geographical location, the development of the automotive industry in CEE occurred later than in Western Europe. The modern improvement of the auto industry in this region mainly took place after the Cold War, accompanied by economic transformations and reconstructions in the area. Meanwhile, the automotive industry in Western European countries faced challenges from industrial restructuring, and that was why the Western European automakers adopted a "go east" strategy (Domański and Lung, 2009). With the assistance of Foreign Direct Investment (FDI) from Western Europe and favorable economic policies in CEE countries, the automobile industry gradually became a significant sector for many countries in the region and even a pillar industry for some. Hence, the auto industry in CEE countries exhibits distinct differences compared to Western European countries.

The link between the automotive industry and the macroeconomy has always been a focal point in the research of industrial economics. The automotive industry in the CEE countries has also been a popular research topic among scholars. Most researchers have drawn similar conclusion that there is a correlation between the automotive industry and the macroeconomy, while the specific correlation according to studies vary among countries, regions, and eras. This article focuses on one of the representative countries in the CEE countries, the Czech Republic, to study the correlation between the automotive industry cycle and the business cycle. The Czech Republic is a typical country relying on the automobile industry. In 2017, it ranked fifth among the largest car manufacturing countries in the European Union. The headquarters of the renowned brand Skoda, owned by Volkswagen, is also located in the Czech Republic, making it one of the country's most successful enterprises. Therefore, this article takes the Czech Republic as the case to examine the correlation between the automotive industry cycle and the business cycle.

So far, researches on the correlation between the auto industry and the business cycle primarily focuses on traditionally developed countries such as the United States, and Japan, which is also focusing on the end of the last century. However, at that time, the automotive industry of CEE countries had not yet characterised. The above shows there is limited attention given to a specific country under the particular circumstance among the CEE countries. At the same time, when we turn to the field studies of this region, they often centers on the overall situation. On the one hand, this paper innovatively takes the Czech Republic as the research object to study the correlation between the auto industry and the business cycle. There is currently no academic research in this field focusing on the link between the Czech macroeconomic situation and its core industry. On the other hand, this paper also considers the link between macroeconomic policy and the auto industry. At present, there are very few papers discussing whether monetary policy has impact on specific industries, and this paper fills this gap. Given the significance of the Czech automotive industry, studying the impact of macroeconomic policies on the industry will enhance our understanding to the interaction between the industry and the business cycle. At the same time, this work is crucial to reveal the relationship between the Czech auto industry and the business cycle as well as to provide an useful reference for policy formulation.

This paper chooses the growth rate of automotive output to represent the Czech auto industry's performance, the growth rate of real GDP and Gross Value Added (GVA) to represent the macroeconomic situation, and the growth rate of the broad money supply (M2) to represent monetary policy. This paper first uses the GARCH (1,1) model to examine the volatility of the industrial cycle and the business cycle. In this paper, the conditional variance obtained by this model is used to plot the volatility graph of each variable, and then analyse the volatility of each variable. The results show that the fluctuation trend of the auto industry cycle is almost the same as that of the business cycle, and both are very sensitive to the impact of the 2008 financial crisis and the 2020 pandemic, and respond more strongly to the 2020 pandemic. But for the volatility of the automobile industry cycle and the business cycle, it is found that the two are not synchronized. The specific difference is that the automobile industry cycle has a significant lag compared with the economic cycle. In addition, the volatility of the money supply is quite different from these two, which proves that business cycle fluctuations are more likely to originate from external shocks than monetary shocks.

Secondly, this paper uses the VAR model and combines the automotive output variable with several macroeconomic variables to establish three sets of binary VAR models, which are: (1) the growth rate of automotive output and the real GDP growth rate; (2) the growth rate of automobile output and GVA growth rate; (3) growth rate of automotive output and growth rate of broad money supply. The VAR model, the Granger causality test, the impulse response function analysis, and the variance decomposition analysis are carried out to analyse the relationship between each set of variables from multiple angles. Based on forecasting purpose, our aim is to examine whether time series in each set can influence each other. Although there are some differences in the results obtained by different analysis methods, the overall trend is similar. The first two sets of results show that there are mutual influences between the auto industry and the macroeconomy, but they are asymmetric. Specifically, the macroeconomy has a significant impact on the improvement of the Czech auto industry, but the auto industry has a weak impact on the overall economic situation, that is, the core industries of the Czech Republic cannot have a great impact on its macroeconomy. In the third set, this asymmetry is even more pronounced. Specifically, the monetary policy has an obvious impact on the auto industry, but the monetary policy is not affected by the auto industry. This also proves that the monetary policy represented by M2 has strong stability and independence.

This article consists of the following four parts: Chapter 1 is the literature review, specifically explaining the economic model adopted in this study and summarising previous research in this field. Chapter 2 covers the introduction of variable selection, hypotheses, and methodology. Chapter 3 involves the process of empirical analysis and the results. Lastly, Chapter 4 presents the conclusions and discussion.

CHAPTER 1 Literature Review

This paper aims to analyse the correlation between the industry output cycle and the business cycle in the Czech automotive industry by reviewing and summarising relevant research literature by past scholars. This section is composed of three main parts.

The first part, theoretical background: reviews theoretical research related to industry and the business cycle. Firstly, the definition of the business cycle and the periodic characteristics of the automotive industry are clarified. Secondly, the theoretical background is determined, and the correlation between periodic industries the and the business cycle is explained from a theoretical point of view; The second part, an overview of the automotive industry, summarises the improvement, characteristics, and current situation of the global auto industry, and also focuses on the current situation of the automotive industry in CEE countries and the Czech Republic; The third part is a summary of the empirical research on the automotive industry and the business cycle, including the impact of macroeconomic factors on the development of the automotive industry, the spillover effect of the automobile industry on the business cycle and the impact of monetary policy.

1.1 Theoretical background

Theoretical development of the business cycle

The study of the business cycle can be traced back as far as the 18th century, although it was not until the late 1890s and early 1990s that a more formal theory emerged. Burns and Mitchell's definition of the study in 1946 is widely accepted and regarded as a significant milestone in the field: "*A cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration, business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own*." (Burns and Mitchell, 1946, p. 3.)

Subsequently, as empirical research developed, three new trends emerged in the work of the business cycle: (1) the increased focus on aggregate supply; (2) the emphasis on preserving the notion of competitive markets upheld by the fluctuations in relative prices; and (3) the assumption of rational expectations (RE) (Zarnowitz, 1992). Scholars have begun to focus on the dynamic and volatile properties of the business cycle.

Towards the end of the 1990s, the Real Business Cycle (RBC) theory gained significant traction and was widely utilised in macroeconomic research. According to the RBC theory, fluctuations in the business cycle are primarily caused by real shocks rather than monetary shocks (Kydland & Prescott, 1990). This theory assumes that full information replaces perfect foresight with rational Expectations (RE), and connects changes in output and employment to actual disturbances, not nominal disturbances mistaken for real ones (Zarnowitz, 1992). In addition, endogenous business cycle theory (Kydland and Prescott, 1982), and New Keynesian business cycle theory are also discussed.

In recent years, with the improvement of globalization, new economic patterns have emerged continuously, and research on the business cycle has also continued to deepen. In particular, the financial crisis in 2008-2009 had a major impact on the progress of the business cycle, and more financial factors were incorporated into the business cycle model. For example, Brunnermeier and Sannikov (2014) incorporated financial friction into the equilibrium state of the economy, and Christiano et al., (2014) augmented a standard monetary dynamic general equilibrium model and found that risk volatility is the most important reason for driving the business cycle. In addition to analysing the business cycle, on the other hand, more methods are also used by policymakers to manage it. Galí (2015) discussed the role of monetary policy in stabilizing the economy in business cycle fluctuations under the framework of New Keynesianism; Claessens and Kodres (2014) emphasized the importance of prudential supervision; some scholars conducted the method of using big data, such as Now-casting (Bańbura et al., 2013) and VAR model (Giannone et al., 2015), to conduct empirical analysis and measurement of macroeconomic variables.

The cyclicality of durable goods and the automotive industry

The concept of business cyclicality in durable goods was first introduced by Mitchell (1951) and it has been widely validated and researched after this. A cyclical industry exhibits cyclical cycles and whose performance is highly correlated with the external macroeconomic environment. This kind of industry is characterised by cyclical fluctuations in demand, prices, and production capacity. The macroeconomic theory posits that an increase in demand causes a rise in product prices and an expansion in capacity to meet indicating an industry peak. Conversely, a decrease in demand causes a fall in product price and a contraction in capacity, indicating an industry bust. Mitchell (1951) found that durable goods are twice as cyclical as non-durable goods. Petersen and Strongin (1996) later contended, following a fresh derivation, that durable-goods industries exhibit three times greater cyclicality, compared to non-durable-goods industries. Deleersnyder et al. (2004) conducted a comprehensive study of durable goods and found that there is an asymmetry in the sensitivity of durable goods to the businesee cycle, i.e. sales of durable goods fall faster during economic contractions than they recover during economic expansions.

Motor vehicles are among the largest consumer durables, surpassed only by housing, making the automotive industry a widely recognised cyclical sector. As durable goods, automobiles are more sensitive to fluctuations in the business cycle than non-durable goods (Klier, 2000; Deleersnyder et al., 2004). Therefore, demand for motor vehicles, the industry's primary product, is highly correlated with changes in various aspects, such as income and overall economic growth (Heneric et al., 2005). The automotive industry is particularly susceptible to cyclical fluctuations during economic booms and busts (Qu, 2011), with production closely tied to market conditions and the global economy (Ajupov et al., 2015). However, Dupor (2019) finds that the cyclicality of the automotive industry is changing, as the average age of cars in the US is increasing, leading to less frequent replacement and potentially affecting industry cyclicality.

Aside from being influenced by economic factors, durable goods can also affect the broader economy. As a significant driver of economic activity, durable goods' cyclical trends serve as crucial indicators of cyclical turning points and economic trends (Ballew and Schnorbus, 1994). Wang (2011) analysed the cyclicality of the Chinese automotive industry about fluctuations in the business cycle, finding generally consistent trends between the two industries, but with more significant intensity in the auto industry.

However, the literature on the cyclical nature of durable goods largely focuses on the end of the last century (Petersen and Strongin, 1996; Ballew and Schnorbus, 1994), overlooking the fact that the CEE countries were in their infancy regarding industrial development at that time. Additionally, existing studies concentrate on developed countries with traditional automotive industries such as the United States (Klier, 2000; Dupor, 2019). However, the cyclicality of automobiles varies by country and is also influenced by changes in competition and consumption attributes (Ajupov et al., 2015). Thus, applying these findings to the Czech Republic's industrial and economic situation may not be appropriate due to differences in time and study subjects. Therefore, this paper aims to fill this research gap for this region and provide new evidence for industry research in CEE countries.

1.2 Overview of the Automotive Industry

The development of the global automotive industry

As a significant component of the international economy, the automotive industry has undergone remarkable development and evolution over the past century. Technological advancements have driven the industry's growth, which can be classified into three distinct periods. The early 20th century was dominated by large-scale manufacturing and consumption, which was described as the "first revolution" of automobile production, and this stage was also called “Fordism” because of the Ford's contribution (Womack, et al., 1990). From the 1980s, the automotive industry entered an era of flexible specialization and service focus, with production techniques entering the lean phase, also known as “Post-Fordism” (Womack et al., 1990; Bai et al., 1990). During this period, the focus is on optimizing and enhancing connections throughout the supply chain (Klier, 2000). Since the mid-1990s, this industry has entered a so-called “hird revolution”, marked by advancements in product creation, design, manufacturing, and life cycles. (Bailey et al., 2010).

The global automotive industry is developing rapidly. According to data from OICA, the total global automotive production has increased by over 45% from 2000 to 2022, reaching 85 million vehicles in 2022. China, the United States, and Japan have consistently held the top three positions in production for over a decade. Although there was a significant decline of -16% in 2020 due to the impact of the pandemic, production steadily rebounded in 2021 and 2022, with growth rates of 3% and 6% respectively. According to Statista, the global automotive manufacturing industry revenue in 2021 was 2.86 trillion U.S. dollars.

The structure of the global automotive industry has been characterised by instability over the past few decades. In the early 20th century, the industry was concentrated in North America, Japan, and Western Europe, which jointly produced 62.9% of all vehicles worldwide in 2006 (Barta, 2012). However, since 2010, the global automotive landscape has been changing rapidly due to the emergence of the Chinese automotive industry, which means the center of the industry structure is shifting towards Asia, although Japan's production has been declining. Europe still accounts for one-fifth of global production and remains one of the most necessary industries in the region, contributing significantly to European GDP (Török, 2022). Moreover, the market share of the automobile industry in terms of domestic value added ranges between 60% and 70% in the main European countries (Timmer et al., 2015). In recent years, with the improvement of new energy vehicles, the automotive industry has seen an increasing connection with various new related industries. This has led to continuous changes in the international automotive industry landscape, both in terms of supply and demand. More emerging brands are entering the market, and some well-established automotive companies are also constantly adjusting their business strategies to adapt to the industry's new changes.

Characteristics of the automotive industry

The auto industry is resource-intensive, technology-intensive, and labour-intensive, and as such the development of the industry often receives a great deal of attention. With the car as the end product of the industry, the industry covers steel, electronics, machinery, and rubber, as well as sales, maintenance, finance, and insurance, with a large number of skilled and unskilled workers involved in each of these processes. The automotive industry is also inextricably linked to government road construction and environmental issues (Meckling and Nahm, 2019).

The automotive industry is a significant participant in global value chains. As an important global industry, the global nature of the automotive industry is reflected in two prominent and interrelated features. Firstly, the supply chain of the auto industry, including funds, production, sourcing, post-purchase support, and R&D activities, is increasingly globalised. Secondly, there have been large-scale reorganizations among giant automotive companies. With the development of economic globalisation, the automotive industry's supply chain has become increasingly complex. The industry has formed a complex value chain system worldwide with distinctive national and market characteristics (Sturgeon et al., 2009). Being a capital-intensive, labor-intensive, and technology-intensive industry, the automotive industry exhibits strong regional characteristics during the globalization process (Bailey, et al., 2010). Currently, it is concentrated in North America, Europe, and Asia. Europe contributes approximately one-fifth of the world's automotive exports and has long been one of the centers for global vehicle and component manufacturing. The region's industry has a unique network structure, promoting specialisation and cooperation within the region (Jurgens, 2004). The rich history and excellent technology have given the European automotive industry significant advantages in various aspects. However, due to historical and political factors, the improvement of the auto industry within the region has not been synchronised.

The automotive industry has undergone rapid evolution driven by technological innovation, from the early days of mass production to the current popularity of new energy vehicles and advancements in autonomous driving (Townsend & Calantone, 2014). OICA (2018) report shows that “In EU, the automotive industry accounts for 27% of total R&D spending, which is the most among all industries.” The creation and popularity of new energy vehicles have significantly impacted the industry's production and structure, resulting in a transition from an emphasis on transportation to an emphasis on technology. (EIA, 2017). Simonazzi et al. (2020) also argued that the rise of new energy vehicles is causing changes in the global automobile industry's landscape. The entry of more competitors from emerging markets and other industries, all vying to master new digital and software technologies, poses a challenge to the traditional structure of the industry.

However, the automotive industry faces various challenges in addition to technological innovation. The industry must address the rise of emerging markets, demand constraints, competencies and distinctions, and connectivity, all of which pose significant hurdles to its growth (Gao et al., 2014). Furthermore, the industry's globalized nature exposes it to external shocks from the macro environment, including economic crises, geopolitical conflicts, and pandemics like COVID-19, which have all undermined the industry's stability.

As the industry continues to evolve, it is undergoing significant changes due to the advent of Industry 4.0, international environmental protection measures, the restrictions imposed by COVID-19, and the automotive industry's development

(Hojdik, 2021). These factors are driving the industry towards a more sustainable and technologically advanced future.

Improvement of the automotive industry in CEE

CEE is becoming one of the most critical regions for the auto industry, but the history of this industry in CEE countries is different from that of drivers and Western Europe. The development of Europe as one of the world's major automotive producers can be identified as early as 1920-1930 (Barta, 2012) and has followed the development of the world's automobile industry in its subsequent development. Although the CEE region is today a non-negligible part of the European auto industry, its auto industry started close to 100 years later compared to the European automotive market as a whole and did not begin to make inroads into the global automotive market until after the 1990s. This is associated with the legacy of World War II, the Cold War. Until the end of the 20th century, when the Soviet Union disintegrated and the Cold War ended, CEE countries gradually transformed from socialist countries to capitalist countries and began an important economic transition. And then joined the European Union in turn, since then, the current European integration pattern has been basically established (Barta, 2012).

“Central and Eastern Europe became a winner of the global production and market reorganisation starting from the 1990s” (Barta, 2012, p.11), comprehensively analysing various factors, the advancement of the auto industry in this region is inevitable. Towards the close of the 20th century, there were structural problems in the improvement of the global automotive sector, the cost increased, the sales volume declined, and industrial restructuring was urgently needed. Therefore, the automotive industry’s entrepreneurs in Western Europe have adopted a "go east" development strategy (Domański and Lung, 2009). CEE countries enjoyed lower transportation costs due to their geographical proximity to Western Europe, according to Domański and Lung (2009) and Pavlínek (2015). Moreover, the region's low production costs made it an attractive market for FDI, as highlighted by Barta (2012). Carstensen and

Toubal (2004) conducted a dynamic panel analysis and found that transition-specific factors, such as the level of privatisation and country risk, also played an essential role in determining FDI flows to CEE countries. Following thirty years of rapid progress, the region has significantly enhanced European competitiveness by leveraging cost-based advantages within a well-developed technological and business environment, as outlined by Pelle et al. (2020).

The Central and Eastern European automotive industry has become the fourth-largest automotive production base after North America, Asia, and Western Europe. The automotive and supply industries in Europe are directing employment opportunities towards CEE, with approximately one million job opportunities flowing from Germany alone to the region. Numerous foreign automotive component manufacturers have also expanded their operations in CEE countries. This trend is closely related to the labor cost advantages, government incentives, and tax benefits present in the CEE region. For instance, in the Czech Republic, investors can apply for cash subsidies from EU funds or benefit from tax incentives (corporate income tax exemptions) as part of the national assistance program.

In addition to the contextual differences, the drivers of the automotive industry's development in CEE are also distinct. Unlike the drivers of Western Europe's automotive industry, foreign direct investment (FDI) is an essential factor for the improvement of the automotive industry in CEE (Pavlínek et al., 2009; Pavlínek, 2015; Barta, 2012; Török, 2022). Due to the promotion of FDI, the automotive industry in CEE countries has achieved huge growth in a short period (Domański and Lung, 2009), and has gradually become the core industry in the region. According to Barta (2012), the region's automotive industry has transformed from a net importer to a net exporter. FDI has boosted productivity and technological advancements in the CEE automotive industry (Radosevic and Rozeik, 2005), helping the region account for 12% of global automotive production by 2010, including the influence of Germany.

However, as Pavlínek and Žížalová (2016) note in their analysis of the Czech Republic, FDI in CEE countries only leads to productivity spillovers, not necessarily technology spillovers. Despite its successes, the CEE automotive industry remains a "peripheral market" (Pavlínek, 2015) dependent on the core Western European market, making it vulnerable to external shocks (Domański and Lung, 2009). Currently, the automobile industry in the CEE countries still faces issues related to market mechanisms' inadequacies and varying standards. Moreover, there remains a technological gap compared to Western Europe. Addressing how to leverage foreign investment for technological advancement and reducing dependence on foreign markets are crucial topics that require significant attention in the advancement of the automotive industry in this region. Therefore, to sustain this progress, the CEE region must prioritize various tasks, including increasing local content and enhancing the competitiveness of domestic enterprises.

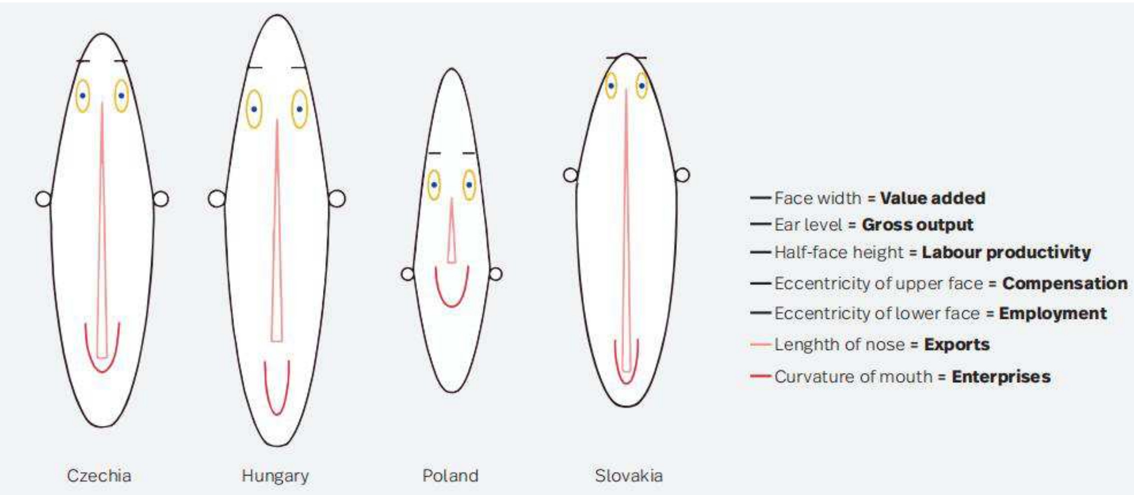
The Czech automotive industry

In the Visegrad four (V4) countries, specifically the Czech Republic, Poland, Hungary, and Slovakia, the largest number of motor vehicle, trailer, and semi-trailer manufacturing enterprises can be found in Poland and the Czech Republic (PEI, 2019). Following Germany, the Czech Republic is the most significant automotive manufacturer in the region (Barta, 2012), with a strong track record of exports, with 90-92% of its production being sold overseas. Between 1997 and 2016, the Czech Republic consistently ranked 12th among global automotive exporters (Török, 2022). According to CzechInvest (2019) data, the Czech Republic boasts over 5,000 research and development personnel, with approximately 20% of private research investment focused on the mobility sector. As the largest industrial sector in the Czech Republic, the automotive industry contributes over 9% to the GDP, 26% to the manufacturing sector, and 24% to the country's exports. Many major players in the international automobile sector have invested in the Czech Republic, establishing branch offices and centralizing their design, innovation, and technological research centers in the country. This has resulted in a dense and comprehensive automotive industry chain, making the Czech Republic one of the world's most concentrated hubs for automotive manufacturing, design, and research. Hence, the automotive sector holds a vital position in the Czech Republic's manufacturing landscape.

However, the Czech automotive industry still faces many problems and challenges. For V4 countries such as the Czech Republic, “the initial comparative advantage of relatively low-cost and skilled labor force is quickly vanishing, as economic growth and rising wages result in record-breaking low levels of unemployment and labor shortages” (Hlušková, 2019, p.24). This means that the comparative advantage of the Czech automotive industry relative to the Western European market and the global market is under threat. Moreover, Pavlínek and Žížalová (2016) conducted interviews with hundreds of Czech and foreign auto companies and found that although Czech domestic suppliers have competitive advantages such as close geographical location and low prices, foreign companies in the Czech Republic still mostly chose foreign companies as suppliers, which may be due to the fact that foreign industry standards are higher than those in the Czech Republic, thereby maintaining the quality of components. At the same time, as a core industry, the digital transformation (Mazurchenko & Zelenka, 2022), labor quality improvement and technical training (Hlušková, 2019) faced by the overall industrial enterprises are also issues that the Czech automobile industry as a whole and the development of enterprises within the industry need to pay attention to. However, this does not mean that the development of the automotive industry in the Czech Republic or Central and Eastern Europe has stagnated. According to research by Velinov and Bradáč (2020), new energy vehicles in most Central and Eastern European countries are also growing, which proves that global automakers are still investing in the region's automotive industry infrastructure for new energy vehicles.

Many studies on the vehicle sector in CEE or the Visegrad Four (V4) countries tend to overlook the unique characteristics of each country. Despite similarities in industrial development among V4 countries, there are notable differences in labor productivity, export performance, and trends. For instance, the automotive industry's impact on the Polish economy is diminishing (Török, 2022), while the Czech Republic has emerged as a leading automotive manufacturer in the region after Germany (Barta, 2012). The differences can be clearly seen through the Chernoff Faces (Figure 1) provided by PEI (2019). Therefore, this thesis will investigate the fluctuations of the auto industry in this region, with a specific focus on the Czech Republic.

Figure 1 Chernoff Faces for the V4 countries



Source: Polish Economic Institute (2019).

1.3 Relationship between Industries and Business Cycle

A study of the relationship between industry and the business cycle

The industry assumes a crucial role in the economy, not only by contributing to economic growth, but also by providing goods and services to society, creating employment opportunities, and facilitating trade and investment, thereby influencing all sectors of the macroeconomy. Before the COVID-19 pandemic, the average share of manufacturing in GDP was 14.2% in industrial economies and 11.6% in developing and emerging industrial economies, according to a report by UNIDO (2022). The industrialization led to the advancement of more sophisticated technologies, higher productivity, and greater exports, and the benefits of industrialization can be disseminated throughout an economy, creating new jobs and contributing to sustainable growth (Chenery et al., 1986). Additionally, the resilience of manufacturing systems has become increasingly critical with the emergence of different and frequent exogenous shocks in this century, such as the COVID-19 pandemic, with countries with stronger manufacturing systems being more likely to weather the crisis (UNIDO, 2022).

Research on the relationship between industry and macroeconomics has been applied to different samples. Behun et al. (2018) carried out work on the relationship between industry and macroeconomics in the EU and found that the manufacturing sector is highly sensitive to internal and external influences that cause fluctuations in the business cycle. By analysing macroeconomic indicators such as GDP, it was found that the manufacturing sector follows or even outperforms the business cycle, and the cyclical fluctuations in economic variables exert a considerable influence on the decision-making process regarding the initiation or cessation of operations in industrial enterprises. The correlation between GDP and manufacturing is extremely strong in most EU countries, except for Greece and Portugal, among others.

In addition to regional analyses, most scholars focus on the internal situation of a specific country. Świadek and Szopik-Depczyńska (2014) studied the impact of the business cycle on innovation in Polish enterprises in the industrial system of the Mazowieckie province and found that economic conditions affect the innovation activity and development of firms. Sala Ríos et al. (2014) analysed the Industrial Production Index (IPI) data for 16 industries in the Spanish manufacturing sector and found that the business cycle in Spain is positively influenced by high-tech and medium-tech industries, and that numerous industries exhibit a strong correlation between employment and cyclical fluctuations. Gan et al. (2014) developed an econometric model on the connection between industrial structure change and macroeconomic growth in China and found that both the process of industrial restructuring and upgrading in China had a distinct phase effect on economic growth, with the former being relatively more stable and the latter showing greater uncertainty and causing economic fluctuations. Additionally, a study by Ahmed et al. (2015) analysed the sensitivity of employment changes in the US industrial sector to long-run real GDP growth from 1991-2001 and found that different industries exhibit varying levels of employment responsiveness to long-term real GDP expansion.

The impact of the economy on the automotive industry

The auto industry is a significant manufacturing sector and is influenced by the business cycle. Studies by Xu and Hong (2014) found that macro factors such as per capita income, fixed capital formation, industrial structure, and exports of automotive products have a vital position in the growth of the auto industry in the US, Germany, Japan, and Korea. On the other hand, Muhammad et al. (2013) found that there was no obvious relationship between automobile sales and macro factors in the long run in the Malaysian automobile market. In the short run, only significant Industrial Production Index (IPI) variables affect car sales in Malaysia. Patra (2017) used cointegration and vector error correction models to work on the correlation between car sales and GDP per capita in India and found a positive long-run relationship between the two, while interest rates and car sales had an inverse relationship. Overall, macro factors do have an impact on the development of the auto industry, but the specific results vary due to regional differences in the analysis.

In the field of analysing the impact of the overall economic environment, the financial crisis and the recent COVID-19 are often regarded as special periods to receive higher attention. The 2008 financial crisis, which is considered to have caused the worst economic recession in this century. Given the crisis, the automotive industry in most countries has been hit hard. Raduteanu (2012) analysed the evolution of the European auto industry during the global financial crisis, showing that the auto industry was severely affected by the crisis, and production and sales dropped sharply, mainly due to the decline in consumer disposable income and lack of confidence. Hagiu and Ungureanu (2010) found through the analysis of Romania that the crisis has had a significant impact on employment in the automotive industry; Similarly, despite having a relatively small share of the automotive industry compared to other EU countries, Greece was significantly impacted by the fall in demand for cars during the financial crisis (Nanaki, 2018); Gaspareniene and Remeikiene (2014) investigated the macro factors that caused the decline of the car industry during the financial crisis and found that new car registrations and GDP had a obvious beneficial impact on vehicle production in the EU, explaining 60% of the change in EU car production.

Another period that has received a lot of attention recently has been the pandemic period. Unlike other crises, COVID-19 was an exogenous shock to the overall economic environment, with profound impacts on the macroeconomic situation and industries. The pandemic's significant public health implications reverberated across various domains, leading to widespread lockdowns and restrictions on physical movement. Therefore, many businesses had to temporarily shut down or adopt remote working practices. The automotive industry, in particular, faced immediate supply chain disruptions, which exacerbated existing risks to the supply chain. This supply chain disruption was further compounded by macroeconomic factors affecting industry demand, which led to a production shortfall. Recent studies have identified COVID-19 as a critical factor in exacerbating existing industry challenges and risks, such as supply chain vulnerabilities (Klein et al., 2021; Nayak et al., 2022).

Torok's (2020) study highlights the significant negative impact of the COVID-19 epidemic on the EU new vehicle market in the first half of 2020. The pandemic triggered panic in the EU new car market, and the median decline in new car sales in member states was calculated to be more than three times higher than the decline in GDP in member states. Additionally, the reduced profitability of car manufacturers could undermine the necessary investments for digital transformation and adaptation to stricter environmental regulations (Klein et al., 2021). Kufelová and Raková (2020) focused on the productivity of the Slovak auto industry during the pandemic, arguing that government-mandated restrictive policies in response to the epidemic necessitated the closure of automotive plants, directly negatively impacting the sector's production. Analysing Czech car manufacturers, Kučera and Tichá (2022) found that car manufacturers suffered greater losses during the COVID-19 pandemic than in the previous year. According to Sun (2022), the COVID-19 pandemic had various implications for the auto industry, but it also potentially expedited research into in-car purification technologies and autonomous driving systems.

The impact of the automotive industry on the business cycle

The automotive industry is considered a core pillar industry in many countries and regions and is known to have significant macroeconomic spillover effects. Ballew and Schnorbus (1994) conducted an analysis of the relationship between the US automotive industry and the macroeconomy and found that although the industry accounted for only 5% of the total GDP in that year, its impact on the US economy was much greater than what this figure suggested, which other components could not achieve.

Similarly, Török (2022) conducted a study using correlation calculations for the Visegrad set (V4) countries and found that countries with a significant and dynamically growing contribution from the automotive sector have a strong positive impact on the automotive sector on GDP growth. However, the specific situation varies from country to country, as vehicle production has increased in the Czech Republic, Hungary, and Slovakia, but has declined in Poland.

In addition to this, the impact of the automotive industry on the economy has been demonstrated from a wider range of perspectives by various scholars. Rechnitzer (2012), from the perspective of the location distribution of the automotive industry, proved that towns with vehicles and automotive industry could achieve higher GDP growth, and they also showed stronger immigration values and closer to lower unemployment. Sugawara and Shibusawa (2010) focused on the analysis of the impact of new energy vehicles, using the input-output method to explore the impact of the industrialization of new energy vehicles on the Japanese economy, and concluded that the gasoline-electric hybrid vehicle industry has a considerable impact on Japan's economy. The national economy has a positive effect, while the pure electric vehicle industry will have a negative effect on the Japanese national economy. In summary, although scholars have different perspectives and subjects to analyse, they have all proved that the role of the automobile industry in the economy is noteworthy.

The impact of policy on the automotive industry

Macro policies are critical for the development of the automotive industry. Such as fiscal policy, monetary policy, environmental policy and special policies aimed at the industry itself or the auto market will have direct or indirect effects on the auto industry. Among them, fiscal policy and monetary policy are the policies most relevant to the business cycle because they are designed to respond to changes in the economy (Woodford, 2003). The central bank and the government adjust and manage the macroeconomic operation by means of different monetary and fiscal policy tools (Keynes, 1936; Blanchard and Fischer, 1989). From a macroeconomic perspective, monetary policy responds faster than fiscal policy, because the central bank can directly adjust money supply and interest rates to achieve its macroeconomic goals, while fiscal policy can only adjust government spending and taxes. In times of crisis, monetary policy is more effective than fiscal policy (Bernanke, 2000; Taylor, 2000). Therefore, in the study of the relationship between policy and the automotive industry, this paper takes monetary policy as an example to examine whether monetary policy has a regulatory impact on the industry.

Over the past decades, scholars have shown great interest in studying the impact of monetary policy on various industries. For example, at the end of the last century, Ganley and Salmon (1997) analysed the impact of monetary policy shocks on the output of 24 sectors of the British economy, and found that the impact of monetary policy tightening seems to be unevenly distributed in various economic sectors; Moreover, Ghosh (2009) examined the industry from 1981 to 2004, using data to determine the correlation between monetary policy shocks and industry value added, the results show that industries respond differently to monetary tightening. What's more, both Rodríguez-Fuentes and Padrón-Marrero (2008) and Ribon (2009) used the vector auto-regression model (VAR) to analyse the responses of different industrial sectors in Spain and Israel to currency shocks, and the results showed that different sectors had an impact on the Spanish national currency There was a marked difference in responses. In conclusion, despite variations in the samples and time intervals studied by different scholars, the overall consensus is that the response of different industrial sectors to monetary policy differs significantly.

Studies on the impact of monetary policy on specific industries have yielded rich insights. Xu et al., (2012) studied China's real estate market and find that China's monetary policy actions were the key driving force behind changes in China's real estate price growth. Mallick (2011) analysed the impact of monetary policy on the construction industry in India, focusing on construction sector output and housing prices. The scholars find that monetary policy, particularly interest rates, has a significant effect on construction sector output and housing prices. The results suggest that monetary policy can be an effective tool for managing cyclical fluctuations in the construction sector. This paper aims to focus on the automotive industry in the Czech Republic and examine whether monetary policy has a considerable impact on the automotive industry, so as to provide ideas and evidence for the government to manage the output and growth of the automotive industry.

CHAPTER 2 Data, Hypothesis, and Methodology

Chapter 2 of this paper provides a comprehensive overview of the variables and data collection process, as well as the relevant assumptions and methodology used. Firstly, the selected variables and the reasons behind their selection, data sources, and the scope of the sample will be introduced. Secondly, the research questions and specific hypotheses will be stated. The final part, methodology, will elaborate on why VAR is chosen as the main model, along with a detailed explanation of other relevant models such as the Granger causality test, impulse response function analysis, and variance decomposition. Lastly, it will describe how the variables are applied to the models introduced.

2.1 Data collection

The data collection for this paper involves three main aspects: the automotive industry, the business cycle, and the policy. The data sources include Eurostat, the Czech Statistical Office (CZSO), and the Czech National Bank (CNB). The chosen data frequency is quarterly, spanning from the first quarter of 2004 to the first quarter of 2023 (2004Q1-2023Q1). The year 2004 is selected as the starting point because it marks the Czech Republic's accession to the European Union, which provided more opportunities for trade and automotive industry production (Blázquez et al., 2013). According to Kureková (2018), the FDI in the late 20th century contributed to the improvement of the Czech automotive industry, and joining the EU in 2004 helped ensure the region's continued progress. Therefore, this paper focuses on data from the Czech Republic's EU accession in 2004 to the present (2004-2023).

Firstly, the primary focus of this paper is on the output data of the automotive industry, with the growth rate of automotive industry output representing the performance of the automotive sector. Therefore, for the industry part, the data selected is the automotive industry output data for the Czech Republic, sourced from the Eurostat database's "Production in industry" (STS_INPR_Q) section, which includes “the manufacture of motor vehicles, trailers, semi-trailers, and other equipment”.

Specifically, the database provides the "Percentage change on previous period" data, which is seasonally and calendar adjusted to ensure accuracy by accounting for seasonal and calendar factors that may influence the results. This variable is denoted as "*auto_growth*" in this paper.

Next, concerning the business cycle, there are numerous relevant macroeconomic variables that various scholars have analysed from different perspectives to study macroeconomic fluctuations. Commonly used macroeconomic factors include GDP (Sawtelle, 2007; Rechnitzer, 2012; Patra, 2017; Behun et al., 2018), the unemployment rate (Hagiu and Ungureanu, 2010; Rechnitzer, 2012), as well as indicators representing overall industrial development such as industrial value added (Qu, 2011) and industrial production index (Rodríguez-Fuentes and Padrón-Marrero, 2008), among others.

Based on the literature referenced above, this study selects the real GDP growth rate and Gross value added (GVA) growth rate as representative variables for the business cycle. Real GDP, being the most commonly used macroeconomic variable, removes the influence of inflation compared to nominal GDP and reflects the overall economic changes and fluctuations in the Czech economy. Additionally, long-term real GDP growth should be reflected in employment growth, which can help economists establish their industrial employment models (Behun et al., 2018). Therefore, this study did not choose the unemployment rate.

In addition to overall macroeconomic indicators, this study also selects another crucial economic variable, Gross value added (GVA), to measure the business cycle. In economics, Gross value added (GVA) measures the value of goods and services produced by a region, industry, or economic sector. The Czech National Bank (CNB) considers GVA a key indicator of economic production capacity and a standard for measuring production process efficiency and competitiveness. Moreover, GVA is a more comprehensive indicator as it includes not only highly volatile and challenging-to-track pre-tax profits but also accounts for wage and fixed capital consumption (Pavlínek and Ženka, 2016). The selected Real GDP growth rate and GVA growth rate data are both sourced from the Czech Statistical Office (CZSO, 2023) and are seasonally adjusted, denoted as "*rgdp_growth*" and "*gva_growth*".

Finally, in the policy section, this study primarily discusses monetary policy and, drawing on Gordon and Leeper (1994) and Qu (2011), selects the broad money supply (M2) as a representative variable to evaluate the impact of monetary policy shocks. In many countries, M2 money supply, rather than M1, is considered to have a long-term relationship with income and interest rates (Bahmani-Oskooee and Chomsisengphet, 2002). M2 is a measure of the money supply, including cash, checking deposits, savings deposits, and money market funds. It is regarded as a comprehensive measure of the money supply as it encompasses M1 (cash and checking deposits) as well as savings deposits and other components of highly liquid, low-risk assets. One commonly used definition of M2 is provided by the Federal Reserve Bank of St. Louis: “M2 includes M1 plus savings deposits, time deposits of less than $100,000, and balances in retail money market mutual funds.” Therefore, in this study, the M2 indicator is chosen to represent monetary policy, and the data is sourced from the Czech National Bank (CNB). The variable name for M2 is denoted as "M2," and the growth rate of M2 is calculated and labeled as "*m2_growth*."

2.2 Hypotheses

The goal of this study is to analyse the correlation between the output cycle of the auto industry and the business cycle. It focuses on a case study of the Czech automotive industry and its correlation with the country's economy. Therefore, the study pays close attention to the fluctuation patterns within the Czech automotive industry itself and its interdependence with the business cycle. The subsequent analysis in this study can be divided into the following three parts:

(1) Analysis of the fluctuations in the Czech automotive industry cycle and the business cycle. Currently, most of the literature focuses on examining the impact of various factors on the fluctuations of the automotive industry, but seldom analyses their individual characteristics of fluctuations. This study first analyses the progress and changes in the Czech automotive industry since its accession to the European Union. It observes how the output of the Czech automotive industry dynamically fluctuates over the selected period, mainly using graphical representations to visualize its cyclic patterns. In addition to focusing on the cycle of the Czech automotive industry, this study also pays attention to the fluctuations in the business cycle and combines the two to observe if their cyclic patterns are consistent. Finally, the paper also looks at the volatility of money supply growth rates over the chosen time horizon.

(2) Measurement of the correlation between the output cycle of the Czech automotive Industry and the Czech economic cycle. As mentioned earlier, this study analyses the output data of the Czech automotive industry in relation to the real GDP and Gross Value Added (GVA) which represent the economic cycle. To examine the interdependence between the two, this study will validate from two directions. Firstly, it will analyse the influence of macroeconomic variables on the development of the Czech automotive industry, specifically by testing whether real GDP and GVA have an effect on the industry's output. Secondly, it will observe whether the Czech automotive industry has spillover effects on the overall national economic situation, examining if there is a correlation between its output and real GDP as well as GVA. The specific hypotheses are as follows:

H1: The output of the Czech automotive industry is correlated with real GDP.

H2: The output of the Czech automotive industry is correlated with GVA.

(3) Measurement of the correlation between macroeconomic policy and the Czech automotive industry. Based on the previous content, this study focuses on the monetary policy, which is responsive and quickly effective. The representative

indicator of monetary policy used in this study is M2, reflecting changes in money supply. The analysis in this section is similar to the previous section, examining whether there is an impact of the automotive industry's output growth rate on the growth rate of M2, and vice versa. The specific hypotheses are as follows:

H3: The output of the Czech automotive industry is correlated with M2.

2.3 Methodology

2.3.1 GARCH (1,1) Model

Before analysing the specific relationship between variables, we first examine the volatility of automobile production and macroeconomic variables. Compared with the ARCH(p) model, if p is large, many parameters need to be estimated, which will result in a loss of sample size. Bollerslev (1986) proposed the Generalized Autoregressive Conditionally Heteroskedastic Models (GARCH) model, which led to a reduction in the number of parameters to be estimated and improved the accuracy of predicting future conditional variance.The fundamental concept is that, on the basis of the ARCH model, plus the autoregressive part. The GARCH (p,q) model is formulated as follows:

$$\sigma_t^2 = \sigma_0 + \sigma_1 \varepsilon_{t-1}^2 + \ldots + \sigma_q \varepsilon_{t-q}^2 + \gamma_1 \sigma_{t-1}^2 + \ldots + \gamma_p \sigma_{t-p}^2 \tag{2.1}$$

Where, p represents the autoregressive order of σ_t^2, and q represents the lag order of ε_t^2.

This paper follows the approach of Billio et al. (2012) and employs the GARCH (1,1) model to analyse the volatility of time series data. The GARCH (1,1) model is currently one of the most widely used GARCH models and is better suited to capture volatility clustering. The GARCH (1,1) model is formulated as follows:

$$\sigma_t^2 = \sigma_0 + \sigma_1 \varepsilon_{t-1}^2 + \gamma_1 \sigma_{t-1}^2 \tag{2.2}$$

In a sense, GARCH (1,1) is equivalent to an infinite-order ARCH model. It is often possible to simplify higher-order ARCH(p) models to GARCH (1,1).

2.3.2 VAR Model

During the literature review, this paper found that most scholars use the vector autoregressive (VAR) model to analyse the correlation between macroeconomics and a certain variable. For example, Rodríguez-Fuentes and Padrón-Marrero (2008) use VAR combined with shock model analysis The impact of the Spanish currency shock on different sectors; Ribon (2009) also used the VAR model to analyse the impact of the Israeli monetary policy. Similar to VAR models include Structural Vector Autoregression (SVAR) model (Sims, 1980) and Bayesian VAR (BVAR) model (Doan et al., 1984). Among them, the former extends the VAR model to include structural shocks; the latter includes prior beliefs or knowledge about model parameters. However, SVAR models are more suitable for analyzing causal relationships, and BVAR models are more commonly used for forecasting. This article aims to analyse the dynamic dependencies among variables, so the VAR model is more suitable.

This article uses the vector autoregressive (VAR) model as the main model, combined with the Granger test to analyse the correlation between variables, answer the above research questions and verify the hypothesis. Before using the VAR model, it is necessary to conduct a stationarity test on the data. In economic analysis, ADF test (Augmented Dickey-Fuller) and PP test (Phillips-Perron) are the two most commonly used unit root test methods.

The ADF test

This test method was first proposed by Dickey and Fuller in 1979. This is a one-sided test method, called the extended DF test (ADF test), which opens up a new way for the sequence stationarity test, which is currently the most widely used A method for testing sequence stationarity. The main principle is to control the high-order serial correlation by adding the lagged difference term of the dependent variable on the right side of the equation.

That is, a time series model is assumed to:

$$y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + \mu_t, \mu_t \sim IN(0, \sigma^2) \quad (2.3)$$

The conversion to a lagged operator polynomial takes the form

$$\phi(L) y_t = \mu_t \quad (2.4)$$

Where L denotes the lag operator:

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_p L^p \quad (2.5)$$

During the process of empirical analysis, this paper usually test the characteristic equation $\phi(L) = 0$, which is whether the sum of the unit roots is 1, which is used as a criterion to test whether the time series is smooth. According to the original hypothesis of the smoothness test given in the previous section, the null hypothesis is $\rho = 1$, and the alternative hypothesis $\rho < 1$. When the null hypothesis holds, it means that the original series is single integer, otherwise the original series y_t is smooth. The time series model (1) can also be expressed as:

$$\Delta y_t = (\beta - 1) y_{t-1} + \sum_{j=1}^{p-1} \phi_j^* \Delta y_{t-i} + \mu_t \quad (2.6)$$

in which,

$$\beta = \sum_{i=1}^{p} \phi_i, \phi_j^* = -\sum_{i=j+1}^{p} \phi_i, j = 1,2, \ldots p-1 \quad (2.7)$$

Set $\rho = \beta - 1$, then equation (2.6) can be rewritten as:

$$\Delta y_t = \rho y_{t-1} + \sum_{j=1}^{p-1} \phi_j^* \Delta y_{t-i} + \mu_t \quad (2.8)$$

If the ADF test-statistic is greater than the critical value, then the null hypothesis is accepted, meaning that the time series obeys a unit root process and is a non-stationary time series; Conversely, if the ADF test-statistic is less than the critical value, then the null hypothesis is rejected, meaning that the time series does not obey a unit root process and is a stationary time series.

The PP test

Another commonly used test for smoothness is the PP test, which was proposed by

Phillips and Perron in 1988 for the same purpose as the ADF test, to determine the existence of a unit root in a time series. First, a linear regression equation is assumed:

$$X_t = \alpha + \rho X_{t-1} + \delta t + e_t \tag{2.9}$$

Where, α represents a constant, e_t denotes a random error, zero mean, but does not require homoscedasticity. If there is no time trend of $\{X_t\}$, but simply follows a unit root process, then for equation (2.9), the null hypothesis is expressed as:

$$H_0: \rho = 1, \delta = 0$$

z_p is used to represent the PP test statistic and is expressed as:

$$z_p = (\gamma_0/\lambda^2)^{1/2} t_{pt} - \left[\frac{1}{2}(\lambda^2 - \gamma_0)/\lambda\right] \times \left(T\sigma_{pt}/S_t\right) \tag{2.10}$$

where, t_{pt}, σ_{pt}, S_t respectively, are the parameter values when equation (2.10) is estimated by the least squares method. It should be noted that:

$$t_{pt} = (\hat{\rho} - 1)/\sigma_{pt} \tag{2.11}$$

where γ_0 and λ can be substituted for.

$$\hat{\gamma}_0 = \frac{1}{T}\sum_{t=1}^{T} \hat{e}_t^2,\ \hat{\lambda}^2 = \hat{\gamma}_0 + 2\sum_{j=1}^{q} [1 - j/(q+1)]\hat{\gamma}_j \tag{2.12}$$

where q is chosen as the value of the first p auto-covariances.

$$\hat{\gamma}_j = T^{-1}\sum_{r=j=1}^{T} \hat{e}_t\hat{e}_{t-j} \tag{2.13}$$

The test statistic z_p obeys an asymptotic distribution.

The PP statistic is similar to the ADF test statistic in that both test the smoothness of a series by calculating the significance level of the series at different confidence levels. Unlike the ADF test, the correction for the PP test uses a non-parametric approach and when using the PP test for smoothness we need to define the truncated lag factor q. The PP test can likewise include a trend term and a constant term.

VAR Model

The VAR model, initially introduced by Sims in 1980, is a multi-equation model without structural restrictions, allowing for endogenous variables to appear on either side of the equation. This makes it easy to estimate and infer the dynamics of the model. The most significant feature of the VAR model is that each endogenous variable is determined by its own lagged values and the lagged values of other endogenous variables in the system, eliminating the need for explicit structural assumptions. The VAR model has been widely applied to analyse the impact of economic variables under different economic shocks. In this thesis, we use a VAR(P) model as an example to illustrate the VAR model, with the expression:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + BXt_t + \mu_t \tag{2.14}$$

Where, y_t is the n dimensional endogenous variable, X_t is the d dimensional exogenous variable, u_t is the vector of perturbations, u_t is allowed to be correlated contemporaneously with each other, but not with its own lagged value nor with the variables on the right-hand side of the equation. $A_1, \dots, A_p$ and B are the coefficient matrices to be estimated. It is assumed that $\sum$ is the covariance matrix of u_t, is a $(n \times n)$ covariance matrix. Eq. (2.14) can be expressed as a matrix:

$$\tilde{y}_t = A_1 \tilde{y}_{t-1} + \dots + A_p \tilde{y}_{t-p} + u_t \tag{2.15}$$

And $\tilde{y}$ is the residual of the regression of y_t on the exogenous variable X_t. Then Eq. (2.15) can be abbreviated as.

$$A(L)\tilde{y}_t = u_t \tag{2.16}$$

Where, the $A(L) = A_0 - A_1 L - A_2 L^2 - A_p L^p$, denotes the $n \times n$ dimensional parameter matrix of the lag operator L, and $A_0 = I$ is a unit matrix.

μ_t is a shock matrix, representing a white noise vector, but μ_t without structural connotations, and is therefore referred to as a shock matrix in simplified form. Equation (2.16) is then commonly referred to as an unrestricted vector autoregressive model (unrestricted VAR).

An unrestricted VAR model can also be transformed into a structural VAR model (SVAR). The SVAR model for a bivariate, first order lagged VAR model is represented as follows.

$$\begin{pmatrix} 1 & a_{1,2} \\ a_{2,1} & 1 \end{pmatrix}\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} \gamma_{1,0} \\ \gamma_{2,0} \end{pmatrix} + \begin{pmatrix} \gamma_{1,1} & \gamma_{1,2} \\ \gamma_{2,1} & \gamma_{2,2} \end{pmatrix}\begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix} \quad (2.17)$$

The model can be expressed in the form of a matrix.

$$A_0 Y_t = \gamma_0 + \gamma_1 Y_{t-1} + \varepsilon_t \quad (2.18)$$

And, $A_0 = \begin{pmatrix} 1 & a_{1,2} \\ a_{2,1} & 1 \end{pmatrix}$, $y_t = \begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix}$, $\gamma_0 = \begin{pmatrix} \gamma_{1,0} \\ \gamma_{2,0} \end{pmatrix}$, $\gamma_1 = \begin{pmatrix} \gamma_{1,1} & \gamma_{1,2} \\ \gamma_{2,1} & \gamma_{2,2} \end{pmatrix}$, $\varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}$

Assuming A_0 invertibility, a simplified form of the VAR model can be derived.

$$\begin{aligned} y_t &= A_0^{-1}\gamma_0 + A_0^{-1}\gamma_1 y_{t-1} + A_0^{-1}\varepsilon_t \\ &= \Phi_0 + \Phi_1 y_{t-1} + u_t \end{aligned} \quad (2.19)$$

Where, $\Phi_0 = A_0^{-1}\gamma_0 = \begin{pmatrix} \phi_{1,0} \\ \phi_{2,0} \end{pmatrix}$, $\Phi_1 = A_0^{-1}\gamma_1 = \begin{pmatrix} \phi_{1,1} & \phi_{1,2} \\ \phi_{2,1} & \phi_{2,2} \end{pmatrix}$, $u_t = A_0^{-1}\varepsilon_t = \begin{pmatrix} u_{1,t} \\ u_{2,t} \end{pmatrix}$

It can be seen that the simplified perturbation term u_t is a linear combination of structural perturbation termsε_t , representing a compound shock.

Granger causality test

The Granger causality test was first proposed by Granger in 1969. The definition of Granger causality between two economic variables is as follows: For a time series, if the prediction of variable Y is improved by including the past information of variable X, compared to predicting Y using only its own past information, i.e., if the explanatory power of Y's prediction can be enhanced by incorporating the past information of X, then we say that variable X Granger-causes variable Y, or in other words, there exists a Granger causality relationship between the two economic variables X and Y (Qu, 2011).

To explain the Granger causality test, we present a simplified VAR model of order P and provide the expression for the Granger causality test. The model is given as follows:

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \alpha_{1,0} \\ \alpha_{2,0} \end{pmatrix} + \begin{pmatrix} \alpha_{1,t-1} & \beta_{1,t-1} \\ \alpha_{2,t-1} & \beta_{2,t-1} \end{pmatrix}\begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \cdots + \begin{pmatrix} \alpha_{1,t-p} & \beta_{1,t-p} \\ \alpha_{2,t-p} & \beta_{2,t-p} \end{pmatrix}\begin{pmatrix} y_{t-p} \\ x_{t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}$$

(2.20)

Where, $\alpha_{1,0}, \alpha_{2,0}$represents the constant term, $y_{t-i}, i = 1, \ldots, p$ represents the lagged variables of variable y, $x_{t-i}, i = 1, \ldots, p$represents the lagged variables of variable x,

$\alpha_{1,t-i}, \alpha_{2,t-i}, \beta_{1,t-i}, \beta_{2,t-i}, i = 1, \ldots, p$ representing the regression coefficients of the variables in the model, $\varepsilon_{1,t}, \varepsilon_{2,t}$ representing error terms with white noise properties.

To test whether there is a causal relationship between two time series, X and Y, you can perform the following tests by constructing two models:

$$\begin{aligned} Y_t &= \alpha + \sum_{i=1}^{m} \alpha_i Y_i + \sum_{j=1}^{k} \beta_j X_j + \mu_t \\ Y_t &= \alpha_0 + \sum_{i=1}^{m} \alpha_i Y_i + \mu_t \end{aligned} \tag{2.21}$$

For the lag selection, we can choose it arbitrarily. If the null hypothesis holds for all cases, where does not significantly cause , then the two variables do not constitute a causal relationship.

Assuming the null hypothesis is:

$$H_0: \beta_j = 0, j = 1,2, \ldots, k$$

Below, we perform regressions for equation (2.21) to obtain the sum of squared residuals ESS_1 and ESS_2, as well as the sum of squared residuals of the combined model RSS_1. Then, we construct an F-statistic as follows:

$$F = \frac{(ESS_1 - ESS_2)/m}{RSS_1/[T-(k-m+1)]} \tag{2.22}$$

The statistic in equation (2.22) follows an F-distribution with the first degree of freedom equal to m and the second degree of freedom equal to $T-(k-m+1)$, at a given significance level α, obtaining the critical value F_α. If $F < F_\alpha$, the F-statistic obtained at the confidence level of $(1-\alpha)$ leads to accepting the null hypothesis H_0, then variable X does not Granger cause variable Y. Otherwise, reject the null hypothesis, which means that variable X Granger causes variable Y.

Impulse response functions and variance decomposition

When using a VAR model for economic analysis, the focus is usually on the system's dynamics when subjected to some kind of shock or when a stochastic disturbance term changes. The VAR model does not require a priori constraints and is treated as a non-theoretical model, making it easy to apply. The Impulse Response Function (IRF) explains the effect of one endogenous variable on the other endogenous variables, that is, the response of the endogenous variable to the shock over time. Similarly, in 1980, Sims proposed the Variance Decomposition method, the main rationale of which is to try to evaluate the importance of different structural shocks by the extent to which they contribute to changes in the endogenous variables (usually measured by the variance) and next.

Impulse Response Function (IRF)

In this paper, the VAR (2) model is used as an example to illustrate the mechanism of the impulse response function.

$$\begin{cases} x_t = a_1 x_{t-1} + a_2 x_{t-2} + b_1 z_{t-1} + b_2 z_{t-2} + \mu_{1t} \\ z_t = c_1 x_{t-1} + c_2 x_{t-2} + d_1 z_{t-1} + d_2 z_{t-2} + \mu_{2t} \end{cases} \quad (2.23)$$

And a_i, b_i, c_i, d_i are parameters, $\mu_t = (\mu_{1t}, \mu_{2t})'$ is the perturbation term, having the following properties

$$E(\mu_t) = 0, t = 0, \pm 1, \ldots$$

$$\text{Var}\ (\mu_t) = E(\mu_t \mu_t') = \sum = \{\delta_{ij}\}, t = 0, \pm 1, \ldots$$

$$E(\mu_t \mu_t') = 0, t \neq s \quad (2.24)$$

Assume (2.24) that the system is active from period 0, and set $x_{-1} = x_{-2} = z_{-1} = z_{-2} = 0$, and set the perturbation term be given at period 0 $\mu_{10} = 1, \mu_{20} = 0$, and after it all 0, which means $\mu_{1t} = \mu_{2t} = 0, t = 0,1,2, \ldots$, then this is said to be the 0th period to give an impulse to x.

When $t = 0$: $x_0 = 1, z_0 = 0$

Substitute into the equation, when $t = 1$:

$$x_1 = a_1, z_1 = c_1$$

The result of the above equation is then substituted into equation (2.23), when $t = 2$:

$$x_2 = a_1^2 + a_2 + b_1 c_1$$
$$z_2 = c_1 a_1 + c_2 + d_1 c_1$$

Continuing with this calculation, the result is set to

$$x_0,\ x_1, x_2, x_3, x_4, \ldots$$

We call this the impulse response function x caused by the shock of x

Similarly, the resulting $z_0, z_1, z_2, z_3, \ldots$ is said to be the impulse response function of z caused by a shock to x. The above process is then extended to a multivariate model. In general, the impulse response function of y_i caused by a shock to y_i is expressed as follows.

$$C_{0,ij}, C_{1,ij}, C_{2,ij}, C_{3,ij}, C_{4,ij}, \ldots$$

and the elements of the i-th row and j-th column of C_s can be represented as:

$$C_{s,ij} = \frac{\partial y_{i,t+s}}{\partial \mu_{jt}}, s = 0,1, \ldots \tag{2.25}$$

Eq. (2.25) describes the situation where the impulse response function is defined as the response to an instantaneous change in $y_{i,t+s}$ after being subjected to a change in y_{it}, provided that the early variables and other variables in period t do not change.

Variance decomposition

Variance decomposition is a method of analysing the extent to which each structural shock contributes to the level of change in endogenous variables (usually measured by the variance), and then evaluating the importance of different structural shocks. The method is described as follows.

According to equation (2.25) and:

$$(I - A_1 L - \ldots - A_P L_P)(I + C_1 L + C_2 L^2 + \ldots) = I \tag{2.26}$$

$$I + \psi_1 L + \psi_2 L^2 + \ldots = I \tag{2.27}$$

Here we get:

$$\tilde{y}_{it} = \sum_{j=1}^{n} \left(\psi_{0,ij} u_{jt} + \psi_{1,ij} u_{jt-1} + \psi_{2,j} u_{jt-2} + \psi_{3,j} u_{jt-3} + \ldots\right) \tag{2.28}$$

The content in parentheses indicates the sum of the effects of y_i on the j-th perturbation term u_j over the period from infinite past to the present point in time. Since $\{u_{jt}\}$ is not serially correlated, its variance can be obtained.

$$E\left\{\left(\psi_{0,ij} u_{jt} + \psi_{1,ij} u_{jt-1} + \psi_{2,j} u_{jt-2} + \psi_{3,ij} u_{jt-3} + \ldots\right)^2\right\} = \sum_{q=0}^{\infty} \left(\psi_{q,ij}\right)^2 \sigma_{ij}, j = 0,1,2, \ldots, n \tag{2.29}$$

In addition, assuming that the covariance matrix $\sum$ of the vector of perturbation terms is a diagonal matrix, then the sum of the n terms of the above variance, i.e. the variance of y_{it} , $r_{ii}(0)$:

$$\mathrm{var}\,(\tilde{y}_{it}) = r_{ii}(0) = \sum_{j=1}^{n} \left\{ \sum_{q=0}^{\infty} \left(\psi_{q,ij}\right)^2 \sigma_{ij} \right\} \tag{2.30}$$

The variance of $\tilde{y}_{it}$ can be decomposed into n uncorrelated effects, and to test the contribution of each perturbation to the variance of $\tilde{y}_{it}$, we define the following equation.

$$RVC_{j\to i}(s) = \frac{\sum_{q=0}^{s-1} \left(\psi_{q,ij}\right)^2 \sigma_{jj}}{\sum_{j=1}^{n} \left\{ \sum_{q=0}^{s-1} \left(\psi_{q,ij}\right)^2 \sigma_{jj} \right\}}, i, j = 1,2, \ldots, n \tag{2.31}$$

Equation (2.31) is known as the Relative Variance Contribution (RVC), which is based on the variance of the shock and measures the effect of the jth variable on the i-th variable in terms of the relative contribution of the j-th variable to the variance $\tilde{y}_{it}$. In practice, we do not use f of s to evaluate, only a limited number of s terms are sufficient. the forecast error for the first s periods of the VAR(P) model is.

$$u_{t+s} + \psi_1 u_{t+s-1} + \psi_2 u_{t+s-2} + \ldots + \psi_{s-1} u_{t+1} \tag{2.32}$$

Therefore, we have:

$$RVC_{j\to i}(s) = \frac{\sum_{q=0}^{s-1} \left(\psi_{q,ij}\right)^2 \sigma_{jj}}{\sum_{j=1}^{n} \left\{ \sum_{q=0}^{s-1} \left(\psi_{q,ij}\right)^2 \sigma_{ij} \right\}},\ i, j = 1,2, \ldots, n \tag{2.33}$$

$RVC_{j\to i}(s)$ has the following properties

$$0 < RVC_{j\to i}(s) < 1\ i, j = 1,2, \ldots, k$$

$$\sum_{j=1}^{k} RVC_{j\to i}(s) = 1,\ i = 1,2, \ldots, k$$

When the $RVC_{j\to i}(s)$ is small, it means that the i-th variable is less influenced by the j-th variable. When the $RVC_{j\to i}(s)$ is large, it means that the i-th variable is strongly influenced by the j-th variable.

This paper first conducts volatility analysis on each time series using the GARCH(1,1) model, and examines the periodic similarities and differences in volatility obtained from the individual time series models. Next, based on the three hypotheses mentioned earlier, the data is divided into three sets to construct VAR models for further analysis. These three sets consist of: (1) automotive output growth rate (auto_growth) and real GDP growth rate (rgdp_growth); (2) automotive output growth rate (auto_growth) and GVA growth rate (gva_growth); and (3) automotive output growth rate (auto_growth) and M2 money supply growth rate (m2_growth). VAR models, Granger causality tests, impulse response analysis, and variance decomposition are used to examine the relationships within each set. Taking the first set as an example, the VAR model simultaneously reveals the interactions between the real GDP growth rate and automotive output growth rate. Specifically, the real GDP growth rate is treated as the exogenous variable (X) in the VAR model, while automotive output growth rate is considered as the endogenous variable (Y). The analysis explores the individual effects of real GDP growth rate and automotive output growth rate on the development of the automotive industry, as well as the outcomes when these two variables are interchanged. The specific analysis process and detailed results will be discussed in subsequent sections.

CHAPTER 3 Analysis

3.1 Descriptive Analysis

Before conducting specific empirical analysis, this study begins with descriptive statistics for a basic understanding of the data characteristics. The sample period selected for this study covers the first quarter of 2004 to the first quarter of 2023, comprising a total of 77 observations. The focus of this research is on a single country - the Czech Republic, specifically exploring the relationship between the Czech auto industry cycle and the business cycle. The chosen variables include automotive output growth rate (auto_growth), real GDP growth rate (rgdp_growth), GVA growth rate (gva_growth), and M2 growth rate (m2_growth). The primary approach of this study is to analyse and model the data from a time series perspective.

Table 1 shows the summary statistics of the variables. From the data in this table, it can be observed that, compared to their respective means, the average growth rate of automotive output in the Czech Republic since its accession to the European Union is 2.379%, significantly higher than the growth rates of real GDP (0.586%) and GVA (0.623%), and slightly higher than the growth rate of M2 (1.84%). This indicates that the development of the Czech automotive industry has outperformed the overall economic growth, leading to the industrial structure in the country's economy. On the other hand, the standard deviation and extreme values of the automotive output growth rate are notably higher than those of the other variables, even approximately ten times greater in absolute value. This suggests that while the automotive industry holds a crucial position in the Czech economy, its stability is comparatively weaker than the overall macroeconomic trends. The industry is susceptible to fluctuations and exhibits a wide range of variability, making it vulnerable to various internal and external shocks. The other three variables related to the macroeconomic situation show more consistent patterns.

Table 1 Summary statistics of variables

stats	auto growth	rgdp growth	gva growth	m2 growth

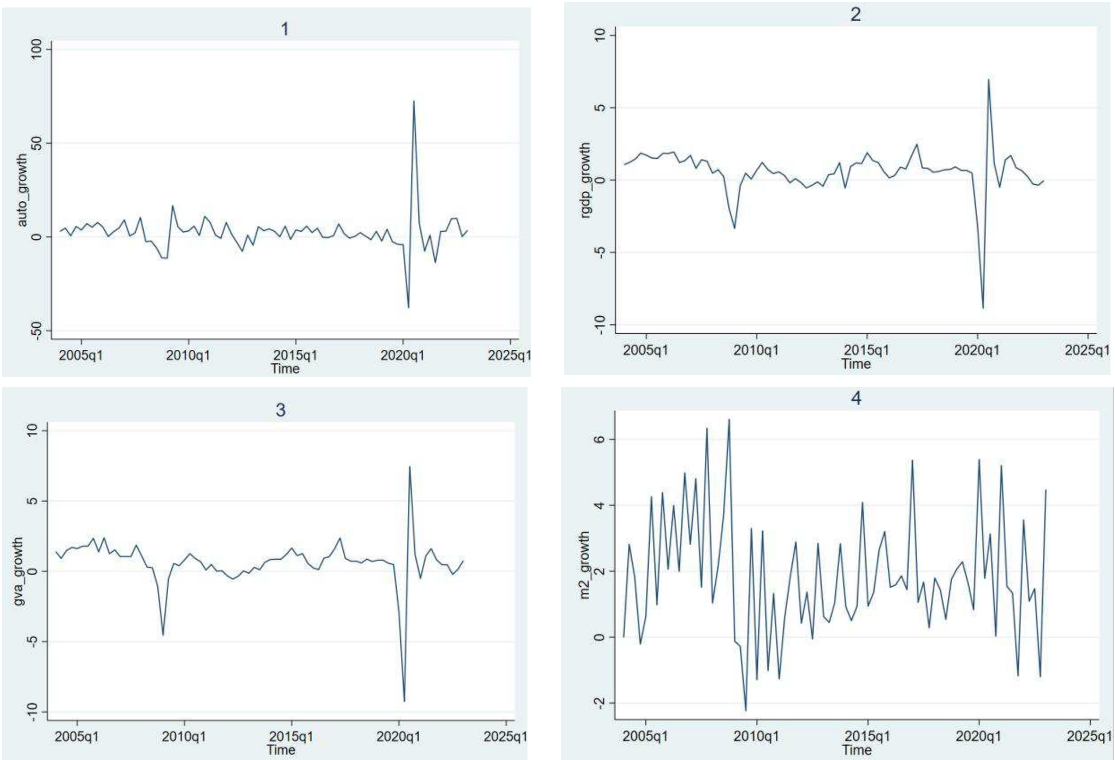
mean	2.379	0.586	0.623	1.840
sd	10.60	1.638	1.706	1.831
min	-37.70	-8.849	-9.247	-2.229
max	72.50	6.953	7.449	6.605

Source: authors' calculation via Stata

To gain a more detailed insight into the fluctuations of each variable within the selected time range, this study has plotted line graphs for the four time series mentioned above. Figure 2 illustrates the changes in each variable over the chosen time period. Through the visual representation, it is evident that the trends in the growth rates of automotive output, real GDP, and GVA are similar. There have been two noticeable fluctuations during the selected period, occurring around 2008 and 2020, respectively, which correspond to two significant crises of this century: the financial crisis and the COVID-19 pandemic. The rest of the time periods appear relatively stable. Moreover, by observing the magnitude of fluctuations, it can be noted that the impact of the second crisis on the automotive industry and the overall macroeconomy was far more pronounced than that of the first crisis. While the financial crisis primarily affected the automotive industry due to financial constraints, the impact of COVID-19 on the supply chain was more directly related to physical isolation and other factors.

Regarding the fourth graph in Figure 2, it is evident that the variation in M2, representing the money supply, shows distinct characteristics compared to the other three variables. Throughout the entire time range, it demonstrates significantly stronger volatility, with the most substantial fluctuation occurring during the financial crisis. However, during the other time periods, no clear patterns can be discerned through the line graph of this time series. Based on the descriptive statistics provided, we have gained a basic understanding of the data. In the subsequent analysis, we will delve deeper into the data to further explore its insights.

Figure 2 Time-series Trend of Variables



Note: 1) auto_growth;2)rgdp_growth;3) gva_growth;4)m2_growth

Source: authors' results via Stata

3.2 Volatility Analysis

Through the above descriptive statistical analysis, this paper has gained a general understanding of the volatility of the growth rates of automotive output, real GDP, GVA, and money supply (M2). The results indicate that the fluctuation trends of the first three variables are similar but vary in magnitude. Specifically, the automotive industry exhibits significantly greater volatility than the overall business cycle. On the other hand, the growth rate of M2 is significantly different from the volatility of other variables.

In order to further explore the data volatility and the periodic changes among variables, as described in Chapter 2, the GARCH (1,1) model is used for analysis. The GARCH (1,1) model is widely used for measuring and estimating volatility in financial time series, as it provides conditional variance estimates. Since this part is not the primary focus of the research, but rather aims to observe the relationship between the volatility of each time series and their comparative volatility, a brief analysis is presented here. The GARCH (1,1) model is directly applied to the four-time series mentioned above to obtain their respective conditional variance predictions.

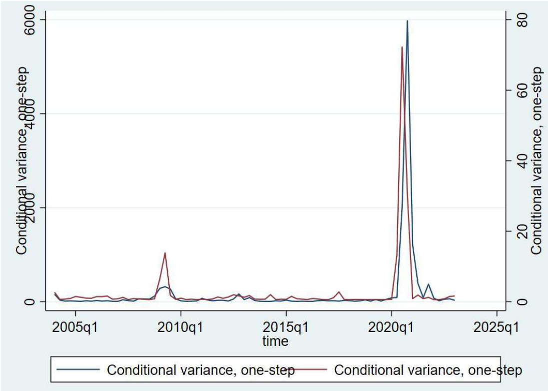
By the hypotheses set earlier, this paper divides the data into three sets for further investigation: (1) the growth rate of automotive output and real GDP growth rate; (2) the growth rate of automotive output and GVA growth rate; and (3) the growth rate of automotive output and M2 growth rate. Line charts depicting the conditional variance series for each set are presented in Figure 3 below. Additionally, to observe the volatility between M2 and the macroeconomy, a graph of the real GDP growth rate and M2 growth rate is included as well (Figure 3-4).

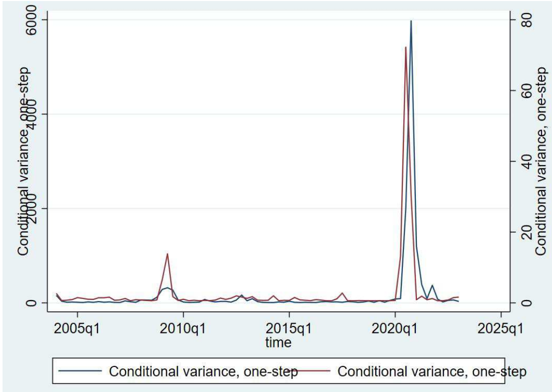
Figure 3 can intuitively show the fluctuation difference of each set of variables in terms of degree and time. Among them, the results of the first set and the second set are relatively consistent, and the meanings they represent are also consistent, that is, the relationship between the volatility of the automotive industry cycle and the business cycle. The blue line represents the conditional variance of the fluctuation of the automotive industry, and the red line represents the fluctuation of the business cycle. From the results of Figures (1) and (2), it can be found that overall, the volatility of the automotive industry lags behind that of the business cycle. During the observation period of this paper, two obvious fluctuations occurred during the financial crisis and the pandemic period. This means, this confirms the view that the automotive industry cycle and the business cycle are highly correlated (Heneric et al., 2005). On the other hand, it also proves that the periodic fluctuations of the two are different, and the industry cycle lags behind the changes in the business cycle, which has the characteristic of fluctuating delay.

Looking at Figures (3) and (4) in Figure 3, we can see that the monetary policy is stable and phased. The volatility of the growth rate of money supply, the fluctuation of the growth rate of automotive output, and the changes in the real GDP growth rate exhibit distinct differences in their rate trends. The specific performance is that from 2004 to 2013, the money supply showed severe fluctuations, but then entered an obvious stability, with only occasional small fluctuations. However, after the pandemic, its fluctuations have become more severe. However, this does not prove that the money supply itself is not affected by the shock. During the observation period of this paper, the two obvious violent fluctuations still appeared during the financial crisis and the pandemic period. However, the fluctuations during the financial crisis were obviously more severe. This comparison result is different from the other sets (shows the fluctuations of the automotive industry and the fluctuations of the business cycle). It proves that, compard with the pandemic, during the financial crisis, the Czech central bank gave more consideration to regulating the operation of the economy by adjusting the money supply. This conclusion can also be explained by the difference in the essential root causes of the occurrence of the two crises and the obstacles to the development of the national economy.

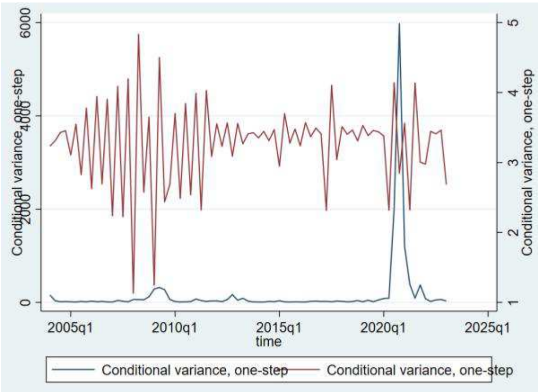
In addition, looking at the graph (4) of Figure 3, it can be seen that there is no obvious correlation between macroeconomic performance and money supply volatility. The drastic fluctuations in monetary policy cannot cause drastic fluctuations in the Czech macroeconomic trend. Comparing the graph (4) with graph (1) and the fluctuation trend in the time range of macroeconomy itself, we can argue that for the business cycle, its volatility comes from real shock ranther than monetary shock, which is also consistent with Kydland and Prescott (1990) to the same conclusion.

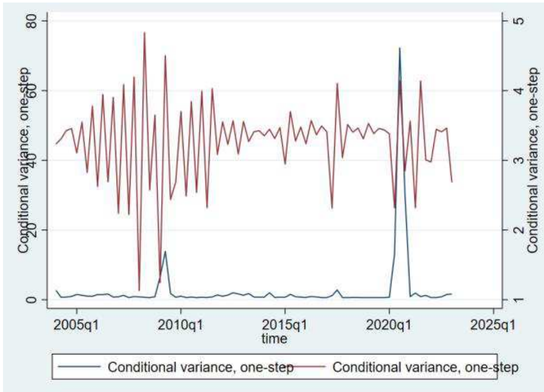
Figure 3 Conditional variance of GARCH (1,1)





(1)Auto_growth and rgdp_growth (2)Auto_growth and gva_growth





(3)Auto_growth and rgdp_growth (4)rgdp_growth and m2_growth

Source: authors' results via Stata

3.3 Empirical Analysis of VAR Model

ADF and PP test

Because the establishment of the VAR model depends on the stationarity of the time series, it is necessary to test the stationarity of the variables before performing VAR modeling on the variables. In this paper, the Augmented Dickey-Fuller (ADF) stationarity test and PP test are two-unit root test methods for the four variables to identify whether each of the above time series is stationary. The results are shown in Table 2. For the four variables, the statistical results are similar when no drift item and trend item, only the drift item and both drift item and trend item are measured respectively. The p-values of the ADF test and PP test results of the automotive output growth rate (auto_growth), real GDP growth rate (rgdp_growth), GVA growth rate (gva_growth) and money supply growth rate (m2_growth) variables are all 0.000, less than 1%, significant at the 1% level, rejecting the null hypothesis of a unit root. Therefore, we can regard that the time series of the Czech car output growth rate, real GDP growth rate, GVA growth rate, and M2 growth rate all have stationary characteristics and can be directly used for subsequent VAR modeling.

Table 2 The results of stationarity test

Variables	ADF test			PP test	
	no	drift	drift and trend	no	drift and trend
auto_growth	-10.733***	-10.733***	-10.671***	-11.207***	-11.144***
rgdp_growth	-7.861***	-7.861***	-7.956***	-7.859***	-7.949***
gva_growth	-8.236***	-8.236***	-8.304***	-8.236***	-8.301***
m2_growth	-9.809***	-9.809***	-9.838***	-9.746***	-9.772***

Note: "**" and "***" indicate that the statistics of the unit root test are significant at the 5% level and 1% level, respectively.

Source: authors' calculation via Stata

VAR model

(1) Automotive output growth rate and real GDP growth rate

First, we combine the time series of automotive output growth rate (auto_growth), which can directly represent the development level of the Czech automotive industry, and the time series of real GDP growth rate (rgdp_growth), which can represent a country's macroeconomic development level and basic operating situation, to construct a binary vector autoregressive VAR (2) model. In order to estimate the VAR model, it is first necessary to determine the lag order of the VAR model according to the information criterion, and the specific results are shown in table Appendix 1.

In table Appendix 1, here are 6 different indicators. And among these indicators, AIC and BIC are the most commonly used, but AIC and FPE may overestimate the lag order. The final result should be viewed in combination with all indicators. As shown in table Appendix 1, the lag orders selected by different information criteria are not consistent (pay attention to the corresponding * mark).

The results show that when building a VAR model for the growth rate of automotive output and the real GDP growth rate, the * standards of LR, FPE, AIC and HQIC all suggest that the optimal order is the fourth order, so we choose the lag order to be the fourth order. And a binary VAR (4) model is established for the time series of automotive output growth rate and real GDP growth rate. The specific model can be expressed as shown in formula (4.1). where a_{ij}, b_{ij}, c_{ij}, d_{ij}, e_i are the parameters to be estimated. The last term εt shock vector is a white noise vector.

$$\begin{pmatrix} auto\_growth_t \\ rgdp\_growth_t \end{pmatrix} = \begin{pmatrix} e_1 \\ e_2 \end{pmatrix} + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} auto\_growth_{t-1} \\ rgdp\_growth_{t-1} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} auto\_growth_{t-2} \\ rgdp\_growth_{t-2} \end{pmatrix} + \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix} \begin{pmatrix} auto\_growth_{t-3} \\ rgdp\_growth_{t-3} \end{pmatrix} + \begin{pmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{pmatrix} \begin{pmatrix} auto\_growth_{t-4} \\ rgdp\_growth_{t-4} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix} \tag{4.1}$$

According to the above equation (4.1), the specific results of the VAR (4) model we constructed for the two are shown in Table 3. When the growth rate of automotive output is an endogenous variable, the p-value of the first-order lag variable of the variable itself is 0.079(less than 10%), and it is significant at the 90% significance level; the p-value of the second-order lag variable is 0.003 (less than 1%), significant at the 1% significance level; the p-value of the fourth-order lag variable is 0.046 (less than 5%), significant at the 5% significance level. The variable’s first-order lag and fourth-order lag have a negative effect on the growth rate of automotive output itself, and the degree is the same, that is, the increase of automotive output in the past period and the past fourth period will cause the decrease of current automotive output. The variable with a two-stage lag has a more obvious positive effect on itself, that is, the change in automotive output with a two-stage lag has a positive effect on the current automotive production.

Of the four lagged variables of the exogenous variable real GDP growth rate, only two variables are significant. The effects of the lagged second-order variable and the lagged third-order variable of real GDP growth rate on the growth rate of automotive output are significant at the significance level of 1% and 5%, respectively. And the two have different influence directions on the growth rate of automotive output. The real GDP growth rate with a lag of the second order has a more obvious negative effect on the growth rate of the automotive industry, but the real GDP growth rate with a lag of the third order has a beneficial effect on the development of automotive output.

Comparing the lagged variables of endogenous variables and exogenous variables, the effect of lagged variables of exogenous variables is more significant. It proves that the past performance of the macroeconomy has a more significant impact on the automotive industry than the past performance of the automotive industry itself, but the direction of the influence is unstable, and it is difficult to judge whether it has a restraining or promoting effect on the development of the industry.

When the two variables are exchanged, which means the real GDP growth rate is used as an endogenous variable, the first-order lag variable and the second-order lag variable of the variable itself are significant at the significance level of 5% and 1%, respectively. But the impact of the two on the real GDP growth rate is the opposite. The variable with a lag of the first order has a positive effect on itself, and the variable with a second lag has a negative effect, and the degree of influence is slightly stronger than that of the first-order variable. The lagged first-order and second-order variables of the growth rate of the exogenous variable automotive output are significant at the 5% and 1% significance levels for the real GDP growth rate, respectively. Among them, the former has a weak negative impact on the real GDP growth rate, and the latter has a weak positive impact on the real GDP growth rate.

Therefore, through this model, it can be found that the past performance of the real

GDP growth rate has a more significant impact on itself and the growth rate of automotive output, on the contrary, the effect of the growth rate of automotive output is weaker.

Table 3 The results of VAR model (auto and rgdp)

		Coef.	Std. Err.	z	P>|z|
auto_growth	auto_growth				
	L1.	-0.3663731	0.2084769	-1.76	0.079
	L2.	0.6079903	0.2079665	2.92	0.003
	L3.	-0.3028838	0.222703	-1.36	0.174
	L4.	-0.332406	0.1665018	-2	0.046
	rgdp_growth				
	L1.	0.3134259	1.245049	0.25	0.801
	L2.	-5.845673	1.417179	-4.12	0.000
	L3.	2.996649	1.582308	1.89	0.058
	L4.	1.299941	1.380725	0.94	0.346
	_cons	3.803929	1.36935	2.78	0.005
rgdp_growth	auto_growth				
	L1.	-0.0733441	0.0361087	-2.03	0.042
	L2.	0.1021238	0.0360203	2.84	0.005
	L3.	-0.01617	0.0385727	-0.42	0.675
	L4.	-0.0027436	0.0288385	-0.1	0.924
	rgdp_growth				
	L1.	0.5418026	0.2156458	2.51	0.012
	L2.	-0.8072829	0.245459	-3.29	0.001
	L3.	0.4225636	0.2740599	1.54	0.123
	L4.	0.0826383	0.2391451	0.35	0.730
	_cons	0.3758096	0.2371749	1.58	0.113

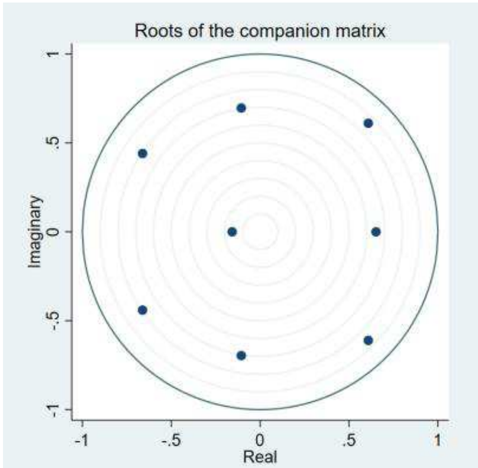
Source: authors' calculation via Stata

To verify the effectiveness of this VAR(4) model, this paper tests its robustness. The results are shown in Figure 4 below. From this figure, it can be observed that all eigenvalues are within the unit root, so the model is stable. We can say the constructed model is reliable. This paper also conducted a residual autocorrelation test on the model (shown in Appendix 2), and the results show that there is no residual sequence autocorrelation, so there is no need to construct an SVAR model.

Next, to have a clearer understanding of the correlation between automotive output and the macroeconomy, this paper conducts a Granger causality test on the two variables based on the VAR model. The null hypothesis of this test is that the "Excluded" term cannot Granger cause the "Equation" term. It should be noted that Granger causality is not a causal relationship in the true sense, but a dynamic correlation, which shows that one variable has "predictability" for another variable. In a sense, it can be considered a necessary condition of causality (if non-linear causality is not considered). At the same time, the Granger causality test is only applicable to the unit root process with a cointegration relationship in the stationary sequence. The variables used in this paper have passed the ADF test and PP test, and are proved to be stationary time series.

The Granger test results for the growth rate of automotive output and real GDP growth rate are shown in Table 4. For the first set of results, the p-value is 0.000 (less than 1%), the result is significant at the 1% significance level, and the null hypothesis can be rejected, so we can see that the real GDP growth rate can Granger cause the growth rate of automotive output. For the second set of results, the p-value is 0.025 (less than 5%), the result is also significant (at the 5% significance level), and the null hypothesis can be rejected, so the growth rate of automotive output can also Granger cause the real GDP growth rate. That is, these two-time series can influence each other. This result can also be used for forecasting. For example, when predicting the growth rate of automotive output, the effect of considering the time series of real GDP growth rate will be better than only considering the time series of the growth rate of automotive output. And vice versa. The result and the results of the VAR model can be mutually confirmed, and both can prove that the macroeconomy has a more obvious impact on the automotive industry, but the automotive industry also has an effect on the macroeconomy.

Figure 4 Robustness test (auto and rgdp)



Source: authors' calculation via Stata

Table 4 The results of Granger test (auto and rgdp)

Equation	Excluded	chi2	df	Prob > chi2
auto_growth	rgdp_growth	23.331	4	0.000
auto_growth	ALL	23.331	4	0.000
rgdp_growth	auto_growth	11.15	4	0.025
rgdp_growth	ALL	11.15	4	0.025

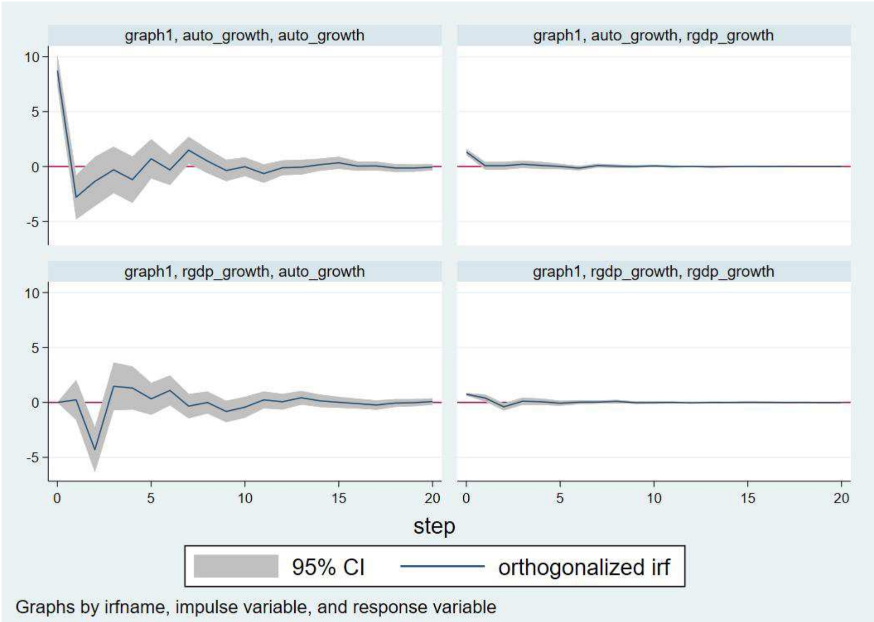
Source: authors' calculation via Stata

Since the VAR model contains many parameters, and the economic significance of some parameters is difficult to explain, this paper continues to use the impulse response function based on the VAR model for analysis to further measure the correlation between the automotive industry and the macroeconomy. This article sets step (20), which is to calculate the impulse response results of 20 periods, each period representing a quarter. The results of the impulse response function analysis are shown in Figure 5, which shows the change path of the shock response over time between the Czech automotive output growth rate time series and the real GDP growth rate time series. This paper draws an orthogonal impulse response diagram. Because non-orthogonal impulse response plots are not meaningful. Among them, the abscissa represents the time interval after the shock, and the ordinate represents the degree of shock response. Figure 4 contains four graphs, which in turn depict the dynamic effect (first row) of the impulse variable on the growth rate of automotive output and the growth rate of real GDP (response variable) using the growth rate of automotive output. And the dynamic effect on the growth rate of automotive output and real GDP growth rate (response variable) with the real GDP growth rate as the impulsive variable (second row).

By analysing Figure 5, it can be found that the growth rate of automotive output has almost no effect on the growth rate of real GDP, but the dynamic effect of the growth rate of automotive output on itself is very obvious. Specifically, after a 1 standard unit positive automotive output growth rate shock occurs, the initial positive effect on the automotive output growth rate variable itself is the most obvious, and the effect is more obvious within 8 periods, but there are fluctuations on the direction of responses to the shock, and not all positive responses are always generated. At the same time, the degree of impact weakens over time, that is, the impact is only temporary and does not have long-term sustainability.

Similarly, looking at the two graphs in the second row of Figure 5, when the real GDP growth rate is used as an impulsive variable, its effect on the variable itself is not obvious, but it has a significant effect on the growth rate of automotive output, and in the figure, the negative shock effect in the third period is the most obvious, with a peak value, and then only fluctuates in a small range and gradually weakens. Similar to the effect of the previous variable, this shock is only temporary and does not have long-term persistence. In general, through the analysis of the impulse response function, it can be found that the growth rate of automotive output is more sensitive to its own response and to the real GDP growth rate. But the real GDP growth rate is barely affected by the shock to the auto output growth rate and the real GDP growth rate itself.

Figure 5 Impulse response function (auto and rgdp)



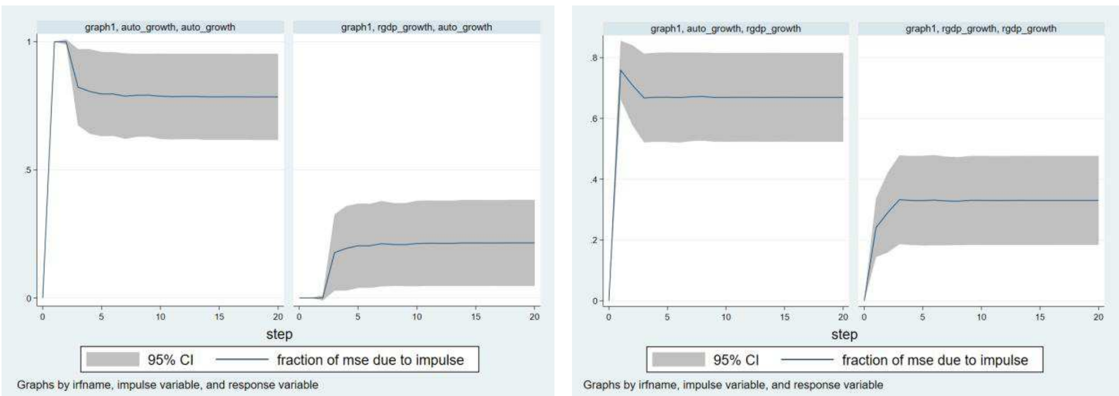
Source: authors' calculation via Stata

One of the uses of the VAR model is forecasting. Finally, this paper uses variance decomposition to analyse the contribution of the influence between the growth rate of automotive output and the growth rate of real GDP. The variance decomposition results of the two are shown in table Appendix 3 and table Appendix 4 (see Appendix). For each row of data, the sum of the contribution proportions to the mean square error of the forecast error is 1. This property is called "Forecast-error Variance Decomposition" (FEVD). It is also called innovation accounting because it attributes the source of forecast error to the orthogonalized innovation of each variable.

Appendix 3 is the result of the variance decomposition of the growth rate of automotive output. Analysing this table, we can find that the forecast variance of the forecast for the growth rate of automotive output for the previous quarter comes entirely from the growth rate of automotive output itself; The contribution is gradually weakening, while the contribution of the real GDP growth rate to the growth rate of automotive production is increasing. Even if the forecast for the 20th quarter is made forward, 78.5% of the forecast variance still comes from the growth rate of automotive output itself. The remaining 21.5% comes from real GDP growth. This means that the growth rate of automotive output is mainly affected by itself, and the variable rgdp_growth has an impact on it, but the effect is significantly smaller than that of the growth rate of automotive output itself. This result can also be shown in Figure 6 (left), which can show this difference more intuitively.

The variance decomposition of the real GDP growth rate is shown in Appendix 4. For the forecast of the real GDP growth rate one quarter ahead, 75.9% of the forecast variance comes from the growth rate of the automotive output variable, and the rest comes from the real GDP growth rate itself. Over time, this ratio gradually decreases and stabilizes in the ninth period. When the forecast is in the 20th period, 66.96% of the forecast variance of the real GDP growth rate comes from the growth rate of automotive output, and 33.04% comes from the real GDP growth rate. The specific diagram is shown in Figure 6 (right). Combining the two sets of results, the growth rate of automotive output will have a greater impact on itself than the real GDP growth rate. The results for real GDP growth rates are similar and stable over time.

Figure 6 Variance decomposition (auto and rgdp)



Source: authors' calculation via Stata

(2) Automotive output growth rate and GVA growth rate

To further analyse the correlation between changes in the Czech automotive industry and changes in the Czech macroeconomy, this paper also measures the correlation between the growth rate of Czech automotive output and the growth rate of Gross Value Added (GVA). GVA is an economic productivity metric, which represents the difference between gross output and net output, and can reflect changes in a country's macroeconomics. According to the ADF test and PP test results above, the auto output growth rate (auto_growth) and Gross Value Added growth rate (gva_growth) sequences are both stationary time series, so we directly construct a binary VAR model for them. Similarly, in order to estimate the VAR model, it is first necessary to determine the order of the VAR model according to the information criterion, and the specific results are shown in Appendix 5. This article takes the higher order as the standard, chooses the standard * of the FPE and AIC criteria, and chooses the lag order as 4th order, and establishes a binary VAR (4) model for the time series of the growth rate of automotive output and the growth rate of GVA. The specific model can be expressed as shown in formula 4.2. where f_{ij}, g_{ij}, h_{ij}, i_{ij}, j_i are the parameters to be estimated. The last term ε_{t2} shock vector is a white noise vector.

$$\begin{pmatrix} auto\_growth_t \\ gva\_growth_t \end{pmatrix} = \begin{pmatrix} j_1 \\ j_2 \end{pmatrix} + \begin{pmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{pmatrix}\begin{pmatrix} auto\_growth_{t-1} \\ gva\_growth_{t-1} \end{pmatrix} + \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix}\begin{pmatrix} auto\_growth_{t-2} \\ gva\_growth_{t-2} \end{pmatrix} +$$
$$\begin{pmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{pmatrix}\begin{pmatrix} auto\_growth_{t-3} \\ gva\_growth_{t-3} \end{pmatrix} + \begin{pmatrix} i_{11} & i_{12} \\ i_{21} & i_{22} \end{pmatrix}\begin{pmatrix} auto\_growth_{t-4} \\ gva\_growth_{t-4} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t,2} \\ \varepsilon_{2,t,2} \end{pmatrix}$$

（4.2）

According to the above equation (4.2), the specific results of the VAR (4) model we constructed for this set of variables are shown in Table 5. When the growth rate of automotive output is an endogenous variable, only the second-order lagged variable of the automotive output growth rate variable is significant at the 10% significance level, and the other lagged orders are not significant. The GVA growth rate presents similar results to the auto industry output growth rate variable itself. Likewise, only the lagged second-order variable is significant at the 1% level. However, the degree and direction of their effects on the growth rate of automotive output are different. That is to say, the growth rate of GVA in the past had a more obvious inhibitory effect on the growth of automotive output. However, the past automotive output has a weak role in promoting the growth of future automotive output.

When the two are exchanged and the GVA growth rate is used as an endogenous variable, the variable of the automotive output growth rate lagging two orders is significant at the 95% significance level. But the coefficient is small. This means that past changes in car production have only marginally boosted GVA. The lagged second-order variable of the GVA growth rate itself is significant at the 1% significance level, and has a negative effect on the variable itself, but the effect is still weak. In general, compared with the results of the first set of automotive output growth rate and real GDP growth rate, when GVA is used to measure the level of macroeconomic development, the relationship between the automotive industry and the macroeconomy observed with the help of the VAR model is weaker.

Table 5 The results of VAR model (auto and gva)

		Coef.	Std. Err.	z	P>|z|
auto_growth	auto_growth				
	L1.	-0.1843869	0.2143872	-0.86	0.39
	L2.	0.3937107	0.2145234	1.84	0.066
	L3.	-0.2557423	0.2250032	-1.14	0.256
	L4.	-0.2431887	0.1674871	-1.45	0.147
	gva_growth				
	L1.	-1.123137	1.224523	-0.92	0.359
	L2.	-3.815125	1.386173	-2.75	0.006
	L3.	2.250519	1.482174	1.52	0.129
	L4.	0.6322363	1.310675	0.48	0.63
	_cons	4.127347	1.432518	2.88	0.004

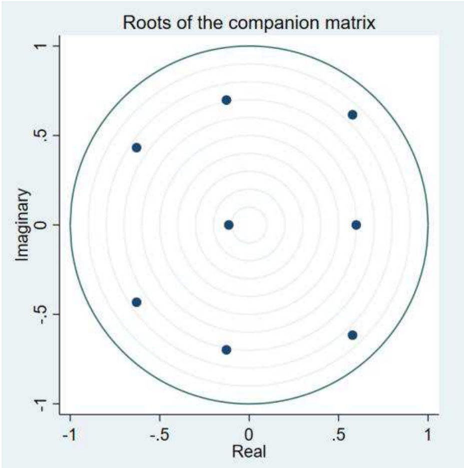
gva_growth	auto_growth				
	L1.	-0.0468494	0.0381997	-1.23	0.22
	L2.	0.0929852	0.038224	2.43	0.015
	L3.	-0.013728	0.0400913	-0.34	0.732
	L4.	0.0095918	0.029843	0.32	0.748
	gva_growth				
	L1.	0.3113875	0.2181865	1.43	0.154
	L2.	-0.6342398	0.2469894	-2.57	0.01
	L3.	0.3892289	0.2640951	1.47	0.141
	L4.	0.0336679	0.2335372	0.14	0.885
	_cons	0.4202788	0.2552472	1.65	0.1

Source: authors' calculation via Stata

Similar to the analysis of the first set, in order to verify the effectiveness of the VAR model, this paper tests its robustness. The results shown in Figure 7 below show that the model is reliable. And this paper also shows the residual autocorrelation test of this set of models in Appendix 6. The results show that there is no residual serial autocorrelation, so there is no need to construct a SVAR model.

Furthermore, we perform the Granger causality test on the two variables. The results show that for the first set of results, the p-value is 0.005 (less than 1%), which is significant at the 1% level, and the null hypothesis can be rejected. Therefore, the GVA growth rate Granger causes the growth rate of automotive output, meaning that the GVA growth rate can influence the growth rate of automotive output, which is significant for predicting automotive output. This finding is similar to the result for real GDP. However, the results for the second set are not significant, and we cannot establish that the growth rate of automotive output Granger causes the GVA growth rate. The results of the Granger test differ from those of the real GDP and automotive output set.

Figure 7 Robustness test (auto and gva)



Source: authors' calculation via Stata

Table 6 The results of Granger test (auto and gva)

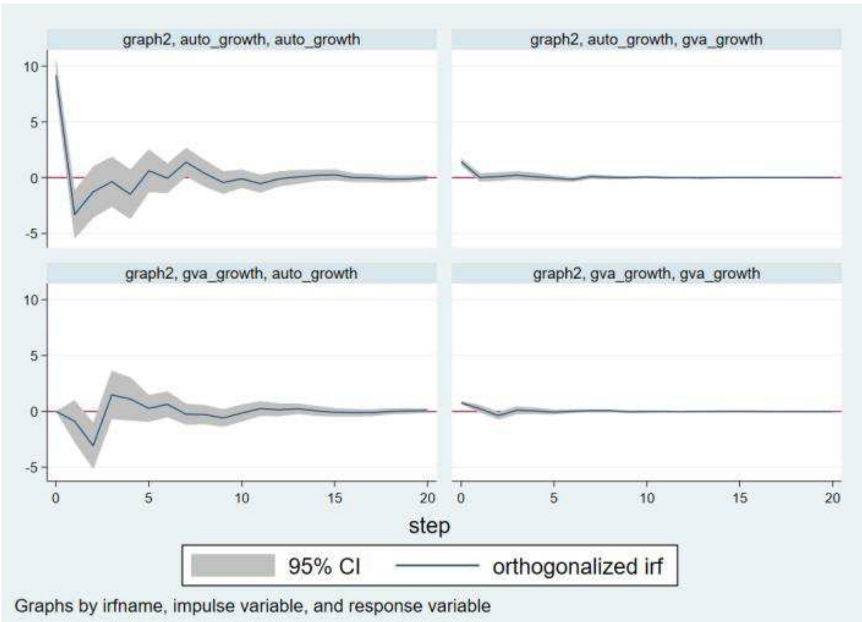
Equation	Excluded	chi2	df	Prob > chi2
auto_growth	gva_growth	14.907	4	0.005
auto_growth	ALL	14.907	4	0.005
gva_growth	auto_growth	7.0951	4	0.131
gva_growth	ALL	7.0951	4	0.131

Source: authors' calculation via Stata

Then, based on the VAR model, we analysed the impulse response function of this set of variables. This paper still sets step (20) for it. The results of the impulse response analysis are shown in Figure 8, which shows the change path of the shock response over time between the Czech automotive output growth rate time series and the GVA growth rate time series. The four graphs included in Figure 8, in turn, depict the dynamic effect (first row) of the growth rate of vehicle output and the growth rate of GVA (response variable) with the growth rate of vehicle output as the impulsive variable.

And the second row shows the dynamic effect on the growth rate of automotive output and the growth rate of GVA (response variable) with GVA growth rate as the impulsive variable. When the growth rate of automotive output is taken as the impulsive variable, the results are consistent with the results shown in Figure 5; When the GVA growth rate is the impulsive variable, that is, when one unit of positive impact is given to the GVA growth rate, it has almost no effect on its variable. On the other hand, the shock effect on the growth rate of automotive output is almost the same as the shock effect of the real GDP growth rate on automotive output, and it does not have long-term sustainability. That is to say, for the results of the impulse response function, using real GDP and GVA to represent the macroeconomic trend is more consistent with the results of the automotive industry.

Figure 8 Impulse response function (auto and gva)

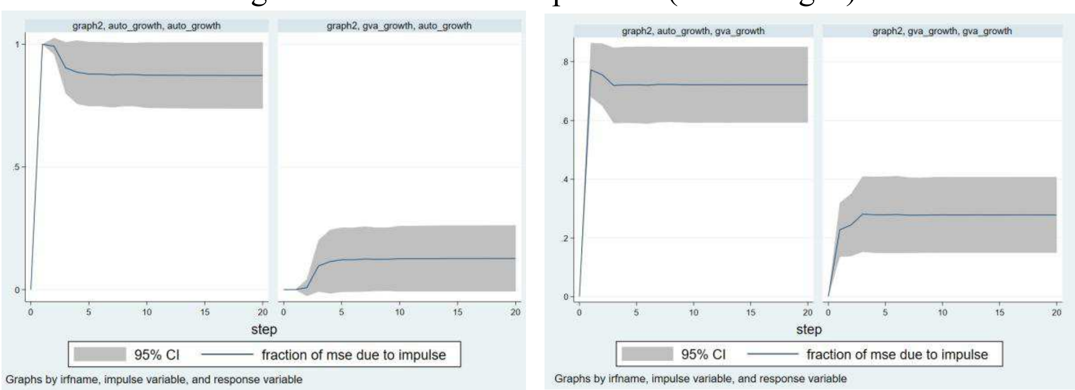


Source: authors' calculation via Stata

Secondly, this paper uses variance decomposition to analyse the relationship between the growth rate of automotive output and the growth rate of GVA. The variance decomposition results for the two are shown in Appendix 7 and Appendix 8 (see Appendix). According to Appendix 7, it can be found that the forecast variance of the forecast for the growth rate of automotive output one quarter ahead comes entirely from the growth rate of automotive output itself, which is consistent with the results of the first set of analysis; as time goes by, the contribution of automotive output growth rate to its own influence gradually weakens, while the contribution of real GDP growth rate to the influence of automotive output growth rate continues to increase. Even if the forecast for the 20th quarter is made forward, 87.3% of the forecast variance comes from the growth rate of automotive output itself, and the remaining 12.3% comes from the GVA growth rate, which is smaller than the real GDP growth rate. This means that the variable, GVA growth rate, has less influence on the growth rate of automotive output than the real GDP growth rate. And it is also significantly smaller than the influence of the growth rate of automotive output itself. This result can be more intuitively shown in Figure 9 (left one).

The variance decomposition of the GVA growth rate is shown in Appendix 8. For the forecast of the GVA growth rate for the first quarter, 77.2% of the forecast variance comes from the growth rate of automotive output, which is similar to the results of the real GDP growth rate. Over time, this ratio gradually decreases and becomes stable in the 4th period. When the forecast is 20th period, 72.16% of the GVA growth rate forecast variance comes from the growth rate of automotive output, and 27.84% comes from the GVA growth rate itself. This gap is also smaller than the first set (auto_growth and rgdp_growth). The specific illustration is shown in Figure 9 (right one).

Figure 9 Variance decomposition (auto and gva)



Source: authors' calculation via Stata

(3) Automotive output growth rate and M2 growth rate

As a pillar industry in the Czech Republic, macroeconomic policies may have a direct or indirect effect on the automotive industry. This paper takes monetary policy as an example to measure the correlation between the automotive industry and macroeconomic policies, and to observe the mutual influence between the two, in order to observe whether the monetary policy has a regulatory effect on the development of the automotive industry and whether changes in the automotive industry affect the formulation of macroeconomic policies. According to the above, this article uses the broad money supply (M2) to represent monetary policy. According to the previous ADF test and PP test, we know that the growth rate of money supply (m2_growth) is a stable time series. And we use the time series of growth rate (auto_growth) and the time series of M2 growth rate (m2_growth) jointly to construct a binary VAR model.

The basis for determining the order of the model can be found in Appendix 9. From the results in the table, it can be found that the * standard of the LR, FPE, AIC, and HQIC indicators all suggest a lag of 4th order, so we choose the lagging order as 4th order to increase the output of auto. A binary VAR (4) model is established for the time series of the automotive output growth rate and the M2 growth rate. The specific model can be expressed as shown in formula (4.3). where l_{ij}, m_{ij}, n_{ij}, o_{ij}, and p_i are the parameters to be estimated. The last term ε_{t3} shock vector is a white noise vector.

$$\begin{pmatrix} auto\_growth_t \\ m2\_growth_t \end{pmatrix} = \begin{pmatrix} p_1 \\ p_2 \end{pmatrix} + \begin{pmatrix} l_{11} & l_{12} \\ l_{21} & l_{22} \end{pmatrix} \begin{pmatrix} auto\_growth_{t-1} \\ m2\_growth_{t-1} \end{pmatrix} + \begin{pmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{pmatrix} \begin{pmatrix} auto\_growth_{t-2} \\ m2\_growth_{t-2} \end{pmatrix} + \begin{pmatrix} n_{11} & n_{12} \\ n_{21} & n_{22} \end{pmatrix} \begin{pmatrix} auto\_growth_{t-3} \\ m2\_growth_{t-3} \end{pmatrix} + \begin{pmatrix} o_{11} & o_{12} \\ o_{21} & o_{22} \end{pmatrix} \begin{pmatrix} auto\_growth_{t-4} \\ m2\_growth_{t-4} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t3} \\ \varepsilon_{2,t3} \end{pmatrix} \tag{4.3}$$

According to the above equation (4.3), the specific results of the VAR (4) model we constructed are shown in Table 7. When the growth rate of automotive output is an endogenous variable, the variables of the first-order lag, second-order lag, and fourth-order lag variables are significant at the significance levels of 5%, 10%, and 1%, respectively. And the three have the same direction of influence on automotive output, all of which are negative. This means the good performance of the auto industry in the past has an inhibitory effect on future performance. Looking at the absolute value of the coefficients, the three have a relatively weak influence on the endogenous variable itself.

The lagged first-order and lagged fourth-order variables of the exogenous variable M2 growth rate are significant at the 10% significance level and have a negative effect on the growth rate of automotive output. The second-order lag variable is significant at the 5% significance level, which has a positive effect on the growth rate of automotive output, and the three variables have similar degrees of effects on the growth rate of automotive output. The effect of the growth rate of output is stronger than that of the lagged variable of the growth rate of auto output itself. That is, when the money supply changes, it will have a significant impact on the automotive industry, but the specific direction of the impact fluctuates.

When the two are exchanged and the M2 growth rate is used as an endogenous variable, only the fourth-order lagged variable is significant at the 1% level, which has a weak positive effect on the M2 growth rate. When the growth rate of automotive output is used as an exogenous variable, its lagging variables are not significant to the growth rate of M2. This means that the Czech monetary policy itself is relatively stable and is almost independent of the corresponding monetary policy in the previous period or the performance of the country's internal core industry.

To sum up, this paper analyses the growth rate of automotive output and the growth rate of M2 through the VAR model and finds that the growth rate of M2 has a significant impact on the growth rate of automotive output, but on the contrary, no influence is observed. The correlation performance of this set shows that there is a difference between the behavior of the Czech automotive industry and the macroeconomy observed with the previous two sets.

Table 7 The results of VAR model (auto and m2)

		Coef.	Std. Err.	z	P>|z|
auto_growth	auto_growth				
	L1.	-0.2397432	0.1097967	-2.18	0.029
	L2.	-0.216788	0.112721	-1.92	0.054
	L3.	-0.120871	0.1142233	-1.06	0.29
	L4.	-0.3063056	0.1115179	-2.75	0.006
	m2_growth				
	L1.	-1.173223	0.6568003	-1.79	0.074
	L2.	1.477426	0.6778101	2.18	0.029
	L3.	-0.1653737	0.6688204	-0.25	0.805
	L4.	-1.114517	0.6624591	-1.68	0.092
	_cons	6.109242	2.611126	2.34	0.019
m2_growth	auto_growth				
	L1.	-0.0030901	0.016736	-0.18	0.854
	L2.	0.0268366	0.0171818	1.56	0.118
	L3.	0.0211337	0.0174108	1.21	0.225
	L4.	0.0123104	0.0169984	0.72	0.469
	m2_growth				
	L1.	0.0082299	0.1001144	0.08	0.934
	L2.	0.1294676	0.1033169	1.25	0.21
	L3.	-0.11492	0.1019466	-1.13	0.26
	L4.	0.5099478	0.100977	5.05	0
	_cons	0.7603697	0.3980075	1.91	0.056

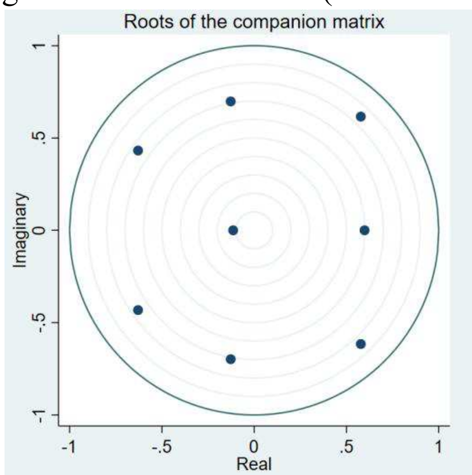
Source: authors' calculation via Stata

In this paper, the robustness of this set of data is also tested, and the results are shown in Figure 10 below. All the eigenvalues are within the unit root, so the model is stable and the results are reliable. This paper also shows the residual autocorrelation test of this set of models in Appendix 10. The results show that there is no residual serial autocorrelation, so there is no need to construct a SVAR model.

Subsequently, we perform the Granger causality test on the two variables, and the results show that for the first set of results, the p-value is 0.048 (less than 5%), which is significant at the 5% significance level, and the null hypothesis can be rejected. Therefore, the increase in the M2 growth rate Granger causes the growth rate of automotive output. However, the results of the second set are not significant, which cannot prove that the growth rate of automotive output Granger causes the growth rate of M2.

Based on the results of the Granger test, we can conclude that changes in the money supply can influence the output of vehicles, and it is meaningful for predicting the performance of the automotive industry. However, the opposite is not hold, meaning that macroeconomic policies have an impact on the automotive industry, but changes in the automotive industry are not sufficient to have a significant effect on a country's macroeconomic policy formulation. This conclusion is also consistent with the results obtained from the VAR model analysis.

Figure 10 Robustness test (auto and m2)



Source: authors' calculation via Stata

Table 8 The results of Granger test (auto and m2)

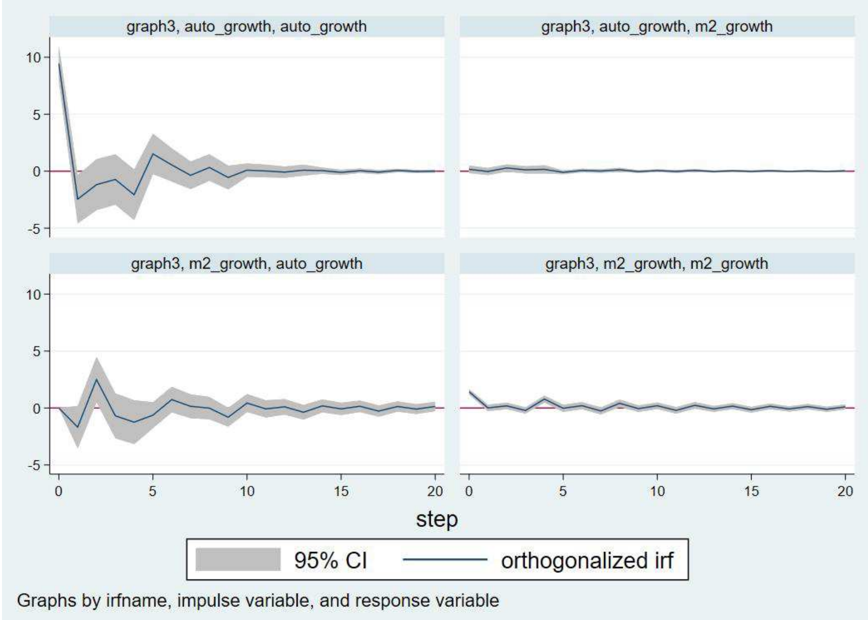
Equation	Excluded	chi2	df	Prob>chi2
auto_growth	m2_growth	9.562	4	0.048
auto_growth	ALL	9.562	4	0.048
m2_growth	auto_growth	3.6735	4	0.452
m2_growth	ALL	3.6735	4	0.452

Source: authors' calculation via Stata

Similarly, based on the above analysis, this paper analyses the impulse response function of this set of variables. We still set step to 20. The results of the impulse response analysis are shown in Figure 11, which shows the change path of the shock response over time between the Czech automotive output growth rate time series and the M2 growth rate time series. In the first row of Figure 11, the growth rate of automotive output is used as the impulse variable. The dynamic effect on the growth rate of automotive output and M2 growth rate (response variable) is similar to the results of the previous two sets, and will not be repeated here.

In the second row, when the growth rate of M2 is taken as the impulse variable, a shock is given to it, which has a significant shock effect on the growth rate of automotive output, and reaches its peak in the third period, and the subsequent effect gradually weakens, but the persistence is strong. Moreover, the direction of the impact continues to fluctuate and is not fixed, which is consistent with the analysis results of the VAR model. On the other hand, m2_growth has a continuous but not severe impact on its existence, and the overall fluctuation is maintained at a positive level. This result is different from the results of the rgdp_growth and gva_growth sets.

Figure 11 Impulse response function (auto and m2)



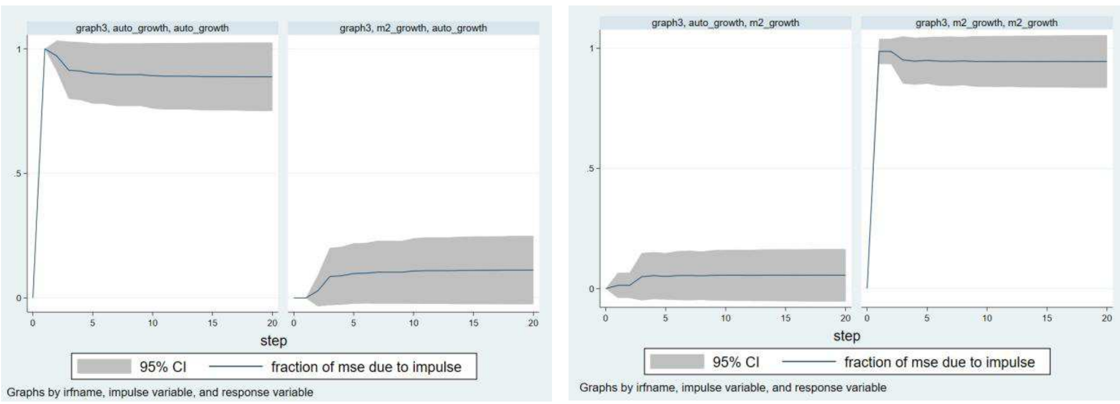
Source: authors' calculation via Stata

Finally, the forecast variance of the growth rate of the initial production of vehicles and the growth rate of the money supply is decomposed to further evaluate the importance of the impact of the growth of automotive production and the growth of the money supply. The variance decompositions for the two are shown in Appendix 11 and Appendix 12 (see Appendix).

According to table Appendix 11, it can be found that the forecast variance of the forecast for the growth rate of automotive output one quarter ahead comes entirely from the growth rate of automotive output itself, which is consistent with the results of the previous two sets of results analysis; as time goes by, although the contribution of Czech's auto output growth rate to its impact is gradually weakening, until the forecast for the 20th quarter is made, 88.8% of the forecast variance still comes from the auto output growth rate itself, and the remaining 11.2% comes from the M2 growth rate. The proportion gap is the largest among the three sets, which proves that the growth rate of money supply has the least contribution to the growth rate of automotive output. This result can be more intuitively shown in Figure 12 (left). Moreover, this result is consistent with the analysis results of the VAR model.

The variance decomposition of the M2 growth rate is shown in Appendix 12. This result is significantly different from the macroeconomic results represented by the real GDP growth rate and the GVA growth rate. From the perspective of variance decomposition, the former two can be observed that most of the contribution comes from the automotive output part. However, for M2, most of the contribution comes from itself. Until the 20th period, the forecast variance of the M2 growth rate is 94.5% from itself. It proves that from the perspective of forecasting, the Czech auto industry can hardly have any influence on the formulation of monetary policy, and monetary policy has strong independence. This conclusion is consistent with the analysis results of the VAR model, Granger test, and impulse response.

Figure 12 Variance decomposition (auto and m2)



Source: authors' calculation via Stata

Summary

Through the above analysis, we can find that different methods focus on different points, and the results are different. Take set (1) of the results as an example: the results observed by the VAR model show that the real GDP has a stronger impact on the auto industry than the auto industry has on itself, and the real GDP has a stronger impact on itself than the auto industry has on the real GDP more obvious. However, variance decomposition leads to an opposite conclusion. The variance decomposition results of auto_growth and rgdp_growth both show that the auto industry accounts for a larger proportion. This paper argues that this is mainly because the models focus on different information. The VAR model pays more attention to the dynamic linear relationship between variables, but the variance decomposition provides the contribution of variables to the overall volatility, so the results of the two may be inconsistent. However, the results can prove that although there is a correlation between the two variables, the correlation is not symmetrical. Based on this, referring to the results of the Granger test, the analysis of the impulse effect function, and the results of set (2) using GVA to represent the macroeconomic situation), this paper concludes that the macroeconomic impact on the Czech auto industry is stronger than the impact of the auto industry on the macroeconomy.

However, for set (3), when macroeconomic policies are considered, the different models used in this paper give consistent results. It proves that the effect of monetary policy on the auto industry is more obvious. On the contrary, the influence of the auto industry on monetary policy is rarely observed. In addition, the past information of monetary policy has a weak but long-lasting impact on the variable itself.

CHAPTER 4 Conclusion

Through the above analysis, this paper mainly studies the correlation between the Czech automotive industry output cycle and the business cycle. The relationship between the industrial cycle and the business cycle has always been a topic of much concern in the field. As a durable goods industry, the automotive industry has cyclical characteristics and is an important global industry, so it has attracted much attention. For Europe, this industry is a critical part of the entire European industry. However, affected by historical and geographical factors, the automotive industry in Central and Eastern Europe has different characteristics from Western Europe. Although it has become a necessary part of the national economy of many countries in Central and Eastern Europe, its development still faces many problems and challenges. In addition, due to the influence of national conditions in specific countries, there may be differences in the relationship between their industries and macroeconomics, and specific issues should be analysed in detail.

In the Czech Republic, one of the representative countries in Central and Eastern Europe, the automotive industry has played a vital role in the development of the national economy. It is a pillar industry of the country and has a significant impact on economic development. Therefore, this paper takes the Czech Republic as the research object and aims to analyse whether the development of the automotive industry and the macroeconomy affect each other, namely: whether changes in the macroeconomic trend have an impact on the improvement of the Czech automotive industry, and in turn, whether the improvement of the Czech automotive industry essential enough to have a noticeable impact on the Czech macroeconomy.

Specifically, in the analysis process, the research content of this paper can be divided into three parts. In the first part, this paper analyses the volatility of the automotive industry cycle and the business cycle. The second part mainly studies the correlation between the development of the Czech automotive industry and the macroeconomy. This paper refers to the literature of past scholars, selects two economic variables to represent the situation of the Czech macroeconomy, and compares the results of the two sets. In the third part, this paper examines the correlation between the development of the Czech automotive industry and macroeconomic policies and analyses it using the broad money supply (M2) as a representative.

The data frequency selected in this paper is quarterly data, and the time range is 2004Q1-2023Q1. The following four variables are selected: the growth rate of automotive output representing the performance of the automotive industry, the growth rate of real GDP and GVA representing the macroeconomy, and the M2 growth rate representing economic policy.

First, this paper constructs a GARCH (1,1) model for each time series, and obtains the conditional variance of each variable to observe the volatility. The results show that the fluctuation trends of the automotive industry cycle and the business cycle are consistent, and both of them show more obvious fluctuations during the financial crisis and pandemic. However, the fluctuation of the automotive industry cycle has a delay, and it is not at the same time as the fluctuation of the business cycle. The volatility of money supply M2 presents its periodic characteristics, but abnormal fluctuations can also be observed during the above two crises.

Secondly, this paper constructs three binary VAR models by taking the growth rate of automotive output and the real GDP growth rate, GVA growth rate, and M2 growth rate in turn. At the same time, this paper also carried out the robustness test, Granger causality test, impulse response function analysis, and variance decomposition for each set of variables. Among them, the VAR model can identify the direction and degree of influence of the endogenous variable itself and the lag variable of the exogenous variable on the endogenous variable; Granger causality detection can identify the relationship between time series, and then consider whether adding another variable to the predicted variable would be helpful for the prediction. In terms of prediction, the role of variance decomposition is more specific, and it can predict the proportion of different variables affecting a variable in a certain period in the future, while the analysis of impulse response function focuses on the effect of the variable on itself and another variable, once a certain variable is given an impact. Therefore, based on the above-mentioned models and analysis methods, this paper observes the mutual influence relationship and prediction effect between each set of variables from multiple angles.

The results show that when considering the development of the Czech automotive industry and the macroeconomy, the output change trend of the Czech automotive industry is consistent with the trend of the Czech national macroeconomic situation, but the volatility of the automotive industry is greater than that of the macroeconomy. In other words, the Czech automotive industry is more vulnerable to external shocks than overall macroeconomic trends. When we consider the correlation, the results from the VAR models can identify that there is the correlation between the automotive industry output cycle and the business cycle, however, their correlation is asymmetric. On the one hand, the macroeconomy of the Czech Republic has an obvious influence and impact on the country's auto industry. In the short term, the macroeconomic situation in the past mainly hurt the future progress of the automotive industry, but as time went on, the effect gradually weakened and was not sustainable. On the other hand, this paper also observes that the automotive industry has an impact on the macroeconomy, but the impact is weaker, and the significance of the GVA set is weaker than that observed in the real GDP set.

For the prediction of a certain variable, the results obtained by the VAR model and the variance decomposition are different. For automotive output, the coefficient of the VAR model shows that the influence of the macroeconomy is stronger than the automotive output itself, but the results of variance decomposition show that in the composition of the forecast variance, the proportion of the automotive output variable itself plays a decisive role. As far as the macroeconomy is concerned, the results demonstrate that whether it is itself or the automotive industry, the impact on the macroeconomy is weak, and the past impact is not obvious enough. When an impact is added to it, the impact on variables is also small. Therefore, compared with the automotive industry, the macroeconomic trend is more stable. Combining the two sets of results and different methods, this paper believes that there is a correlation between the Czech auto industry and the macroeconomy, but the correlation is not symmetrical. Specifically, the macroeconomy has a stronger impact on the auto industry.

This paper also considers the correlation between the Czech automotive industry and macroeconomic policies. The results show that the correlation between macroeconomic policies and the advancement of the automotive industry is poor, and the asymmetry is more obvious. That is to say, the macroeconomic policy has an obvious effect on the development of the automotive industry, which may be transmitted to the industry through the level of corporate funds and consumer demand. It is mainly reflected in the fact that if the money supply is increased and the credit level is expanded, the Czech automotive Industry will have a positive development. Correspondingly, reducing the money supply level will also negatively impact automotive production. However, the automotive industry has almost no influence on macroeconomic policies. This result is specifically reflected in the fact that there is only unilateral Granger causality among the variables, and the effect of the automotive industry on M2 policies cannot be identified. And if only the M2 variable itself is considered, based on the variance decomposition, most of the information comes only from the variable itself. This means that the Czech central bank has little influence from developments in the automotive industry when setting monetary policy. In other words, although the Czech automotive industry has played a vital role in the economic development of the Czech Republic, driving the Czech industrial development, employment, and technological progress, a specific industry will not affect the formulation of national macroeconomic policies, which also proves that stability of the Czech monetary policy.

In summary, the results of this paper show that the Czech Republic's auto industry cycle and business cycle share similar trends and patterns. While talking about the co-movements, the automotive industry output cycle keeps lagging behind the business cycle. Further analysis found that there is a correlation between the performance of the Czech auto industry and the macroeconomy, while the correlation is asymmetrical and does not have long-term sustainability; for macroeconomic policies, the asymmetry is more obvious, and the monetary policy has shown greater independence, with little influence from core industry. This paper analyses the relationship between Czech core industry and economic situations from the perspective of interrelationship as well as considering monetary policy, on which no one in this field has conducted similar research of Czech. At the same time, this article still has questions about the direction in which macroeconomics specifically affects the automotive industry. Therefore, this will be the author's further research direction.

This paper aims to provide evidence and reference ideas for the Czech automotive industry to fit in and utilize the economic situation while insisting on a development strategy suitable for itself. It also aims to provide assistance to scholar and researchers interested in topics such as the automotive industry, the relationship between the industry cycle and business cycle, and industry and economic policies.

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List of Appendices

Appendix 1 Results of the number of lags (auto and rgdp)

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-369.966				164.987	10.7816	10.8073	10.8464
1	-346.907	46.118	4	0	94.9684	10.2292	10.3063	10.4235*
2	-341.556	10.702	4	0.03	91.3585	10.19	10.3185	10.5138
3	-337.014	9.0848	4	0.059	90.0136	10.1743	10.3542	10.6276
4	-327.504	19.02*	4	0.001	76.8483*	10.0146*	10.2458*	10.5974
5	-326.249	2.5091	4	0.643	83.4217	10.0942	10.3768	10.8065
6	-324.679	3.1399	4	0.535	89.8347	10.1646	10.4986	11.0065
7	-322.692	3.9739	4	0.41	95.7087	10.223	10.6083	11.1943
8	-319.794	5.7971	4	0.215	99.4679	10.2549	10.6916	11.3558
8	-319.794	5.7971	4	0.215	99.4679	10.2549	10.6916	11.3558

Source: authors' calculation via Stata

Appendix 2 Results of residual series autocorrelation（auto and rgdp）

lag	chi2	df	Prob>chi2
1	1.2324	4	0.87273
2	3.2659	4	0.51435
3	3.2338	4	0.51949
4	2.3525	4	0.67124
5	1.4004	4	0.84413
6	2.274	4	0.68551
7	2.093	4	0.71865
8	3.8202	4	0.43089

Note: H0: no autocorrelation at lag order

Source: authors' calculation via Stata

Appendix 3 Variance decomposition (auto - auto and rgdp)

	(1)	(2)
step	auto_growth	rgdp_growth
0	0	0
1	1	0
2	0.999357	0.000643
3	0.822619	0.177381
4	0.806229	0.193771
5	0.796068	0.203932
6	0.796214	0.203786
7	0.78793	0.21207
8	0.79125	0.20875
9	0.791699	0.208301
10	0.787284	0.212716
11	0.786013	0.213987
12	0.786414	0.213586
13	0.786411	0.213589
14	0.785184	0.214816
15	0.785094	0.214906
16	0.785307	0.214693
17	0.785234	0.214766
18	0.784864	0.215136
19	0.784874	0.215126
20	0.784905	0.215095

Note：(1) irfname = graph1, impulse = auto_growth, and response = auto_growth

(2) irfname = graph1, impulse = rgdp_growth, and response = auto_growth

Source: authors' calculation via Stata

Appendix 4 Variance decomposition (rgdp - auto and rgdp)

	(1)	(2)

step	auto_growth	rgdp_growth
0	0	0
1	0.759389	0.240611
2	0.709933	0.290067
3	0.667516	0.332484
4	0.669857	0.330143
5	0.670102	0.329898
6	0.668921	0.331079
7	0.671423	0.328577
8	0.672094	0.327906
9	0.669665	0.330335
10	0.669569	0.330431
11	0.669889	0.330111
12	0.669887	0.330113
13	0.669605	0.330395
14	0.669705	0.330295
15	0.669729	0.330271
16	0.66966	0.33034
17	0.669619	0.330381
18	0.669646	0.330354
19	0.669651	0.330349
20	0.669631	0.330369

Note：(1) irfname = graph1, impulse = auto_growth, and response = rgdp_growth

irfname = graph1, impulse = rgdp_growth, and response = rgdp_growth

Source: authors' calculation via Stata

Appendix 5 Results of the number of lags (auto and gva)

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0				-371.83	174.145	10.8356	10.8613	10.9004

1	-349.768	44.123	4	0	103.18	10.3121	10.3892*	10.5064*
2	-346.356	6.8242	4	0.145	104.995	10.3292	10.4576	10.6529
3	-343.286	6.1404	4	0.189	107.96	10.3561	10.5359	10.8094
4	-333.746	19.079	4	0.001	92.0913*	10.1955*	10.4268	10.7784
5	-333.009	1.4748	4	0.831	101.478	10.2901	10.5727	11.0024
6	-332.075	1.8679	4	0.76	111.313	10.379	10.713	11.2208
7	-327.128	9.8939*	4	0.042	108.84	10.3515	10.7369	11.3229
8	-326.444	1.3676	4	0.85	120.615	10.4477	10.8844	11.5485
7	-327.128	9.8939*	4	0.042	108.84	10.3515	10.7369	11.3229
8	-326.444	1.3676	4	0.85	120.615	10.4477	10.8844	11.5485

Source: authors' calculation via Stata

Appendix 6 Results of residual series autocorrelation (auto and gva)

lag	chi2	df	Prob>chi2
1	1.2464	4	0.87039
2	1.523	4	0.82257
3	3.0037	4	0.5572
4	3.3402	4	0.50259
5	0.4345	4	0.97955
6	2.8889	4	0.57659
7	2.3885	4	0.6647
8	3.813	4	0.43191

Source: authors' calculation via Stata

Appendix 7 Variance decomposition (auto - auto and gva)

	(1)	(2)
step	rgdp_growth	gva_growth
0	0	0
1	1	0

2	0.991997	0.008003
3	0.903826	0.096174
4	0.885898	0.114102
5	0.878468	0.121532
6	0.878325	0.121675
7	0.875219	0.124781
8	0.876784	0.123216
9	0.876316	0.123684
10	0.873909	0.126091
11	0.873749	0.126251
12	0.873585	0.126415
13	0.873439	0.126561
14	0.873013	0.126987
15	0.873037	0.126963
16	0.873056	0.126944
17	0.872938	0.127062
18	0.872841	0.127159
19	0.872856	0.127144
20	0.872855	0.127145

Note：(1) irfname = graph2, impulse = auto_growth, and response = auto_growth

(2) irfname = graph2, impulse = gva_growth, and response = auto_growth

Source: authors' calculation via Stata

Appendix 8 Variance decomposition (gva - auto and gva)

	(1)	(2)
step	auto_growth	gva_growth
0	0	0
1	0.772424	0.227576
2	0.755775	0.244225

3	0.719235	0.280765
4	0.721104	0.278896
5	0.721288	0.278712
6	0.720398	0.279602
7	0.72272	0.27728
8	0.722629	0.277371
9	0.721715	0.278285
10	0.721466	0.278534
11	0.721677	0.278323
12	0.721673	0.278327
13	0.721555	0.278445
14	0.721635	0.278365
15	0.72162	0.27838
16	0.721578	0.278422
17	0.721574	0.278426
18	0.721587	0.278413
19	0.721588	0.278412
20	0.721578	0.278422

Note：(1) irfname = graph2, impulse = auto_growth, and response = gva_growth

(2) irfname = graph2, impulse = gva_growth, and response = gva_growth

Source: authors' calculation via Stata

Appendix 9 Results of the number of lags (auto and m2)

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-403.482				435.872	11.7531	11.7788	11.8179*
1	-399.23	8.503	4	0.075	432.752	11.7458	11.8229	11.9401
2	-392.848	12.766	4	0.012	404.033	11.6767	11.8052	12.0005
3	-391.938	1.8198	4	0.769	442.285	11.7663	11.9461	12.2196
4	-374.98	33.916*	4	0	304.28*	11.3907*	11.6219*	11.9735

5	-374.4	1.1586	4	0.885	336.836	11.4899	11.7725	12.2022
6	-373.414	1.973	4	0.741	368.916	11.5772	11.9112	12.419
7	-372.487	1.8538	4	0.763	405.302	11.6663	12.0517	12.6376
8	-371.84	1.2937	4	0.862	449.63	11.7635	12.2002	12.8643

Source: authors' calculation via Stata

Appendix 10 Results of residual series autocorrelation (auto and m2)

lag	chi2	df	Prob>chi2
1	1.2464	4	0.87039
2	1.523	4	0.82257
3	3.0037	4	0.5572
4	3.3402	4	0.50259
5	0.4345	4	0.97955
6	2.8889	4	0.57659
7	2.3885	4	0.6647
8	3.813	4	0.43191

Source: authors' calculation via Stata

Appendix 11 Variance decomposition (auto - auto and m2)

	(1)	(2)
step	auto_growth	m2_growth
0	0	0
1	1	0
2	0.971292	0.028708
3	0.914185	0.085815
4	0.910664	0.089336
5	0.901603	0.098397
6	0.900511	0.099489
7	0.896527	0.103473

8	0.896466	0.103534
9	0.89656	0.10344
10	0.891847	0.108153
11	0.890399	0.109601
12	0.890355	0.109645
13	0.890277	0.109723
14	0.889238	0.110762
15	0.888964	0.111036
16	0.888932	0.111068
17	0.888752	0.111248
18	0.888218	0.111782
19	0.888084	0.111916
20	0.888018	0.111982

Note: (1) irfname = graph3, impulse = auto_growth, and response = auto_growth

(2) irfname = graph3, impulse = m2_growth, and response = auto_growth

Source: authors' calculation via Stata

Appendix 12 Variance decomposition (m2 - auto and m2)

	(1)	(2)
step	auto_growth	m2_growth
0	0	0
1	0.01319	0.98681
2	0.013557	0.986443
3	0.049223	0.950777
4	0.054008	0.945992
5	0.05087	0.94913
6	0.054037	0.945963
7	0.054412	0.945588
8	0.053324	0.946676

9	0.054911	0.945089
10	0.055218	0.944782
11	0.055369	0.944631
12	0.054823	0.945177
13	0.05521	0.94479
14	0.055374	0.944626
15	0.055329	0.944671
16	0.055108	0.944892
17	0.05532	0.94468
18	0.055366	0.944634
19	0.055317	0.944683
20	0.055266	0.944734

Note: (1) irfname = graph3, impulse = auto_growth, and response = m2_growth

(2) irfname = graph3, impulse = m2_growth, and response = m2_growth

Source: authors' calculation via Stata