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FORECASTING EMPLOYMENT IN SMALL BUSINESSES IN RUSSIA: THE RELEVANCE OF BUSINESS TENDENCY SURVEYS

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FORECASTING EMPLOYMENT IN SMALL BUSINESSES IN RUSSIA: THE RELEVANCE OF BUSINESS TENDENCY SURVEYS[3]

The Article Studies The Predictive Capabilities Of Qualitative Assessments Of Employment Expectations Obtained From Business Tendency Observations Of Entrepreneurial Activity, Which Are Currently A Widespread Source Of Economic Information Both In National And International Practice. The Study Is Based On Market Surveys Conducted By Rosstat, Which Characterize The Expected Level Of Business Activity In The Segment Of Small Enterprises From The 1st Quarter Of 2008 To The 2nd Quarter Of 2019. The Aim Of The Study Is To Prove The Existence Of A Stable Statistically Significant Relationship Between Predicted Estimates Of Employment With The Dynamics Of Growth Rate Cycles Of The Corresponding Quantitative Statistical Macro-Aggregates In Various Sectors And, Therefore, The Relevance Of Predictive Models Of Employment Change Based On The Results Of Business Surveys. It Is Shown That Entrepreneurial Assessments And Expectations Are Effective Predictive Indicators For Predicting Employment Dynamics In The Short Term (Two To Four Months) And Identifying Turning Points In Employment Dynamics In The Small Sector. Small Business, As One Of The Most Sensitive Segments, Is One Of The First To React To The Current Changes, Which Makes Forecasting In This Segment Especially Important.

JEL Classification: C15, C22, C53, E24, E27, J21, L11, L60, L70, L81.

Keywords: Small Business, Business Tendency Surveys, Employment, Forecasting, Russia.

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1. Introduction

In most countries of the world, small enterprises (hereinafter referred to as SEs) make up the majority of the entire set of economic agents and are the backbone of the national economy, making a significant contribution to the dynamics of its development (Mazzarol and Reboud, 2020; Nel, 2019; Audretsch et al., 2019; Sebikari, 2019). In OECD countries, SEs account for 99% of all enterprises, and between 50% and 60% of value added, and in many regions, they are the main driving force behind employment growth (OECD, 2020).

In Russia, according to Sberbank and Rosstat data cited by RBC, in recent years, small businesses, together with micro-enterprises, were responsible for the employment of about a quarter of the total average number of employees and more than a quarter of the total turnover of enterprises (Nazarova, 2019). In terms of their share in the total turnover in the first half of 2020, it was the small retail and wholesale trade organizations (excluding microenterprises) that were in the lead; their share, together with the repair of vehicles and motorcycles amounted to 56.9%. They were followed by manufacturing industries (13.2%) and construction (7.7%), with a significant lag.

A special priority within the framework of economic policy in assessing the effectiveness of small businesses is given to the creation of new jobs, which is associated with the need to absorb the released labor force in other segments of the national economy (Falman, 2019; Chepurenko, 2013). Thus, the initiatives adopted in Russia within the framework of the national project "Small and Medium Enterprises and Support of Individual Entrepreneurial Initiatives" (implementation period: 2018-2024) suggest an increase in the number of small businesses due to an increase in the influx of workers from large enterprises. According to the May decree of the President of the Russian Federation, within the framework of the national goal "Decent, effective work and successful entrepreneurship", by 2024 the number of employees of small and medium-sized enterprises should be 25 million people. The "Strategy for the development of small and medium-sized businesses in the Russian Federation for the period up to 2030" approved in 2016 provides for an increase in the turnover of small and medium-sized businesses to the level of 2014 by 2.5 times; labor productivity (in constant prices) by 2 times; the share of small and medium enterprises in the manufacturing industry is up to 20%; the share of people employed in this sector of the economy is up to 35%; mandatory government procurement quota for small and medium-sized enterprises up to 25%.

The stagnation trends in the economy characteristic of Russia in recent years, the decline in real disposable cash incomes of the population, and the contraction of business activity in the markets have so far served as a negative background limiting the development dynamics of the

SEs segment. In 2020, the situation was further exacerbated by the unprecedented economic shock caused by the effects of the COVID-19 pandemic.

Moreover, one of the specific elements of pandemic destabilization for the economy as a whole and the small business (in addition to the obvious negative phenomena) turned out to be an impulse to the digitalization processes unfolding in Russia, on which the development of the segment in the coming decade will largely depend. In particular, the intensification of technological transformation can act as a trigger for key changes in the short-term period in the labor market in the SEs, displacing the usual niches of employment with intelligent automation and robotization of processes, which in turn emphasizes the relevance of reliable predictive estimates for the rapid diagnosis of trends due to increased volatility of employment.

An increase in investment in digital technologies is statistically associated with an increase in the employment of highly skilled workers and a decrease in the employment of low-skilled workers, as a study by Balsmeier and Woerter (2019) shows, and this is mainly due to end-to-end automation technologies in production: intelligent robotics, 3D printing, the Internet of Things. In general, technological progress has led to the closure of some jobs, but new ones have emerged in their place, so the net effect of digitalization in terms of overall employment is ambiguous (Radosavljević et al., 2020). If we talk about SEs, then digital technologies significantly expand the flexibility of enterprises in terms of the possibilities of working with the personnel fund, however, in the Russian context the potential available to them in this area will be realized only in the coming years, which also increases the relevance of those based on various sources of research and measurements of employment in SEs.

Thus, the current economic state of the segment is characterized by increased uncertainty, and, in particular, the scale of the consequences of the current crisis – and not necessarily negative ones – has yet to be assessed. The effect and cumulative impact of various trends that have unfolded in the past few years, in the light of the need for a consistent economic policy, increase the relevance of research in the field of economic forecasting, the further development of existing statistical methods and tools in this area, as well as the development of completely new approaches to assessing such an important aspect of the national economy as SEs. In particular, forecasting the parameters of economic activity in the SE sector is highly valuable for understanding the duration of cyclical processes in the economy, the scale of the economy's response to external shocks, and the duration of the economy's recovery from recession. The peculiarities of SEs, such as high flexibility and, at the same time, increased sensitivity to changes in the economic situation, allow using these forecast estimates not only for this segment but also to the entire economy.

In this paper, the subject of consideration is predictive assessments as a source of prompt response to current and expected trends in employment dynamics in key sectors of the Russian economy in the SE sector. From our point of view, one of the most promising sources of data here can be business tendency observations of entrepreneurial activity, which are currently a widespread source of economic information both in national and international practice and play an important role in measuring the dynamics of employment in countries and industries, acting as an additional statistical tool (Siliverstovs, 2013; Croux et al. 2005; European Commission, 2007).

The research question is formulated as follows:

Are short-term estimates based on the results of business tendency observations capable of acting as reliable benchmarks of the dynamics of employment in SE industries?

The study aims to prove the existence of a stable statistically significant relationship between predicted estimates of employment with the dynamics of growth rate cycles of the corresponding quantitative statistical macro-aggregates in various sectors and, consequently, the relevance of predictive models of employment change based on the results of business surveys. Thus, the contribution of this article is to study the predictive capabilities of qualitative assessments of employment expectations for the most representative industries in the SE segment. We complement the existing literature by examining the situation in four sectors separately, which is done for the first time in the case of analyzing the dynamics of employment using survey data.

Additionally, using the survey results, based on business tendency assessments, we build a demo test forecast for the most sensitive segment of the studied today – retail trade. It is worth noting that the latest data used in the study dates back to 2019 and, accordingly, does not take into account all the trends in the business environment caused by the 2020 pandemic shock. Consequently, the forecast presented in the paper is, first of all, testing the capabilities of the data, the predictive potential of which is investigated in the study, rather than the actual forecast model.

2. Dynamics of employment in small enterprises: retrospective quantitative estimates

According to Rosstat, the dynamics of the average number of employed in the last decade are disappointing and broadcasts a rather accentuated series of trends, the prevailing of which is negative[4]. In the graphs below, both for all industries as a whole (Fig. 1), and separately for the manufacturing industry, construction, and wholesale and retail trade, together with the repair services sector (Fig. 2), there is a similar trend with a negative trend during the 2010s only with different scales of volatility.

[4] Rosstat. (2020). Institucional'nye preobrazovaniya v ekonomike [Institutional transformations in the economy]. URL: https://rosstat.gov.ru/folder/14036 (accessed 23.10.2020).

In Fig. 1, we see a decline in this indicator in 2008-2009, caused by the global financial crisis. Then from 2010 recovery began, but the compensation dynamics turned out to be unstable, and since 2012 there has been a clear trend towards a slow decline in SEs' employment. The dynamics of the indicator after 2012 was primarily due to structural reasons. At the same time, we can interpret this as a signal from the business community, indicating the instability of its position and expectations of further shocks leading to a contraction in the number of workers.

In 2016, after the unfolding of the crisis trends in the Russian economy associated with the imposition of the sanctions regime and counter-sanctions in the SEs, there was a severe decline in employment associated with a drop in demand, devaluation of the ruble, and a deficit of finance, which partly justified negative expectations. The indicator collapsed to levels even below the crisis level of 2009. In 2017, the positions were restored almost to the level of 2015, however, in subsequent years, the overall downward trend remained, even slightly strengthening in comparison with the pre-crisis one.

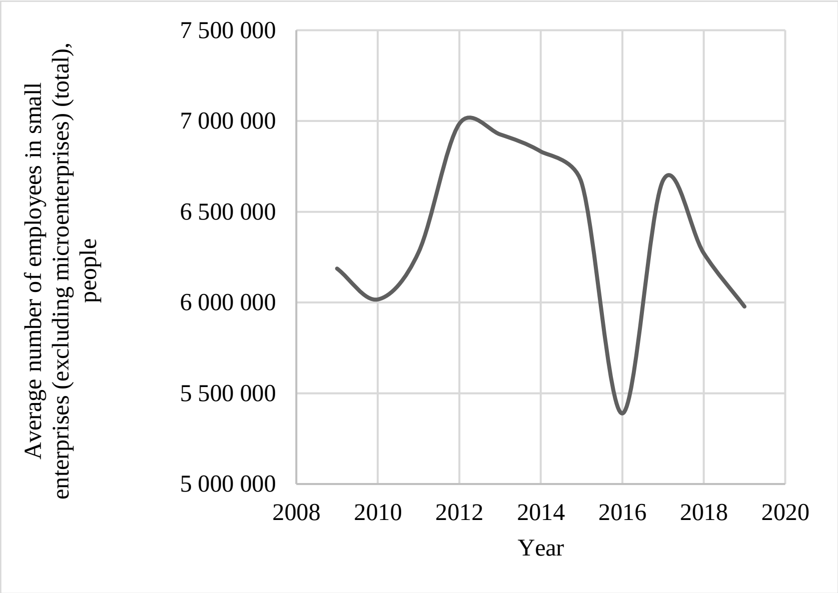

Fig. 1. Dynamics of the average number of SEs' employees (excluding micro-enterprises) in Russia from 2009 to 2019 (total)

Source: authors' calculations based on Rosstat data (URL: https://rosstat.gov.ru/folder/14036, accessed 23.10.2020).

Fig. 2 shows the dynamics of the same indicator in the context of individual industries, also provided by Rosstat. In general, in each of the industries, there are similar trends, as in the entire segment, adjusted for the absolute scale. Nevertheless, it can be noted that the situation in the wholesale and retail trade, along with repair services, was characterized by slightly more volatility, while in the manufacturing industry and construction, the indicator was approximately the same throughout the entire period under review.

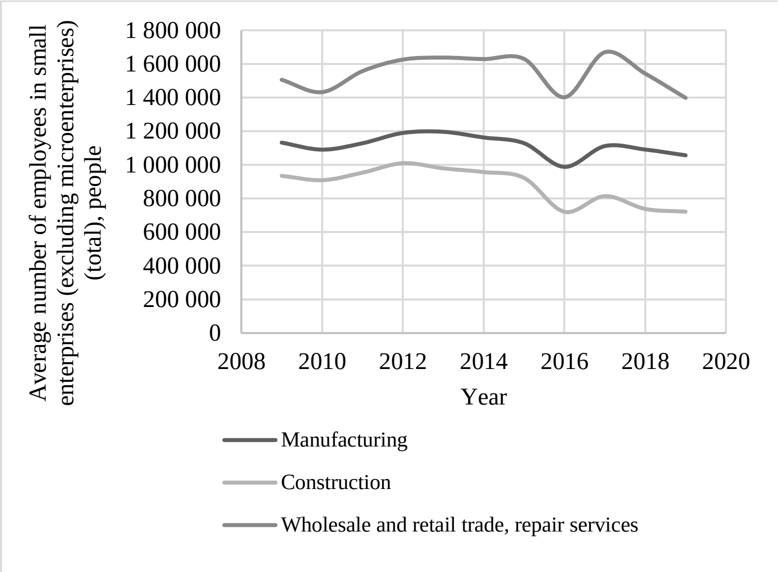

Fig. 2. Dynamics of the average number of SEs' employees (excluding micro-enterprises) in Russia from 2009 to 2019 (in manufacturing, construction, wholesale and retail trade, and repair services)

Source: authors' calculations based on Rosstat data (URL: https://rosstat.gov.ru/folder/14036, accessed 23.10.2020).

3. Literature review

If we talk about the statistical analysis of the SE segment using the method of business tendency surveys, then there are not so many studies for the variables of the labor market directly based on qualitative assessments (dos Santos, 2003; Abberger, 2007b; Graff et al., 2012; Siliverstovs, 2013; Lehmann and Weyh, 2016; Varyash and Zubets, 2016; Mkhitaryan and Sarycheva, 2017). Most studies assess the predictive power of indicators for standard economic variables such as gross domestic product (Hansson et al., 2005; Abberger, 2007a), industry production (Hanssens and Vanden Abeele, 1987; Fritsche and Stephan, 2002; Croux et al., 2005) or inflation (Ang et al., 2007). Overall, most research confirms that qualitative information is useful for predicting real economic activity (Carriero and Marcellino, 2011; Frale et al., 2010; Giannone et al., 2009; Klein and Özmucur, 2010; Lemmen et al., 2005). Moreover, Banbura and Rünstler (2011) and Keeney et al. (2012) show that delays in the release of quantitative, reliable data are indeed an important reason why survey information is valuable. The usefulness of the surveys has been confirmed by Hansson et al. (2005) for Sweden, Matheson (2010) for New Zealand, Lahiri and Monokroussos (2013) for the US, Luciani and Ricci (2014), and Martinsen et al. (2014) for Norway, Modugno et al. (2016) for Turkey, and Bragoli (2017) for Japan; business and consumer survey indicators are used to forecast economic performance in the OECD, European Commission. Nevertheless, it should be noted that some examples of such more specialized studies based on qualitative data on the labor market are still available in foreign practice.

For example, dos Santos (2003) investigated the relationship between a large number of qualitative indicators (including employment expectations) and several different macroeconomic variables in Portugal. Through cross-correlation analysis, it was possible to find a statistical relationship between employment expectations and the annual growth rate of employment in some sectors (for example, in the manufacturing industry).

Abberger (2007b) investigated whether employment expectations from Germany's monthly ifo Employment Barometer could be used as a leading indicator for annual changes in employment. Taking different approaches, he found that the survey-based indicator works for two to four months and can date turning points in employment growth. In the Swiss context, Siliverstovs (2013) used the KOF Employment Indicator, developed by the Swiss Economic Institute KOF, to assess whether this survey-based indicator improves the accuracy of "in-sample" and "out-of-sample" employment forecasts in Switzerland. He found that the barometer has one-quarter predictive power. A study by Graff et al. (2012) confirmed their findings by showing that the KOF Employment Indicator, as well as a survey-based indicator built by the Swiss Federal Statistical Office, can predict employment for the quarter ahead.

Separately, we can highlight the study of Lehmann and Weyh (2016), during which the authors investigated the predictive ability of expected changes in employment to predict changes in the number of workers in 15 European countries on a quarterly basis from 1998 to 2014. Researchers concluded that for most countries of the sample, the expected change in the number of employed is an effective indicator for predicting changes in employment in the short term (for a quarter ahead). In the course of business surveys, entrepreneurs express their expectations in the short term, therefore, it is expected that the effectiveness of forecasting in the context of longer periods (up to four quarters) is lost. However, in the case of some countries such as Belgium, Estonia, and France, the model that includes the qualitative indicator still significantly outperforms the reference models in the long run.

In Russian practice, there are noticeably fewer examples of labor market research using business tendency observations. In the context of studies of the labor market, in particular, the dynamics of employment, it is worth noting the paper (Mkhitaryan and Sarycheva, 2017), in which a methodology for constructing predictive estimates of employment by type of economic activity, based on econometric models, was developed and tested. It proved the importance of the influence on the employment of demand factors, labor productivity, and demographic situation. The authors concluded that the population employed in wholesale and retail trade will gradually increase, absorbing flows of labor resources from manufacturing and agriculture.

Only a small number of studies have focused on the predictive properties of qualitative indicators. For example, in the article Varyash and Zubets (2016), the question of the ratio of the method for calculating leading indicators characterizing the directions of economic activity, based on the balanced approach and the PMI (Purchasing Management Indexes) method, is discussed. Also, a statistical model that determines the tightness of the relationship between the actual parameters of the development of the domestic mining industry and the calculated indicator, which is ahead of the output indicator, was presented.

Along with publications on the classic measurement of employment dynamics, there is a growing number of papers focusing on studies of the transformation of labor markets in connection with digitalization, the introduction of technologies, including attempts to model industry scenarios taking into account technological transformations. This issue is especially widely discussed at the OECD platform (OECD, 2019; Calvino and Criscuolo, 2019; Calvino et al., 2018). The next section provides a brief overview of the main trends within this aspect of the problem.

4. Digital development and the escalation of its effects on labor markets

The digitalization of labor practices and processes is an important aspect of the global trend in the digital transformation of the economy. The role of these processes seems to be key for understanding the prospects of the labor market in the SE segment. What opportunities and challenges are associated with it in the short and long term?

The most common forecasts here include growing inequality in the labor market, precarization, labor automation, as well as the growing role of new forms of work in the so-called platform economy or gig economy. Despite the popularity of the view that digitalization will lead to significant structural changes in labor relations, it is advisable to be careful in assessing the speed of the escalation of the effects of digital development.

The problem of predicting the impact of digitalization on the labor market is associated with the complexity of assessing the resulting influence of factors that contribute to the growth of employment and factors that contribute to the growth of unemployment. Let us try to highlight them.

Factors that contribute to employment growth:

- the emergence of jobs due to new professions;
- the increase in demand for existing professions in the IT sector due to its expansion;

- the reduction in the time spent looking for a job because an increasing number of people will use Internet services for these purposes (reduction of frictional unemployment);
- the increase in the number of jobs where you can work remotely, which allows you to use additional segments of the workforce.

Factors that contribute to the rise in unemployment:

- the automation of workplaces, which will make several professions unclaimed;
- the time lag between the emergence of the need for highly skilled workers and the training of workers, as a result of which structural unemployment is possible.

Labor market trends that have had an impact in the recent past are likely to continue to accelerate along with digitalization. This means more flexibility in the form of individual temporary work and service contracts and more freelance work. In general, firms will increasingly employ a temporary design work format and, at the same time, concentrate their core workforce at the desired minimum in segments where there is no shortage of skilled workers. In OECD countries, at the state level, great attention is paid to accelerating the spread of digital innovations in the SE segment and ensuring that they keep up with the digital transformation, which is expressed in providing advanced training for workers in SEs, expanding innovation networks and links between SEs and other segments, and leveling the playing ground in commodity markets, government procurement, and 'leading' innovation markets (OECD, 2019).

In the context of the latest structural changes, primarily in the real sector, and the structural transformation of the labor market, the Internet of Things is one of the most significant promising areas for the introduction of digital technologies. Its implementation transforms enterprises into open systems where operational and information technologies are integrated. At the same time, all production chains are included in a single information space – from development and production to sales and service, which ensures an increase in efficiency by reducing capital and labor costs.

New production technologies, new business practices, and management models that have arisen in connection with the introduction of digital technologies are transforming the structure of the labor market and changing the requirements for professional qualities and competencies of employees. As a result of digitalization, this market, like the economy as a whole, receives new development opportunities, but at the same time, new threats and risks may arise that affect both employees and employers and the state as a market regulator. In turn, the labor market itself, which in Russia has long been a stable socio-economic system, is a very important component of the overall environment for the development of the digital economy. Therefore, when assessing the dynamics, directions, opportunities, and limitations of the introduction of digital technologies, one must take into account both macroeconomic and structural and institutional characteristics of this market.

In our opinion, one of the promising areas for future research can be the study of the intensity of digitalization in the sectors of the economy and the ongoing changes in the labor market in the relevant sectors of the economy. These studies may, in particular, include the calculation of indicators of the intensity of industry digitalization, digital labor and a comparative analysis of the relationship between the calculated indicator of the intensity of industry digitalization and the indicator of the intensity of digital labor, as well as certain important indicators characterizing the labor market (for example, the number of employees, the number of IT professionals, etc.).

5. The empirical base of research

The empirical basis for this study are the results of business tendency surveys characterizing the expected level of business activity in the SE segment from the 1st quarter of 2008 to the 2nd quarter of 2019, carried out on a quarterly basis by Rosstat. The aggregate sample included more than 14 thousand enterprises from four sectors: manufacturing (about 3.7 thousand small industrial enterprises), construction (4.5 thousand small construction firms), retail and wholesale trade (over 6.5 thousand small organizations). Depending on the industry of the enterprise, the data were collected, respectively, based on statistical reporting forms No. DAS, No. DAP-1, No. 1-conjuncture, and No. 1-conjuncture (wholesale).

Key for our research is one of the survey indicators – the expected employment, harmonized with the European Business Trends Survey Program and calculated in the same way in all the sectors represented.

The quantitative referent was the rate of change in employment (referent). Data on the average number of workers in small enterprises (excluding microenterprises) were collected from the official website of the Unified Interdepartmental Statistical Information System (UISIS), adjusted for seasonality, and converted to growth rates (from quarter to quarter).

6. Methodology

6.1.Business Tendency Surveys: Methodological Aspects

Business surveys provide an opportunity to collect digitized responses from respondents to many fundamental questions that are often missing in official quantitative statistics, allowing to capture the expectations and sentiments of the business community regarding future trends. Short-term information obtained in the course of qualitative surveys describes the perception of the economic situation by the economic community, while standard quantitative statistics reflect only changes in static objective conditions, which is why their adjustment to market shocks is reflected in them with a longer lag. The data obtained with the help of business tendency observations represent the answers directly from the heads of enterprises who have the most complete understanding of the aspects of the business and digital activity of the organizations they lead and who have the necessary level of competence about the questions asked.

In the case of the indicator used in the study – expectations of changes in employment – the respondents had three answer options to assess the change in the average number of employees in the next quarter compared to the current one: “increase” (+), “no change” (=) and “decrease” (–). The main way to quantify such qualitative data collected in business tendency survey is the balance method, widely used in the practice of statistical studies of the OECD and the EU (Croux et al., 2005; Claveria et al., 2007). The balances are calculated as the difference between the proportion of firms whose managers reported an expected increase in employment and the share of firms whose managers expected a decrease in the average number of employees (European Commission, 2007).

Seasonal adjustment is a prerequisite for analyzing time series of the activities of trading companies since these economic activities are inherently subject to significant seasonal fluctuations. In particular, the second and fourth quarters are the most active phases in trade, while the beginning and the middle of the year, excluding cases of force majeure, demonstrate a steady trend of development according to the inertial scenario of previous periods. As a result, a comparison of such series, without excluding the seasonal component, does not allow us to correctly identify industry events and identify short-term trends. For the procedure of decomposition of seasonal time series, the TRAMO / SEATS algorithm was implemented.

6.2.Granger causality analysis

At the initial stage of the study, a cross-correlation analysis was carried out, within the framework of which we compared the balance values of the expected change in the average number of workers in small enterprises with the rate of change observed in the current quarter. Significant cross-correlation coefficients at a zero-lag should indicate a link between the expectations expressed in the previous quarter and the observed rate of change in the number of employees in the current quarter. In turn, significant cross-correlation coefficients at lag (-1) indicate the predictive ability of entrepreneurs' expectations.

The next stage of the study was a more formal test of the assumption about whether sectoral estimates of expectations of changes in employment can act as an indicator for short-term forecasting of the rates of change in employment in the considered sectors of the Russian economy using the Granger causality test. A necessary condition for checking Granger causality is the stationarity of the considered time series. To obtain complete and reliable information on stationarity, two tests were used: the Ng–Perron (NP) test and the Kwiatkowski–Phillips–Schmidt–Shin test (KPSS). In the NP test, the unit root is considered as the null hypothesis, while in the KPSS test, stationarity is taken as the null hypothesis.

The NP and KPSS tests were applied to the referent and qualitative indicator levels in four industries. All series turned out to be stationary across levels, so there was no need to transform the data (for example, use the first differences).

To test the Granger causality, the following two equations were estimated:

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j x_{t-j} + \varepsilon_{1,t}, \qquad (1)$$

$$x_t = \sum_{j=1}^{q} \gamma_j x_{t-j} + \sum_{i=1}^{p} \delta_i y_{t-i} + \varepsilon_{2,t}, \qquad (2)$$

The rate of change in employment was denoted as y_t, and the expectation of employment as x_t. A maximum of four lags was allowed for p and q in equations (1) and (2).

It was checked whether the indicator x_t has a significant impact on the target variable y_t. The Granger causality test can lead to four different cases: (1) only employment expectations cause an increase in the employment rate, (2) there are feedback effects between the two series, (3) only the employment rate change causes an employment rate change, and (4) there is no relationship. When case (3) occurs, employment expectations are probably not a suitable predictor of the dynamics of the rate of change in employment. The same applies to the fourth case. In cases (1) and (2), employment expectations can probably be used as an indicator to predict the rate of change in employment, i.e., forecasting of the variable y can be improved with additional information about x.

Granger causality test results can be sensitive due to the maximum lag lengths p and q. Therefore, we have tested various p and q specifications to obtain reasonably reliable results. The necessary assumptions (for example, homoscedasticity or lack of autocorrelation) were also tested to evaluate the models of equations (1) and (2), and the results of the test confirmed the relevance of the chosen method for our data.

6.3.Pseudo-Out-of-Sample Analysis and the Demonstrative Predictive Model

At the final stage of the study, a pseudo-"out-of-sample" analysis was carried out, involving the division of the existing aggregate sample into two subsamples (Inoue and Kilian, 2005). In this case, the first subsample is used to build a forecast, and the second is used to evaluate it by comparing the model results with real data.

For our purposes, we used the following Autoregressive Distributed Model (ADL) model:

$$y_{t+1} = \alpha + \sum_{i=1}^{p} \beta_i y_{t+1-i} + \sum_{j=1}^{q} \gamma_j x_{t+1-j} + e_{t+1} \qquad (3)$$

where y_{t+1} is the forecast for the rate of change in employment one step ahead, and x_t is the expectation of employment. A maximum of two to four lags was allowed for our target variable (p) and employment expectations (q). The period for evaluating equation 3 was set from Q1 2008 to Q4 2012 (T_E=20). The first forecast y_t was calculated for the 1st quarter of 2013, and the last one – for the 2nd quarter of 2019 (T_F=26).

To assess the prediction accuracy of the models, prediction errors for the equations were calculated. At the same time, as $\hat{y}_{t+1}$ the forecast was one step ahead obtained at time t, the resulting forecast error as $FE_{t+1} = y_{t+1} - \hat{y}_{t+1}$, and the corresponding forecast error of the autoregressive model chosen as the reference model is $FE^{ARp}{}_{t+1}$. To assess the effectiveness of models based on qualitative indicators, the roots of the mean squared forecast error (RMSFE) were calculated as a loss function for forecasting based on a qualitative indicator one step ahead:

$$RMSFE_1 = \sqrt{\frac{1}{T_F} \sum_{n=1}^{T_F} (FE_{t+1,n})^2} \qquad (4)$$

The RMSFE for the autoregressive reference model has been designated $RMSFE_1^{ARp}$ to determine whether the use of employment expectations is more effective than the autoregressive process, the RMSFE ratios were calculated between the qualitative indicator models and the reference ones.

$$rRMSFE_1 = \frac{RMSFE_1}{RMSFE_1^{ARp}} \qquad (5)$$

Based on the ADL model used in the pseudo-out-of-sample analysis, the paper additionally proposed the visualization of predictive estimates using the results of business tendency surveys. On the graph, the actual values of the rate of change in employment (referent) were compared with the leading estimates of the referent values predicted using the model based on the qualitative indicator.

7. Results

A preliminary cross-correlation analysis confirmed that employment expectations in the considered sectors of the Russian economy can act as indicators for predicting the rate of change in employment, showing coefficients of more than 0.6 in all sectors. International experience of working with the results of business market research shows that for quality indicators this value can be considered significant and acceptable, which is confirmed by both foreign and Russian practice of relevant research (OECD Composite Leading Indicators, 2012; Fulop and Gyomay, 2012; Kitrar and Ostapkovich, 2013).

The results of testing Granger causality are shown in Table 1. The fourth column indicates whether the indicator has leading characteristics (+), whether there are feedback effects between the two series (FB), or whether the indicator has no predictive ability or there is no relationship at all (X). In general, the results indicate that in all the industries under consideration, employment expectations are leading indicators for the referent. Feedback effect was also found in the construction sector. Also, it should be noted that in this industry, in contrast to the other three, the best statistical reliability of the relationship was observed not at lag (-1), but lag (-2). In other words, in the construction sector, entrepreneurs can predict the dynamics of the rate of change in employment not in one quarter, but in two (which is quite logical based on the specifics of the activity). In other industries, the best results were observed at lag (-1). The most reliable data were obtained for wholesale trade. By the type of activity, wholesale trade is one of the most effective leading indicators, as the experience of longitudinal industry business tendency monitoring in Russia shows.

Table 1. Granger causality test results for the four selected industries

Industry	**Employment Expectations → Employment Change Rate**	**Employment Change Rate → Employment Expectations**	**Result**	**Lag**
Retail trade	0,030**	0,364	+	-1
Wholesale trade	0,001***	0,273	+	-1
Construction	0,092*	0,007***	FB	-2
Manufacturing	0,013**	0,226	+	-1

***** Sig. level 0,1

** Sig. level 0,05

*** Sig. level 0,01

Source: authors' calculations

Summing up, it should be noted that the "in-sample" analysis revealed the potential predictive ability of the expected change in the average number of SEs' workers for the observed change in the growth rate of the average number in all sectors of the Russian economy considered in this study – retail and wholesale trade, construction and manufacturing.

Table 2 presents the calculated rRMSFE ratios for four sectors of the Russian economy considered in this study. For all of them, namely retail and wholesale, trade construction, and manufacturing, the entrepreneurial employment expectation models are characterized by lower forecast errors compared to standard autoregressive models, since the rRMSFE ratios are less than one in all cases.

Table 2. Calculated rRMSFE values for the four selected industries

rRMSFE values	
rRMSFE in the retail trade	0,870
rRMSFE in the wholesale trade	0,858
rRMSFE in the construction	0,909
rRMSFE in the manufacturing industry	0,899

Source: authors' calculations

Thus, the results of the pseudo-"out-of-sample" analysis confirm our conclusions obtained in the course of cross-correlation and "in-sample" analysis – entrepreneurial employment expectations can act as an indicator for predicting changes in the number of people employed in small businesses. The short-term nature of predictive ability is largely because entrepreneurs are expressing their expectations for the next coming quarter.

Fig. 3 shows a test predictive model built for the retail segment for the period from the beginning of 2014 to the 3rd quarter of 2019. The series on the graph correspond to the actual values of the rate of change in employment (referent) and its values predicted using the ADL model (model based on qualitative indicator). The figure illustrates the results obtained for the predictive capabilities of models that include qualitative data. In particular, the dotted lines mark the areas of the crisis recession in 2016 and the subsequent recovery, which was reflected ahead of time in the model based on the predictive capabilities of predictive estimates of business tendency observations.

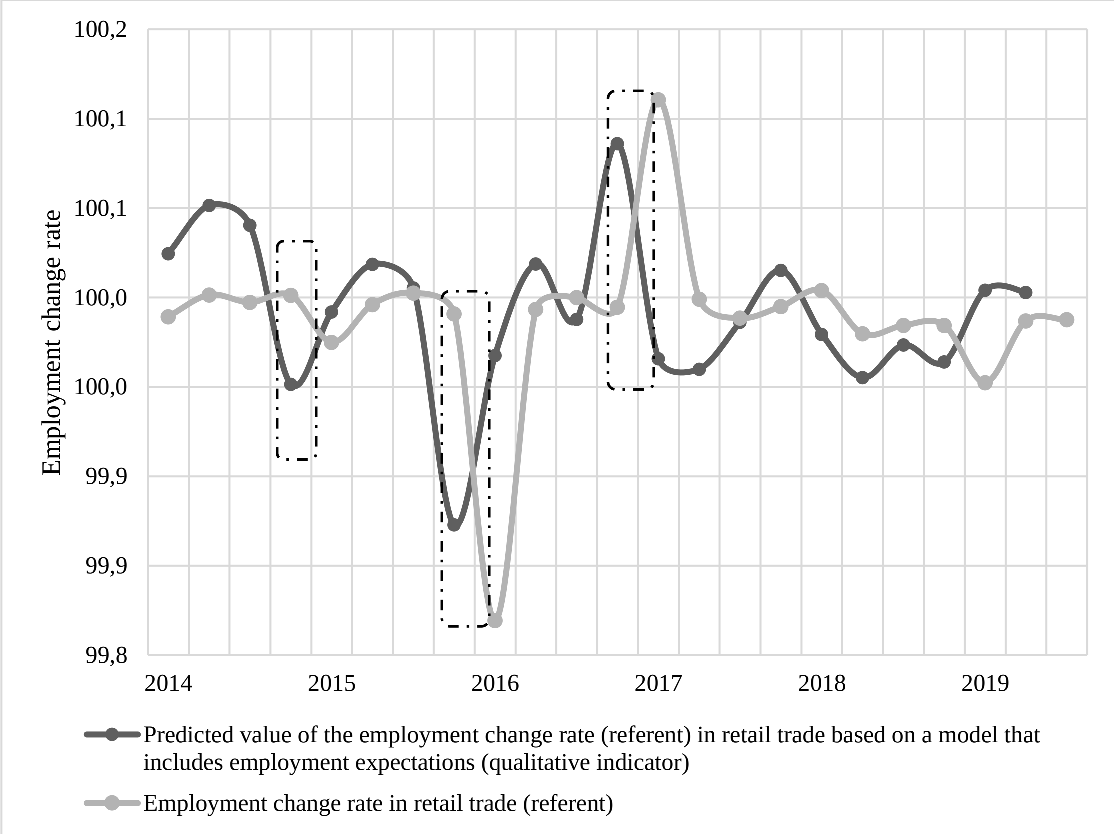

Fig. 3. **Forecast of the employment change rate based on ADL models**

Source: authors' calculations

8. Conclusion

According to the results obtained based on "in-sample and pseudo-"out-of-sample" analysis, in all the industries under consideration, entrepreneurial estimates and expectations are effective relevant predictive indicators for forecasting employment dynamics in the short term (two to four months) and identifying turning points in employment growth in the SE segment. Since the data used here become available before quantitative data and then does not undergo major changes, they can serve as an objective additional source for analyzing the state of the economy in real time.

The value of our contribution lies in the fact that for the first time we studied on an expanded sample (more than 14 thousand respondents) the possibilities of business tendency surveys for forecasting labor market indicators in small businesses in the sectoral context, considering separately retail and wholesale trade, construction, and manufacturing. This gives us a broader picture of how the use of business tendency survey results can work in different situations, reflecting the sentiments of respondents from opposite industries.

In particular, the most sensitive predictive estimates were found in the retail and wholesale sectors, with the best results obtained for wholesale. This gives the right to recommend the use of quality indicators from these sectors to monitor the level of employment and unemployment in the first place. For example, this data has successfully identified signs of a possible decline in 2016. The construction sector, due to its specificity, was characterized by a longer lag between the dynamics of expectations and the referent, which should be taken into account when building predictive models. In the case of manufacturing, the inclusion of employment expectations also improves the forecasts, but the performance of the market indicators for employment was slightly lower compared to other industries.

Forecasting employment in small businesses is especially relevant in connection with the growing influence of the digital economy, which entails fundamental shifts for the labor market and the development of certain industries in connection with the restructuring of employment models and formats. In these conditions, timely observation and forecasting of changes using additional analysis tools, such as the methodology proposed in our study, becomes especially important. The combination of approaches based on various sources of statistical data (quantitative, qualitative) will allow achieving the highest level of predictive objectivity in decision-making, as well as in assessing the results of government programs and measures to support the economy.

The development of the proposed methodology in the future should include the expansion of the presented range of industries, consideration of the service sector by type of economic activity, including financial services, IT services, etc. Also, the further direction of analysis is related to forecasting other indicators of SEs' economic activity not related to the labor market. Here, the possibility of constructing systems of equations entirely based on time series of nonparametric indicators seems to be especially interesting. This will make it possible to use the results of business tendency surveys not only as an additional tool that increases forecasting efficiency, but also as an alternative base for macroeconomic analysis using techniques such as modeling exogenous shocks, scenario analysis, and sensitivity analysis, which becomes especially relevant during periods of crisis dynamics of the national and world economy. Due to the very specifics of information, business tendency surveys have an advantage in terms of the potential to reflect various aspects of the activities of individual enterprises and industries, including parameters of technological and digital development, which are significantly worse reflected in quantitative statistics.

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