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STRESS TESTING AS A TOOL FOR MONITORING AND MODELLING THE DYNAMICS OF BUSINESS ACTIVITY OF MANUFACTURING ENTERPRISES IN RUSSIA IN THE FACE OF MARKET SHOCKS: SHORT-TERM SCENARIOS OF INDUSTRY TENDENCIES

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STRESS TESTING AS A TOOL FOR MONITORING AND MODELLING THE DYNAMICS OF BUSINESS ACTIVITY OF MANUFACTURING ENTERPRISES IN RUSSIA IN THE FACE OF MARKET SHOCKS: SHORT-TERM SCENARIOS OF INDUSTRY TENDENCIES[4]

The article proposes a methodology for using macro-level stress testing based on the results of business tendency surveys to study possible scenarios for the development of crisis dynamics triggered by external unforeseen supply and demand shocks, as in the case of the COVID-19 pandemic, as well as a review of existing approaches in the field of stress testing and building stress indices with an emphasis on methods based on vector autoregressive models and their various modifications.

The basis for empirical calculations is data from business tendency surveys of the leaders of Russian manufacturing enterprises, reflecting their combined estimates of the current state of business activity. Based on the results of business tendency surveys, four composite indices were formed reflecting various aspects of business activity of enterprises: demand index, production index, finance index and employment index. Index values calculated monthly from 2008 to March 2020 were used to build the Bayesian vector autoregressive model (BVAR). This model was used to predict the dynamics of indices under the condition of four possible shock scenarios: short-term shock, V-shaped shock, W-shaped shock and U-shaped shock. Moreover, for each of the scenarios, cases of a shock of demand, a shock of production, and a simultaneous shock of demand and production were separately considered.

The results indicated the key role of demand in the dynamics of all the indices under consideration, the W-shaped shock, as the worst of the considered scenarios, as well as the relatively greater sensitivity of the employment index to the demand index and the finance index to the production index.

Keywords: stress testing, business tendency studies, scenario analysis, manufacturing, vector autoregressive model, Bayesian methods, digital Indicators, COVID-19.

JEL: C32, E27, E37, G17.

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Introduction

The pandemic of the coronavirus infection COVID-19 that arose in 2020 was the most significant shock for the global economy after the financial crisis of 2008. Measures used to restrain the further spread of the virus “freeze” production, creating problems for the functioning of supply chains, and lead to a significant decline in consumption, which indicates a combination of elements of a demand shock and a supply shock [Gurevich et al., 2020; Fornaro and Wolf, 2020; Baldwin and Di Mauro, 2020; Smith, 2020].

According to McKinsey estimates, a decrease in final consumption in Russia may be from 4.9 to 10,5 trillion rubles [Gurevich et al., 2020]. Industries oriented towards final demand, suffer from the crisis to the highest degree. Most of the damage is felt in the services sector, retail and wholesale, manufacturing and the financial sector [Dun and Bradstreet, 2020].

Over the past decade, the state of the economic situation in Russia has been characterized by an increased level of uncertainty faced by economic agents and a big number of large-scale unpredictable shocks of various nature. In many respects, this distinguished Russia from developed countries, where the general trend for reducing the volatility of business cycle fluctuations was generally maintained, and the financial crisis of the late 2000s was the only significant shock that went against this trend to strengthen stability.

One of the key findings of the experience of the late 2000s lies in the fact that ex-ante crisis forecasting is still a challenging task, complicated by the fact that crises often take different forms and are launched by qualitatively different triggers. The huge scale of the current shock is becoming an additional obstacle. For example, the current situation has already surpassed the worst-case scenario foreseen in the OECD forecast of March 2, 2020 [OECD, 2020]. Nevertheless, the scenario forecasting tool remains essential for monitoring the economic situation – even if it is necessary to adjust the scenarios as the situation changes and gain access to new data.

In our opinion, the high level of uncertainty associated with the current crisis requires a multi-instrumental approach based on the use of various statistical techniques and methods in the development of forecasts. Along with traditional approaches to macroeconomics in econometric modelling of real business cycles, from our point of view, data from business tendency surveys that are available to users before quantitative aggregates such as GDP can be used to make operational decisions during a crisis. Highly sensitive to changes in business trends, "soft" indicators of business tendency surveys and composite indices built on their basis can serve as the most sensitive tool for identifying new "black swans" with serious potential consequences for the economy, as well as to track the distribution of shocks that have already occurred in the real-time mode.

Our goal in this article is to adapt existing methods of macro-level stress testing to use them based on the results of business tendency surveys. Based on business tendency monitoring indicators, composite indices were constructed in the study, reflecting the aggregate opinions and assessments of the business community in the industrial sector relative to the current and expected economic situation in the near future in terms of demand, production, company finance and employment. Based on the methodology of the scenario approach in stress testing and the analysis of time series using the Bayesian Vector Autoregression (BVAR) model, we model the possible reaction of the economy to demand and production shocks depending on the future development of the crisis caused by the pandemic. The proposed technique can serve as an alternative source of information, serve as an early response tool and complement existing macro-level stress testing practices based on quantitative data.

The stress testing that we use with the calculation of composite indices reflecting the economic situation in industry can be considered as an alternative to analysis using stress indices, risk tolerance indices, and economic potential indices.

There are several essential differences between stress tests and indices due to the different roles of these tools in economic analysis. In particular, stress testing provides a clearer picture of the potential damage from shocks, while indices measure the current state of the system. Thus, stress tests and indices are, in many ways, complementary methods and measuring instruments, providing consistent alternative approaches to the analysis of similar risks.

Stress Testing and Stress Indices: An Overview of Approaches

Stress testing techniques are most common in financial research. However, they have a broader potential for use, being a way of assessing the stability of an object in adverse conditions. The approaches in the framework of stress testing one way or another involve modelling stressful events and measuring their negative effects on the studied object, from which conclusions are drawn about its ability to withstand external shocks.

The traditional field of application of stress testing is the analysis of the effectiveness of individual portfolios and the assessment of the sustainability of individual financial institutions – primarily banking [Basel Committee on Banking Supervision, 2018]. Along with banking organizations, stress tests at a similar micro-level are used to analyze the stability of the economic situation in insurance companies [EIOPA, 2019], pension funds and other financial organizations. After the global economic crisis of 2008, macro-level stress tests used to assess the stability of the financial system as a whole in the framework of macroprudential analysis gained popularity [Aymanns et al., 2018].

Stress tests are always based on four main elements. Firstly, they include a set of risks, the stability against which is tested during stress testing. Secondly, based on these risks, potential exogenous shocks are expressed that describe stress scenarios. Thirdly, a model is set that displays the effect of these shocks on the studied object and the distribution of stress impulses in the studied system. Fourth, stress testing includes indicators that measure the degree of impact and allow us to formulate the final results of the analysis.

Existing stress tests have different forms, although having many common features, but representing a set of similar analytical tools rather than a single analysis tool. Stress tests can be divided into two main types:

- sensitivity analysis, with the help of which we strive to determine the response of indicators of interest to changes in economic variables reflecting the level of risk;
- scenario analysis, based on the analysis of the stability of the object in the event of some extreme, but plausible stress scenario or scenarios.

Stress testing is used to a lesser extent to assess risks in companies of the real sector, in contrast to financial institutions [Sal'nikov et al., 2012]. At the same time, the very capabilities of the methodology do not preclude its use in these conditions with the study of a broader range of possible risks, including not only financial ones. Various approaches are possible here: on the one hand, a managerial look at the micro-level [McKinsey & Company, 2017] and, on the other hand, macro-level stress tests based on the analysis of systemic relationships and at the same time focused on the specifics of the real sector.

In financial stress testing, value-at-risk (VaR) models are often used to assess residual risks in a portfolio in the presence of the "heavy tails" effect, due to which standard methods can lead to underestimation of the true value of residual risk [So and U, 2017].

Recently, this technique has spread to macroeconomics. For example, [Boucher and Maillet, 2015] estimated the value at risk for US GDP using quantile regressions and predicted future growth rates for industrial production. This use of quantile regression emphasizes the importance of taking into account outliers and non-linearity in data that are ignored in standard regression analysis. Outliers are associated with extreme events, undoubtedly providing valuable information for modelling and predicting similar events in the future. This is confirmed by the results of [Covas et al., 2014] using quantile autoregressive models with a fixed effect to capture the non-linear dynamics of bank losses and incomes, as well as to forecast capital shortages.

Along with quantile regressions, more traditional approaches for structural modelling can be used here. We rely on literature in which the VAR-like models are used for stress testing. For example, [Hoggarth et al., 2005] propose a linear VAR model to take into account the dynamics between the indicators of the ratio of record and grant credits in banks and the main macroeconomic variables. [Drehmann et al., 2007] use VARs with third-order approximations to study the dynamics of corporate defaults and macroeconomic variables, as well as the local forecasting method to study the corresponding impulse characteristics.

There is an active field of empirical research using non-linear models of the VAR type. Sims and Zha [2006] use a multivariate mode switching model for US monetary policy in the VAR structure. The interaction of inflationary expectations and nominal and real macroeconomic variables in Britain after World War II was investigated by Barnett et al. [2010] using MSVAR (Markov Switching VAR). The results show that the effect of shocks on inflation expectations and real inflation has changed since the 1970s; similar findings were obtained for oil price shocks and real demand shocks.

[Mallick Sousa [2013] used the Bayesian vector autoregressive model (BVAR) to study the real effects of financial stress, showing that an unexpected change in financial stress leads to a significant increase in production volume volatility. The predictive properties of BVAR models have been successfully tested on Russian data [Demeshev and Malahovskaya, 2016].

Thus, VAR structure models can be successfully used in macro-level stress testing and provide useful information for calibrating macro stress scenarios, as well as help to determine the extent of risks caused by structural shocks. Nevertheless, the methodology used in the article is mainly experimental, because although the data from business tendency surveys are actively used in structural economic models, the stress testing approach with their use has not yet been widely presented in the literature.

As with stress testing, the central area of application of the stress index methodology remains finance. In the vast majority of cases, we are talking about the financial stress index (FSI), which acts as an indicator of the severity of financial crises, showing that financial stress is aggravated due to the greater fragility of financial systems and exogenous shocks. [Illing and Liu, 2006] defined financial stress as episodes when economic agents face a situation of extreme uncertainty and expectations of various losses in financial markets. Other authors have developed their own versions of the FSI, including, for example, [Hakkio and Keeton, 2009] for the Federal Reserve Bank of Kansas City; [Hollo et al., 2012] – for European markets; [Misina and Tkacz, 2009] – for selected countries with developed economies; [Yiu et al., 2010] – for the Hong Kong Monetary Authority. In addition, international institutions and private financial institutions such as the International Monetary Fund (IMF), Organization for Economic Co-operation and Development and Development (OECD), Bank for International Settlements (BIS), Goldman Sachs, Bloomberg and Citigroup have developed FSI in order to have access to early warning indicators.

The use of FSI has advantages for the monetary authorities and financial regulatory and supervisory authorities in that they combine various indicators of the state of the financial market into a common index in order to measure aggregate stress in the financial market, thereby eliminating the dependence on one or more narrow indicators in assessing risks. It is worth noting that the methodology for constructing the FSI has the potential to expand beyond the study of the financial market: for example, the Daily Economic Stress Index calculated by HSE Centre of Development Institute includes indicators that characterize the situation in the commodity, currency, money and stock markets, as well as in banking and real sector of the Russian economy[5]. Risk tolerance indices [Lola and Bakeev, 2020] and potential indices, calculated by the ISSEK NRU HSE in 2020, are indicators similar to stress indices based on data from business tendency surveys.

A large section of the FSI literature is devoted to the study of the relationship between financial stress and economic activity. For example, Davig and Hakkio [2010] found that the US economy fluctuates between episodes of low financial stress and high economic activity, and then high financial stress and low economic activity. Other studies in this area are devoted to the contribution of the financial stress index to improving forecasts of economic activity. Ng [2011] showed that the use of FSI allows to obtain more accurate forecasts of the level of industrial production on the horizon of 2–4 quarters for the US economy.

Despite the devastating effects of the crisis, especially in emerging market economies, it is not always easy to trace the growth of full-blown economic problems. As reality shows, FSI and stress indices, in general, can help with forecasting impending economic shocks. However, even in the current crisis, stress testing seems to be more relevant, allowing us to work out the future exit and recovery scenarios.

Data

Specially calculated composite indices based on the results of monthly business tendency surveys of industrial enterprises in Russia were selected as time series for the model. The components of the indices were the balances of current assessments and respondents' expectations regarding the dynamics of survey indicators with procyclical parameters.

In surveys for 2020, the entire set of observation units is represented by more than 3,000 enterprises. For the analysis in the framework of this study, enterprises in the manufacturing sector were selected (section C of the classification of OKVED 2). The sample is representative of all observation units, multidimensional, stratified,

[5] URL: https://dcenter.hse.ru/desi

and representative of the basic economic parameters of the Russian manufacturing industry.

The predictive model involved the following specially developed composite indices:

1. The demand index of manufacturing enterprises. Its components:
    - Current estimates of changes in the level of domestic demand for the main product manufactured by the enterprise;
    - Expected changes in the level of domestic demand for the main product manufactured by the enterprise;
    - Current estimates of changes in the level of stocks of finished products in the enterprise;
    - Expected changes in the level of stocks of finished products at the enterprise;
    - Expected changes in the level of stocks of raw materials.
2. The production index of manufacturing enterprises. Its components:
    - Current estimates of changes in the level of output of the main product manufactured by the enterprise;
    - Expected changes in the level of output of the main product manufactured by the enterprise;
    - Expected changes in the level of stocks of finished products at the enterprise.
3. The finance index of manufacturing enterprises. Its components:
    - Current estimates of changes in the level of own financial assets;
    - Expected changes in the level of equity;
    - Expected changes in the level of borrowed funds;
    - Expected changes in profit margins.
4. The employment index of manufacturing enterprises. The components:
    - Current estimates of changes in the level of employment in the enterprise;
    - Expected changes in the level of employment in the enterprise;

- Expected changes in the economic situation at the enterprise.

These indices were calculated using the principal component method and normalized to a value of 100. In Fig. 1, their dynamics since 2008 is presented. The results of long-term empirical studies indicate the high adaptability of the algorithm used to construct composite indicators based on international recommendations of the OECD, the EC and Russian experts.

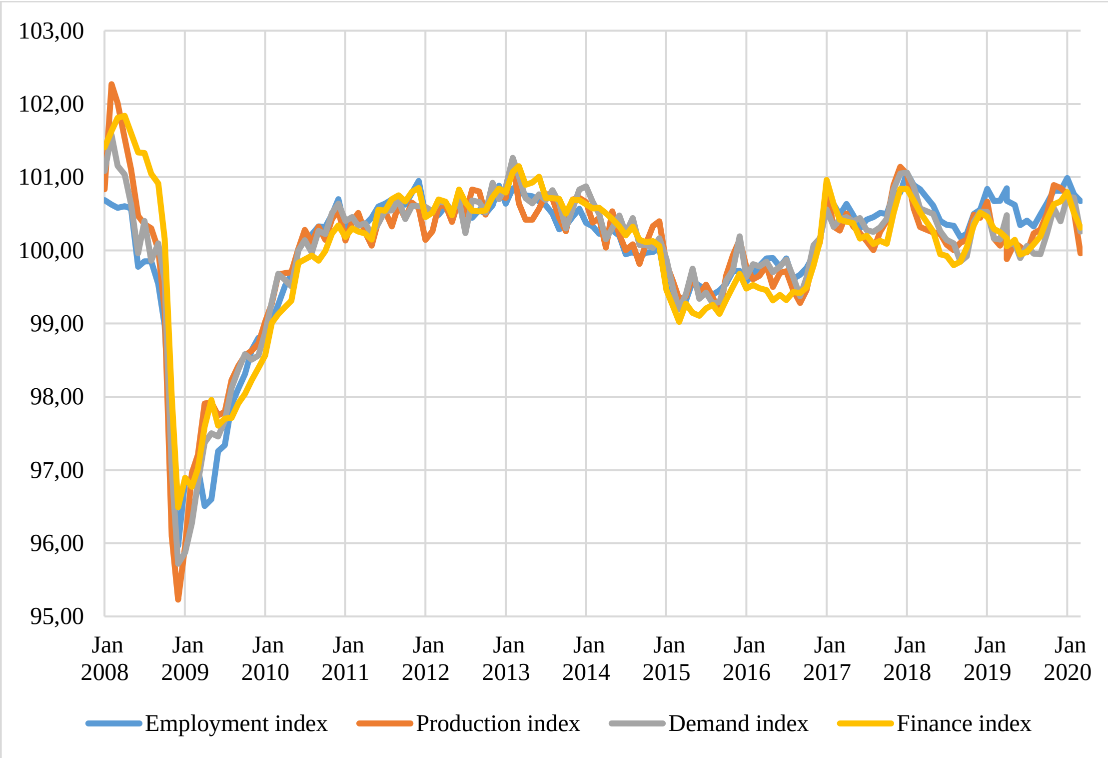


Fig. 1. The dynamics of the demand index, production index, financial index and employment index (%)

Composite indices based on nonparametric information have high stability and a statistically significant relationship with the corresponding quantitative macro-aggregates. The high correlation dependence of such measures with the dynamics of quantitative time series characterizing the rate of change is empirically proven, which allows them to be considered an actual and reliable source of empirical data and used both in industry macroeconomic analysis and short-term forecasting.

In order to verify this statement, a cross-correlation analysis was carried out in the study, the results of which indicate the presence of a statistically significant (at a significance level of 0.01) stable relationship between all composite indices and the corresponding quantitative macro-aggregates (for example, the production index showed a stable relationship with the GDP volume index with a synchronous correlation coefficient of 0.9).

Methodology

This section presents the main methodological principles for building models and the results of intermediate tests. All the calculations presented below were performed using the EViews 10 statistical package.

The stationarity of the studied time series is an important condition for constructing an adequate VAR model, therefore, at the first stage, using the Augmented Dickey-Fuller test (ADF-test), we analyzed the variables for stationarity, the results of which are shown in Table 1. According to the obtained coefficient values, all variables other than the employment index are stationary.

Table 1. Results of the stationarity tests

Variable	t-statistic	Critical value	p-value
Finance index	-2.8814	-3.1998	0.022
Employment index	-2.8814	-2.1623	0.2211
Demand index	-2.8814	-3.0915	0.0294
Production index	-2.8814	-3.9074	0.0026

Source: authors' calculations

In order to obtain complete and reliable information on the stationarity of the series under consideration, the Ng-Perron (NP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test were also carried out, according to which the employment index is a stationary series, like all other indices considered. Thus, the time series for the variables selected for inclusion in the model turned out to be stationary in levels so that we can proceed to the construction of an unrestricted VAR model.

As part of the construction of the VAR model, the lag order was determined at which the most significant results were obtained, and the stationarity of the model as a whole was checked, as well as the decomposition of volatility and impulse responses was calculated.

The choice of the number of model lags was made based on the Akaike Information Criteria (AIC). Table 2 shows the AIC values depending on the number of lags in the model. The considered maximum number of lags was taken to be 6, in accordance with the experience of empirical studies based on monthly data [Brooks and Tsolacos, 2010]. Models with the optimal number of lags are characterized by the smallest AIC. Thus, in our case, the optimal model is the model with 6 lags (p = 6).

Table 2. Lag order selection

Lag order	**AIC**
0	3.2195
1	-2.094
2	-2.1636
3	-2.4166
4	-2.3218
5	-2.3671
6	-2.5942*

Source: authors' calculations

The model was also checked for stationarity: all roots lie inside the unit circle, which satisfies the stationarity condition.

Since one of the objectives of our study was to analyze the effect of demand (demand index) and supply (production index) shocks on financial and employment indices, we checked the existence of the corresponding relationships within the model, for which the Granger test was applied, the results of which are shown in Table 3.

Table 3. Results of Granger tests

Hypothesis	Chi-square statistic	p-value	Conclusion
The production index depends on the demand index	16.2303	0.0126	Accepted
The finance index depends on the production index	10.9603	0.0896	Accepted
Finance index depends on the demand index	10.2042	0.1163	Does not reach the level of significance
Employment index depends on the finance index	15.5435	0.0164	Accepted
Employment index depends on the production index	14.9879	0.0204	Accepted

Source: authors' calculations

Test results for all hypotheses except one show that p-values were less than 0.1, therefore, at the 10% significance level, hypotheses are accepted that there are dependencies of employment and finance indices on demand and production indices. The hypothesis about the dependence of the financial index on the demand index cannot be accepted since the p-value exceeds 0.1; however, the value is close to acceptable.

Based on identical variables and the lag order defined above, we built the standard VAR model and the Bayesian VAR (BVAR) model with the prior distribution of Minnesota. In the case of the BVAR, we follow [Bańbura et al., 2010] and set $\delta i = 0$, since all the series under study are stationary.

The VAR model was used as part of a general variance decomposition of the model variables and impulse responses analysis. The objective of this stage was to assess the impact of changes in demand and production indices on financial and employment indices. Variance decomposition of the last two variables allows us to interpret the VAR model under consideration. For the variance, as well as for orthogonalization of impulse responses, the Cholesky decomposition was used [Probability in the Engineering and Informational Sciences, 1988]. When considering the variance decomposition of the finance and employment indices, the following arrangement of variables in the Cholesky order was used: demand index, production index, finance index, employment index. A period of 2 years (24 months) was selected.

Having determined the degree of influence of demand and production indices on finance and employment indices in different periods, we can proceed to the analysis of impulse responses, the purpose of which is to monitor the effects of changes in one endogenous variable on another. The impulse response itself is defined as the percentage change in the endogenous variable equal to one standard deviation as a result of the shock in random errors of other endogenous series [Potter, 2000]. The number of periods, as well as the location of Cholesky, were chosen similarly to those that were used in the decomposition of volatility.

The next step in the study was the development of short-term scenario analysis. Four scenarios were considered in the study:

- Scenario 1: The short-term shock followed by a quick recovery. The negative outburst, then a short stagnation at this level and the subsequent quick return to the normal dynamics of the business cycle.
- Scenario 2: The recession (V-shaped dynamics). The negative ejection, short stagnation and slow recovery.
- Scenario 3: The recession with a repeated shock (W-shaped dynamics). Similar to the previous scenario, but after the first negative outburst, the second occurs, and recovery to the pre-crisis level is delayed.
- Scenario 4: The long recession (U-shaped dynamics). The negative release and further long-term drop in indicators with subsequent stagnation and slow recovery.

For each of these scenarios, three possible options for the occurrence of shocks were considered: the shock of the demand index, the shock of the production index and the simultaneous shock of the demand and production indices.

At this stage, we chose between the VAR and BVAR models. Their predictive effectiveness was compared using pseudo-out-of-sample analysis using the static forecasting method. Models were calculated based on data from January 2008 to December 2014, while forecasts were built for the period from January 2015 to March 2020,

To evaluate and compare the effectiveness of our BVAR and VAR models, the root mean squared forecast errors (RMSFE) were calculated as a function of the losses. To determine which model is more efficient, the RMSFE relationships between the models were calculated (Table 4). If the ratio is less than 1, the BVAR model is preferable to the VAR model.

Table 4. Pseudo out-of-sample analysis

Ratios of the BVAR's RMSFEs to VAR's	
Demand index	0.7083
Production index	0.7172
Finance index	0.9173
Employment index	0.8374

Source: authors' calculations

Since the ratios of the RMSFE of the BVAR model to the VAR for all four included variables are less than 1, we can conclude that the BVAR model is more efficient for forecasting, so further scenario analysis was carried out on its basis.

The next section presents the results of its forecasts, provided that the negative shocks described above occur as if they were recorded in the second and fourth quarters of 2019, respectively.

Results

According to Table 5, the demand index has a diminishing effect on the finance index after reaching the highest value in the 1st period. This means that the theoretical shock that will occur in the demand index will have a major impact on the finance index in the 1st month. At the same time, the production index has a growing effect on the finance index from the 1st to the 3rd period and a decreasing one – from the 4th to the 24th. In other words, a possible shock in the production index will have the greatest impact in the 3rd month.

Table 5. The variance decomposition of the finance index with the arrangement of variables according to the Cholesky method (demand index, production index, finance index, employment index)

Shock	Maximum impact, percent (month)	Minimum impact, percent (month)	Behavior of the variable
Demand index	67.0494 (1)	49.5411 (24)	After reaching a peak in the 1st month, the impact of the shock of the demand index on the finance index begins to decline smoothly
Production index	15.4847 (3)	6.5589 (1)	After reaching a peak in the 3rd month, the impact of the shock of the production index on the finance index begins to decline smoothly

Source: authors' calculations

In turn, the influence of the demand index on the employment index has an increasing trend from the 1st to the 2nd period and decreasing after from the 3rd to the 22nd period, as follows from Table 6. This means that the strongest impact of the shock in the demand index on the index employment would be observed in the 2nd month. Similarly, the influence of the production index on the employment index increases from the 1st to the 3rd month and decreases from the 4th to the 24th, reaching the highest value in the 3rd month.

Table 6. The variance decomposition of the employment index with the arrangement of variables according to the Cholesky method (demand index, production index, finance index, employment index)

Shock	Maximum impact, percent (month)	Minimum impact, percent (month)	Behavior of the variable
Demand index	58.7072 (2)	37.4124 (22)	After reaching a peak in the 2nd month, the impact of the shock of the demand index on the employment index begins to decline smoothly
Production index	16.0852 (3)	9.2999 (24)	After reaching a peak in the 3rd month, the impact of the shock of the production index on the employment index begins to decline smoothly

Source: authors' calculations

Let us turn to the results of scenario analysis. The calculations for scenario 1 (short-term shock) are presented in Fig. 3 (production shock) and Fig. 4 (shock of demand). In general, the calculations show that in this case, relatively little damage occurs and all series are quickly restored along with the index acting as a shock trigger. The shock drop in the production index by 3 pp (percentage points) at the peak is reflected in the negative deviation of the demand index from the normal path by 0.8 pp, as well as the finance index – by 0.6 pp, the employment index – by 0.5 pp (Fig. 3). At the same time, the effect of a similar anomalous fall in the demand index is slightly weaker: the supply index at the peak falls by 0.4 pp compared to the real values, the finance index – by 0.5 pp, and the employment index – by 0.6 pp (Fig. 4). In the case of a simultaneous supply and demand shock, the effects add up, and the employment and finance indices deviate negatively by about 1 pp at the peak, and then also quickly recover.

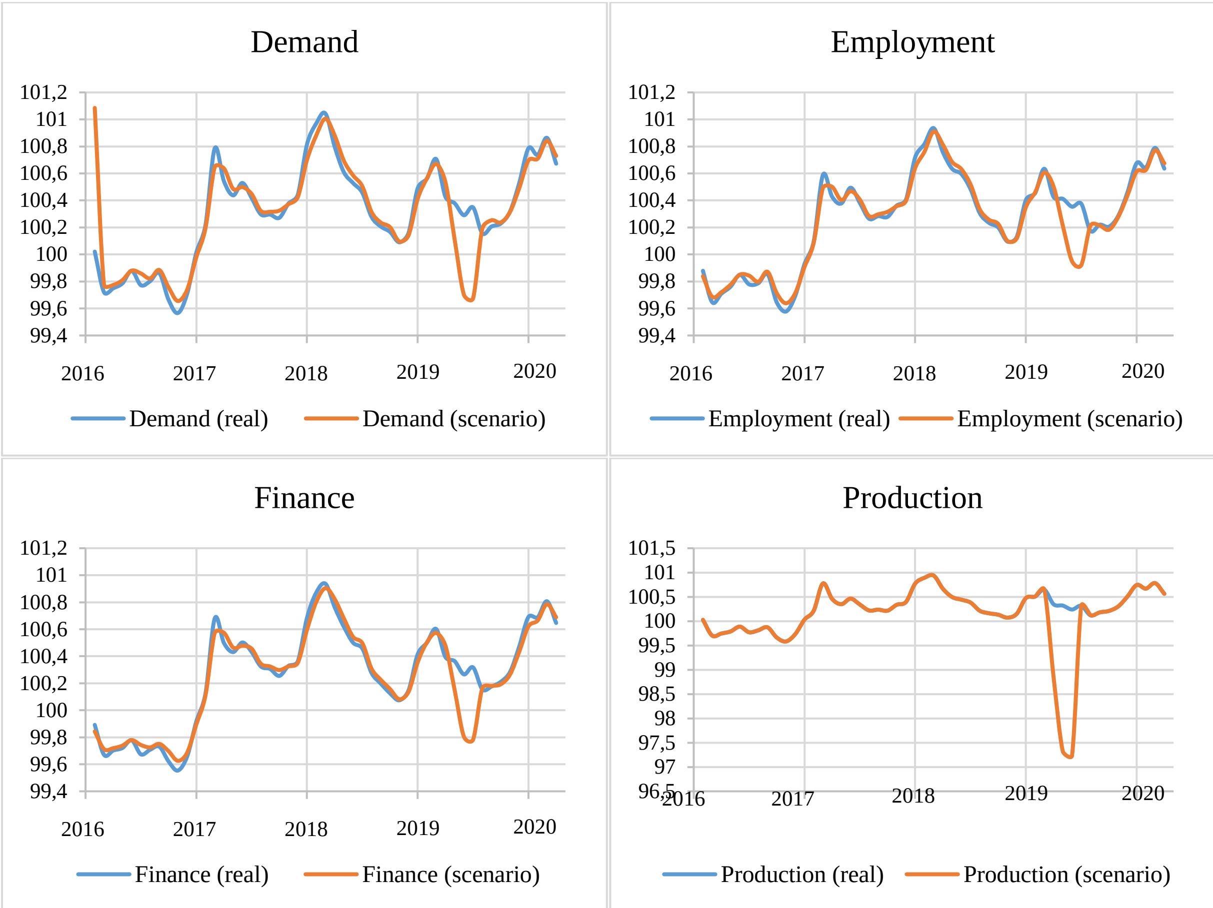


Fig. 2. Scenario 1: shock of production.

Source: authors' calculations

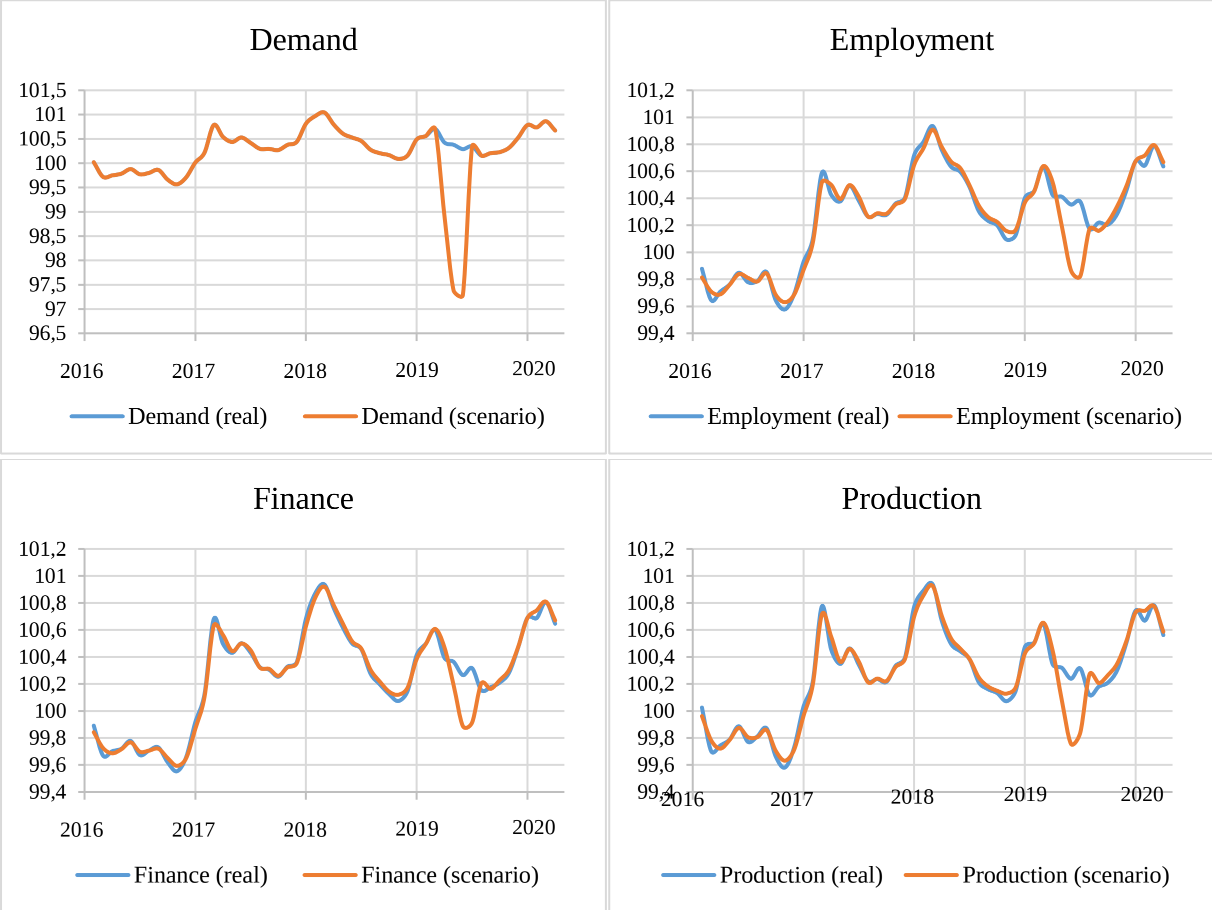


Fig. 3. Scenario 1: shock of demand.

Source: authors' calculations

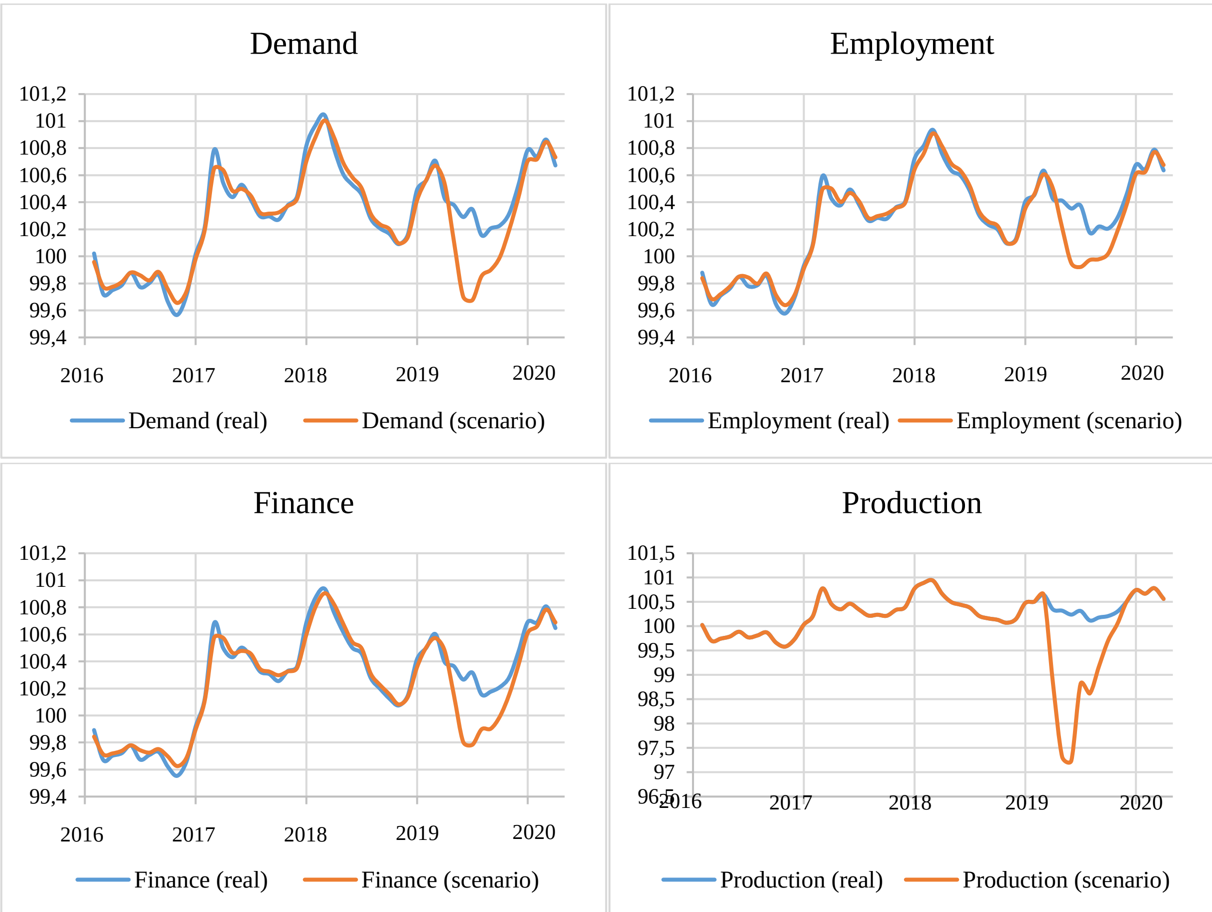


Fig. 4. Scenario 2 (V): shock of production.

Source: authors' calculations

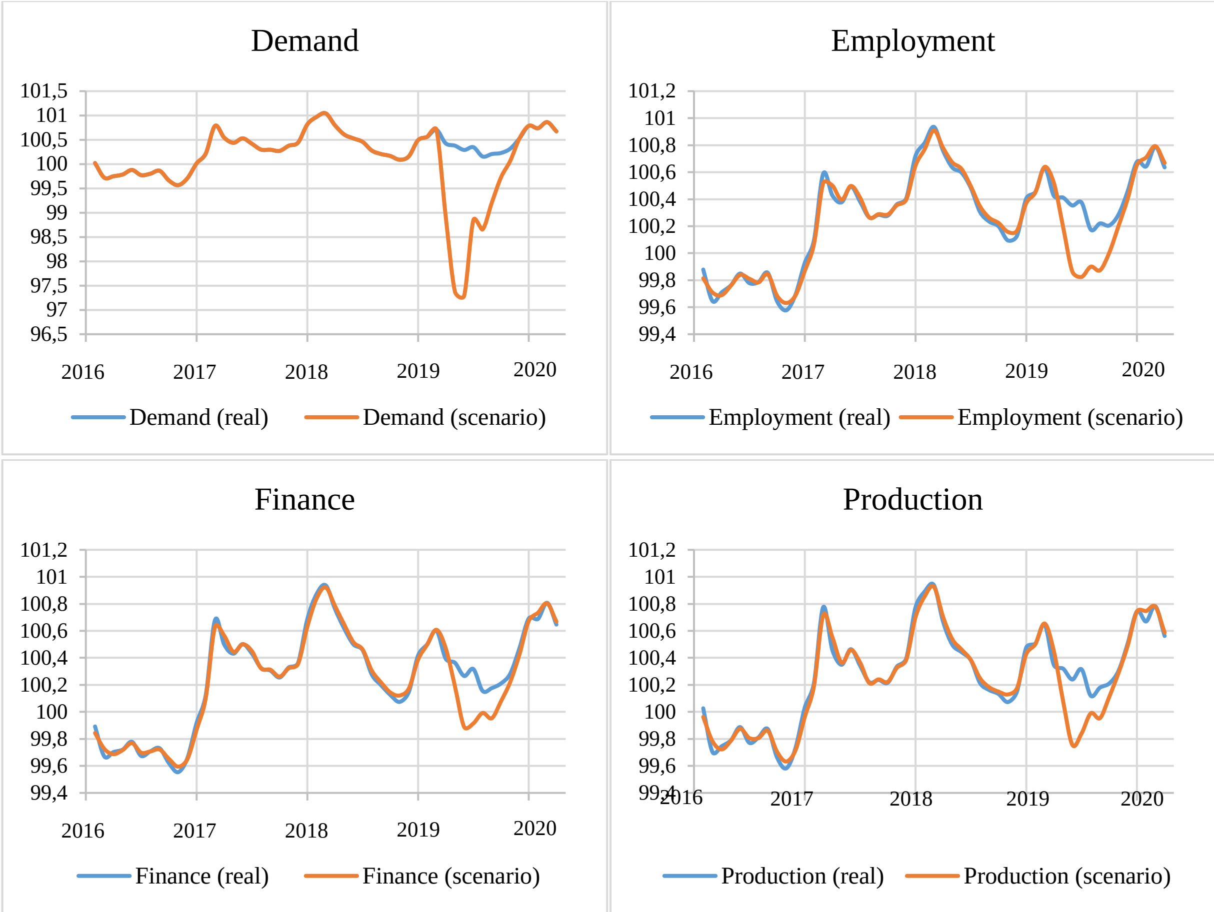


Fig. 5. Scenario 2 (V): shock of demand.

Source: authors' calculations

Analysis of scenario 2 (V-shaped recession) reveals similar trends (Fig. 5, Fig. 6). As in the case with scenario 1, the shock of production affects demand the most and employment is least affected (Fig. 5). The fall in the finance index is rather significant (about 0.6 pp at the peak). The shock of demand on it is reflected weaker (about 0.4 pp, Fig. 6) and weakly affects the deviation of the production index. Most strongly, its effect is noticeable in the case of the employment index. If production and demand shocks occur simultaneously, then during the quarter, finance and employment show a similar drop in value up to 1 pp, and then a longer recovery takes place, unlike cases with single shocks, finally occurring only at the very end of the year.

Scenario 3 is similar to scenario 2, with the exception that it includes an additional shock that occurs six months later. Such dynamics of the production index leads to a collapse in the demand index (by 3 pp) and its subsequent slow recovery until the end of the year without a pronounced reaction to a new shock in production, the expectations of which, most likely, are already reflected in the initial drop (Fig. 7). In the case of the financial and employment indices, individual reactions to shocks are distinguishable, while the effect on the financial index, which falls first by 0.8 pp and then by 1 pp, is expressed quite strongly. The employment index reacts weaker to production shocks, deviating from real values both times by about 0.4 pp. Strong demand shocks keep financial and employment indices in the zone of significant negative deviations (about 1 pp) and do not allow them to recover down to until the end of the year (Fig. 8). The fall in the production index is practically the same significant, but recovery is faster. With simultaneous repeated shocks of production and demand, the dynamics of the finance and employment indices do not differ fundamentally from what is shown in Fig. 8.

Scenario 4 assumes a U-shaped delayed recovery and stagnation at the bottom for a certain period of time (Fig. 9, Fig. 10). If a production shock is modelled in this way, this leads to a slowdown in the growth of finance and employment indices, which reach real values only at the beginning of next year (Fig. 9). At the same time, demand relatively successfully adapts to the situation, not falling much and quickly playing back the emerging negative deviation from real values. In the event of a similar crisis dynamics on the demand side, the finance and employment indices behave identically, and the production index reacts more strongly, falling by 0.6 pp and recovering only towards the very end of the year (Fig. 10). Simulation of a simultaneous shock in demand and production does not make fundamental changes.

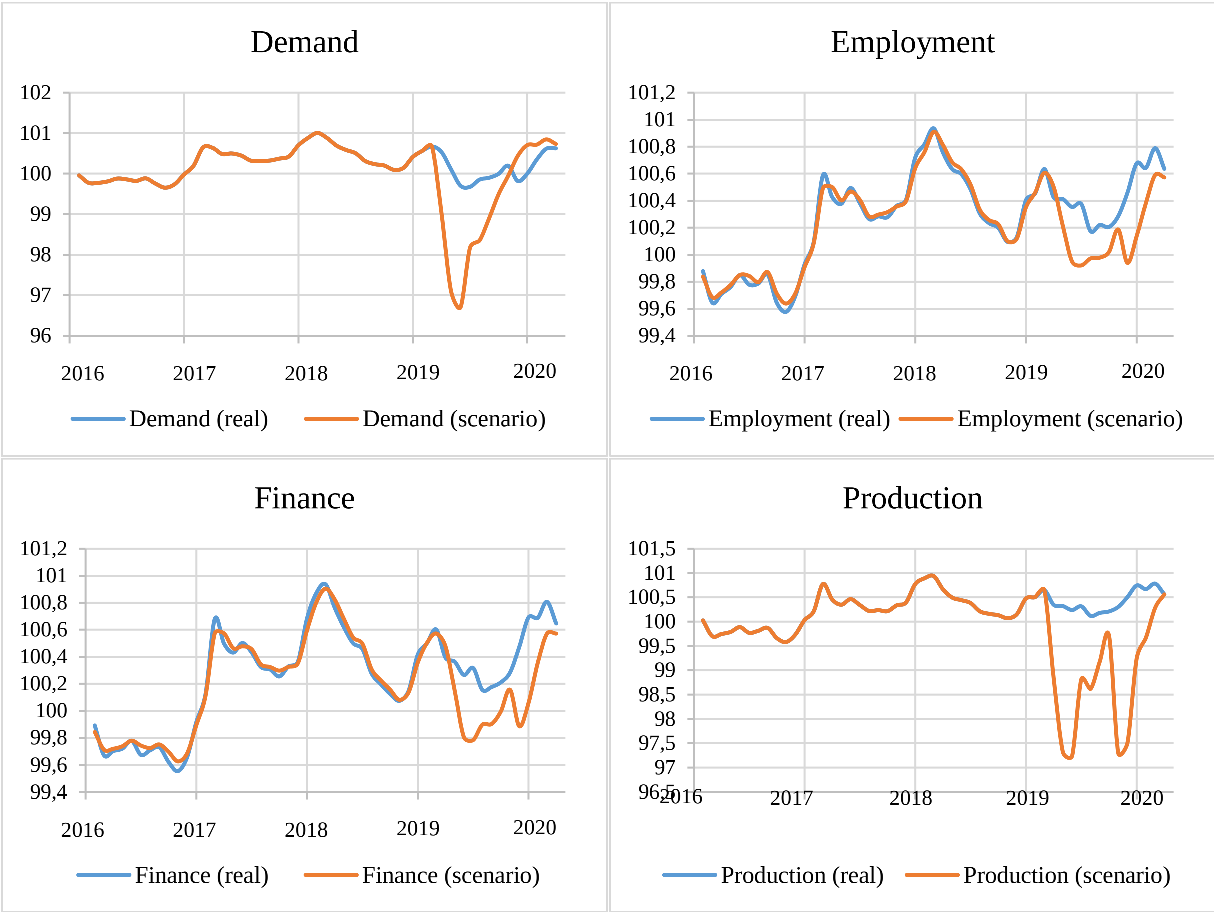
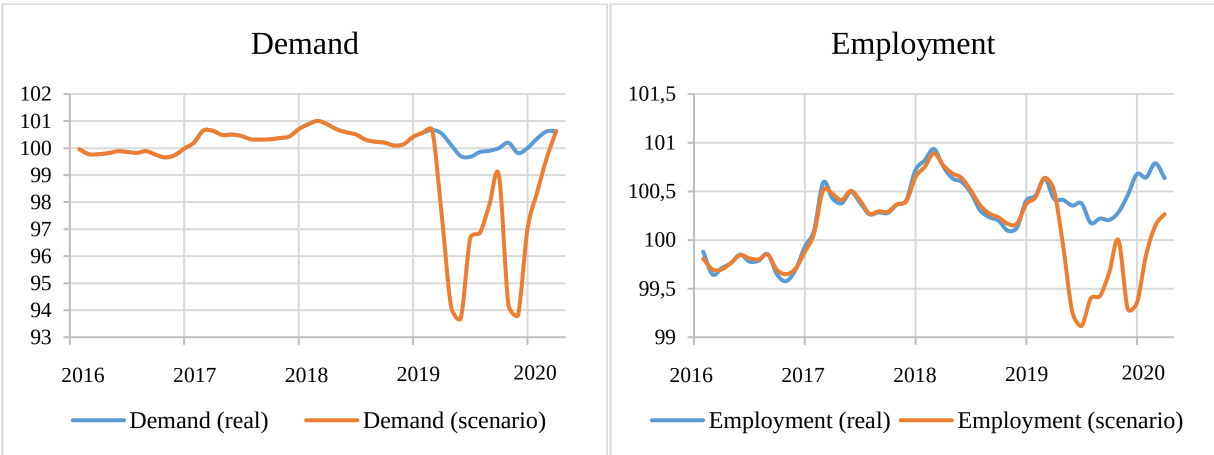


Fig. 6. Scenario 3 (W): shock of production.

Source: authors' calculations



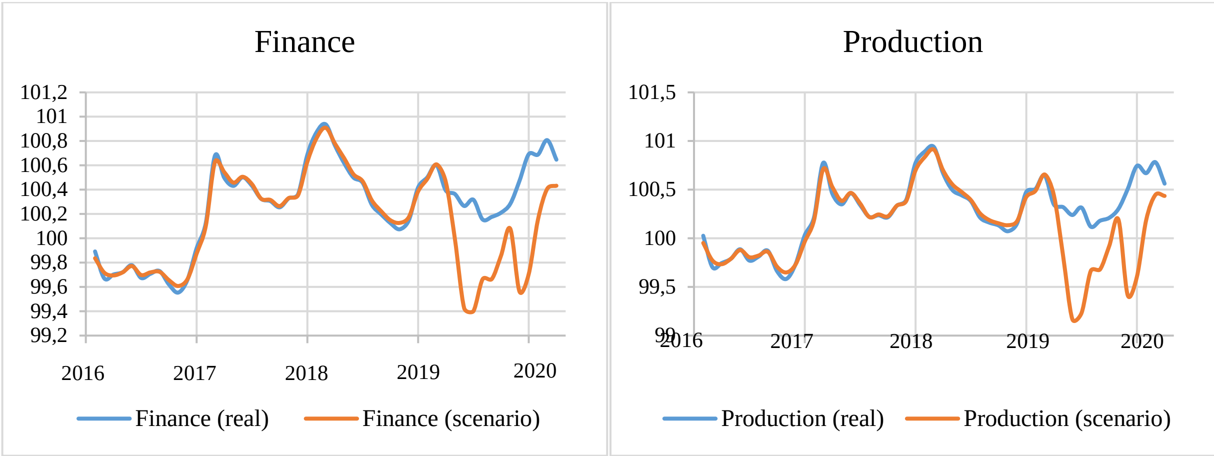


Fig. 7. Scenario 3 (W): shock of demand.

Source: authors' calculations

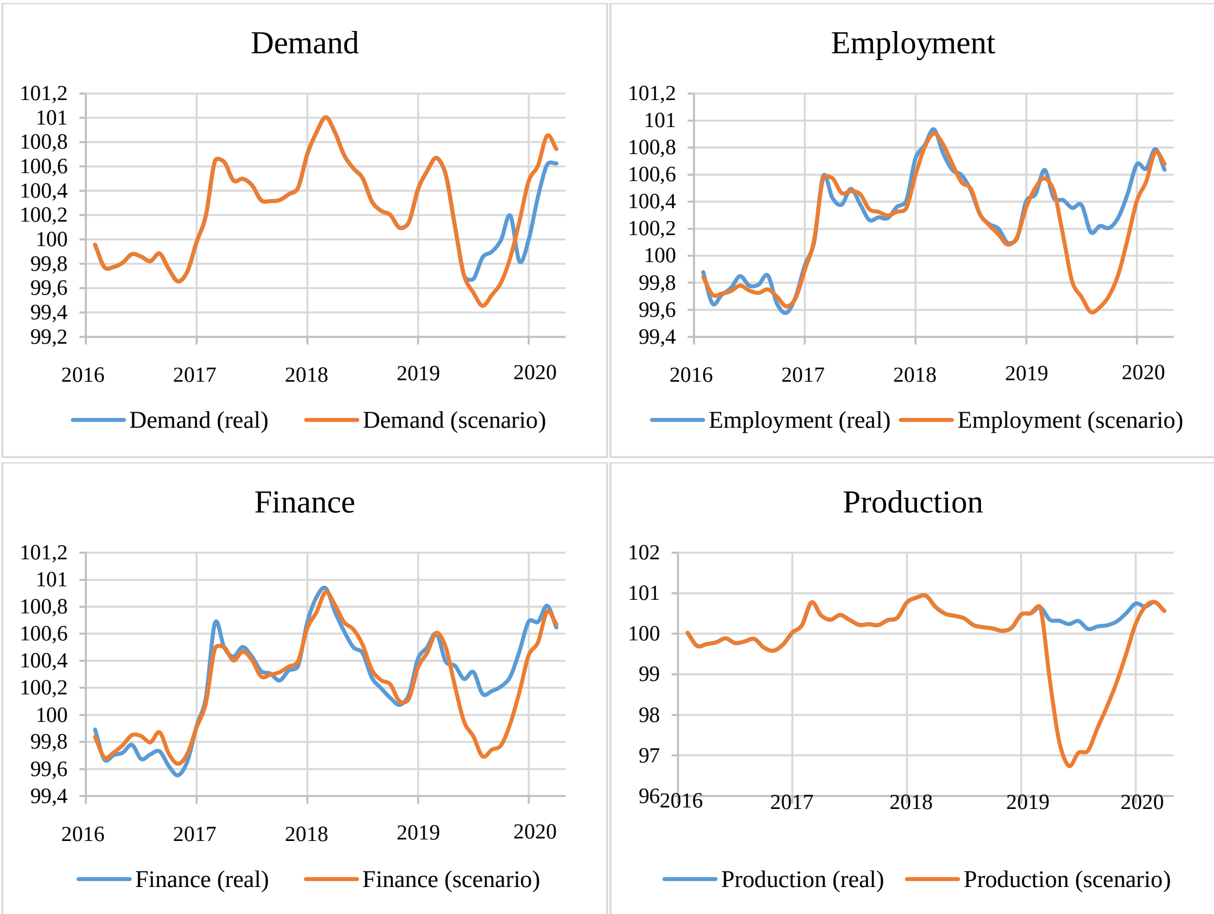


Fig. 8. Scenario 4 (U): shock of production.

Source: authors' calculations

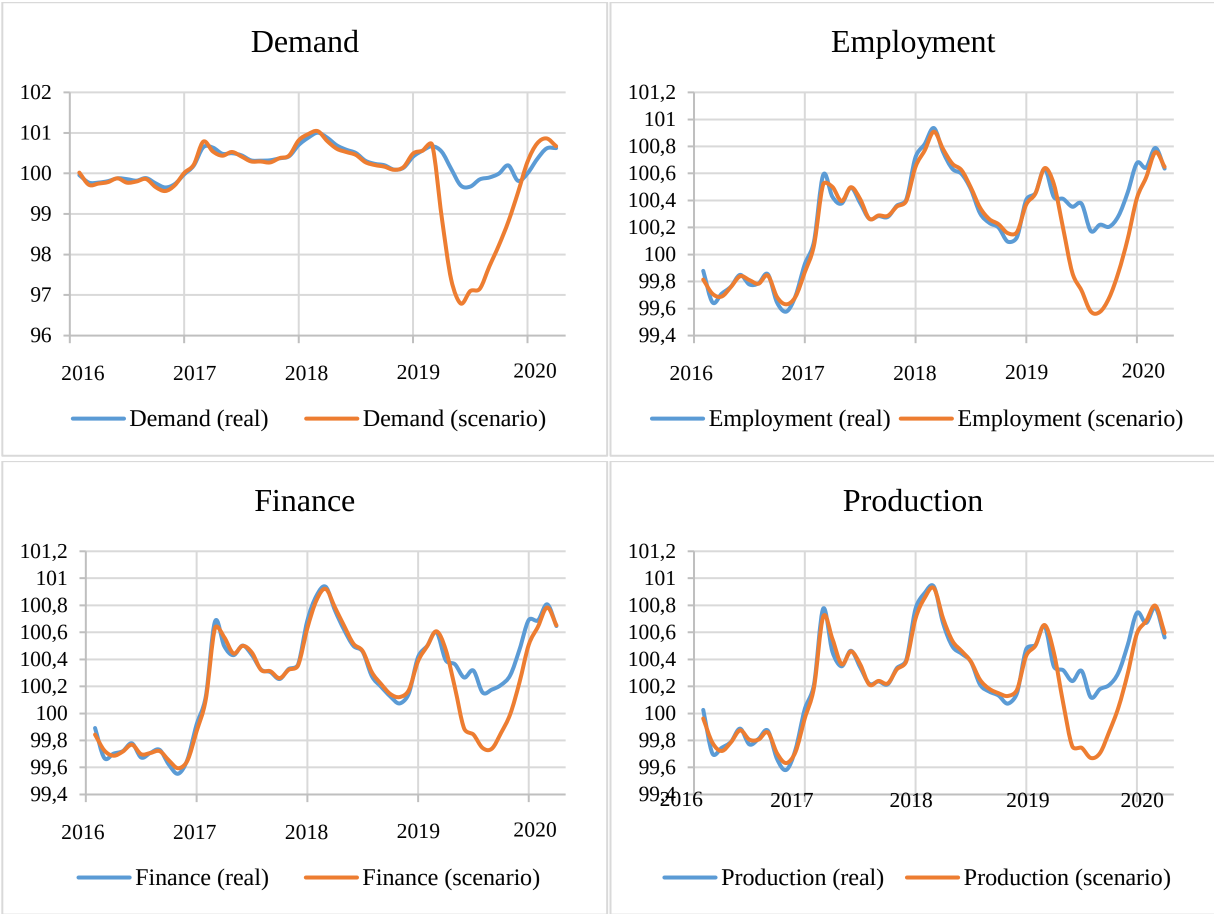


Fig. 9. Scenario 4 (U): shock of demand.

Source: authors' calculations

Digital and Technological Indicators in Stress Testing: Development Prospects

From our point of view, an additional direction of research in the framework of stress testing is associated with the expansion of the approach beyond exclusively economic problems and the inclusion of indicators reflecting technological and digital aspects of development. In recent years, a new stage in the process of digital transformation has been observed all over the world, characterized by active and breakthrough dynamics in transforming global markets and the social sphere. The variety and number of digital services is increasing exponentially, innovative products based on a set of advanced technologies appear. The transition to the digital industry is associated with an increase in observability, speed, accuracy, flexibility, and so the more perfect controllability of all production and technological processes. This gives rise to significant macro- and microeconomic effects, including the reduction of the time spent on design and production, a significant increase in productivity, the increase in the number of new products and technological complexes, profits, adaptability to external shocks and risk tolerance.

Since the adoption in 2017 of the state program Digital Economy of the Russian Federation[6], organizations and enterprises in Russia are actively involved in the transformational processes of digitalization. In the context of Industry 4.0, the Russian manufacturing sector in its current state is ready to take a leading role in digital transformation, adapting to new trends and changing realities.

The current stage of development of the digitalized industry is described in the framework of the Industry 4.0 concept [World Economic Forum, 2018], which approves digital technologies as the basis for creating high-precision, ultra-fast and high-performance automatically controlled systems capable of mass production of a highly customized product that best meets individual customer requirements [Idrisov et al., 2018]. Digital transformation in the spirit of Industry 4.0 is a top priority for many industries around the world as an engine of economic growth, opening up opportunities that could not be realized in the past waves of digital technology development.

The potential for a high level of digitalization was especially deeply revealed after the negative economic events triggered by the spread of the COVID-19 in 2020. The coronavirus pandemic caused a surge in initiatives based on digital solutions. For example, according to a European survey, about 70 percent of executives from Austria, Germany, and Switzerland said that a pandemic is likely to accelerate the pace of their digital transformation [McKinsey & Company, 2020]. According to the third phase of the Econsultancy and Marketing Week study [Econsultancy, 2020] on the impact of the pandemic on the marketing industry, out of more than 300 respondents representing global corporations, one in five (19%) said that they invested additional funds in strategic initiatives in the field of digital transformation

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[6] URL: https://digital.gov.ru/ru/activity/directions/858/

in the first half of 2020, a quarter (23%) noted that they increased their costs or invested new funds in technology or infrastructure. In addition, more than half (54%) of respondents from large enterprises indicated that the response of their business to the outbreak of coronavirus is best described as a greater focus on digital achievements, digital products, and digital services. In the current context of falling barriers to improvisation and experimentation, companies can learn and progress in digital transformation faster than ever before. The way they adapt to the current crisis may have a profound impact on their future performance, making it possible to maintain greater flexibility as well as closer relationships with customers, employees and suppliers.

At the same time, it is worth noting that the possibilities for monitoring the dynamics of the digitalization process in manufacturing and forecasting in the field of industrial technological development in Russia are limited. This is partly due to a lack of quantitative data: official statistical monitoring of the use of digital technologies in business so far has mainly included only “first wave” technologies: computerization, process automation, telecommunications [Kitrar and Lola, 2019]. Among the technologies of the second wave (online platforms and cloud computing) and the third wave (Industry 4. 0), only cloud computing is taken into account in it.

Under such conditions, indicators of business tendency surveys and composite indices based on them can be a useful empirical basis for studying technological and digital transformation in manufacturing using statistical methods. Such macro aggregates, along with the indices of economic activity considered in this paper, will allow us to take into account the contribution and impact of digital development in the industry dynamics, as well as using them as relevant additional indicators in the stress testing methodology.

In our opinion, depending on the objectives of the study, various indices of digital activity are possible, which include an assessment of various aspects of the technological transformation of the industry.

In particular, a Digital Transformation Index, compiled on the basis of entrepreneurial estimates of the level of dissemination of digital technologies, the digital practices in their enterprise or in the industry as a whole, can reflect the basic functions in the field of ICT (use of digital devices, access to the Internet, presence in social media), and also take into account the wider range of technologies and practices including the most advanced ones related to Industry 4.0: Internet of Things (IoT), cloud and edge computing, machine learning training, artificial intelligence, mobile computing, robotic systems, augmented and virtual reality, blockchain, additive manufacturing (3D printing), and so on.

The next important measure may be the Index of the Level of Digitalization of Labor, which may include entrepreneurial opinions, estimates and expectations regarding the number of people employed in the field of digital technologies in the enterprise, the performance by the enterprise employees of various functions in the field of ICT, the level of digital literacy of employees in the enterprise etc.

At the same time, an important instrument in the stress testing methodology can be a group of indices characterizing the level of innovation and investment activity in industries, including the opinions and expectations of entrepreneurs regarding investments in digital technologies, investments in improving the environmental and resource efficiency of production, return on investment in the field of digital transformation etc.

Indices of stress resistance or risk tolerance may be also considered, based on indicators reflecting the attitude of entrepreneurs to factors that impede the transition of industrial enterprises to digital technology.

In our opinion, the Digital Potential Indicator may be especially useful in technological forecasting, based on the expectations of entrepreneurs regarding trends in digital activity in the near future.

The inclusion of the proposed indicators of digital activity in the stress testing methodology can pursue various goals. Possible applications may relate to the study of inter-industry relations of technological development, diffusion of innovations, identification of structural relationships between indicators and forecasting based on this information. In the stress testing format, their inclusion has the potential to increase the accuracy of forecast estimates by adding new dimensions to the studied system of time series and thereby expanding it to an interconnected economic and technological complex in which the analysis of technological development helps more effectively determine the trends of economic development and vice versa. In addition, it becomes possible to conduct technological stress tests when trends and scenarios of technological development are separately considered.

Conclusion

The results of the presented scenario analysis allow us to evaluate possible reactions to various trajectories of development of crisis trends in the economy, including those caused by the spread of COVID-19. The indices of demand, production, finance and employment constructed on the basis of business tendency surveys of manufacturing enterprises reflect the basic aspects of economic activity, and the study of direct and indirect structural relationships existing between them can help in studying the economic consequences of various shocks unforeseen in terms of strength and scale, such as, for example, the COVID-19 pandemic, along with more traditional methods based on quantitative statistics.

The decomposition of the volatility of the finance and employment indices showed that the dynamics of demand, in general, are more important in terms of its impact on the financial performance of enterprises and the level of employment compared to the supply side. This underlines in the current economic environment the particular importance of measures to maintain demand in order to overcome the current crisis with the least losses.

The proposed stress testing technique in the form of a scenario analysis confirmed the critical importance of the demand side. An important aspect of the results obtained is that we have identified increased demand adaptability, the sensitivity to shocks of which weakens during protracted crises, which cannot be said about employment or finances.

The most severe scenario out of the four we examined turned out to be scenario 3 – recession with repeated shock (W-shaped). In this case, the finance and employment indices deviate from the known real values to the negative zone deeper and longer than all the others. After scenario 3 in severity, scenario 4 (U-shaped) follows, then scenario 2 (V-shaped). The damage in scenario 2 is less significant due to the faster recovery of index values. As expected, scenario 1 describes the best situation.

Of course, this study represents only the initial stage of embedding the results of business tendency surveys into the framework of the classical methodology of macro-level stress testing. Our further research will be aimed at expanding its application in other sectors, such as agriculture and trade (see the study on the use of VAR on the basis of business tendency surveys of retail enterprises [Lola and Gluzdovskij, 2018]).

An additional area of research in the framework of stress testing is associated with the expansion of the approach beyond exclusively economic problems and the inclusion of indicators reflecting technological and digital aspects of development. This will require further pilot business tendency surveys of the digital activity of various industries, which will allow us to consider digital development in dynamics and use similar econometric methods to study it.

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