ARE INDUSTRIAL COMPANIES IN THE CZECH REPUBLIC ABLE TO PREDICT THE SHORT-TERM FUTURE OF THE ECONOMY?

VERONIKA PTÁČKOVÁ
University of Economics, Prague, Faculty of Informatics and Statistics,
Department of Economic Statistics,
W. Churchill Sq. 4, Prague, Czech Republic
e-mail: veronika.ptackova@vse.cz

LUBOMÍR ŠTĚPÁNEK, VÍT HANZAL
University of Economics, Prague, Faculty of Informatics and Statistics,
Department of Statistics and Probability,
W. Churchill Sq. 4, Prague, Czech Republic
e-mails: stel04@vse.cz, xhanv16@vse.cz

Abstract

Economists, politicians or managers always want to know what mood the economy is in. Economic surveys, Short-term statistics and Business tendency survey, can give the answer to this question. However, the short-term business statistics describe real data about companies; the results are published with a two months delay. By way of contrast, the Business tendency survey indicates predictions of this economic development. Since the Business tendency survey is based on opinions of selected companies, a quality and confidence of predictions in the previously mentioned survey is opened to discussion.
The article focuses on evaluation predictions and the real development of industrial companies in the Czech Republic. Authors are comparing results from Short-term statistics in the industry and the Business tendency survey. The Czech Statistical Office collects data from the both surveys. Using mathematical and statistical methods, authors want to scale and categorize real data-based economic development, recorded by short-term business statistics, into categories corresponding within predictions, offered by Business tendency survey, such that the appropriate categories from the both sources correlate themselves enough. The categorization attempt is performed for real data of two economic indicators – employment and sales.
In case the categorization of real data is successful, Business tendency surveys published without any significant delay can provide sufficient and early idea about near future economic development. Furthermore, the results of the analysis can help to understand respondents´answer in the Business tendency survey and possibly update methodology, will be used to assemble indicators of the trust.

***Keywords**: business tendency survey, prediction accuracy, short-term statistics, industry*

***JEL Codes**: C10, C22, C82*

1. Introduction

Short-term business statistics are one of the key indicators to assess and monitor the development of the economy – not only in the European Union, but across the entire Eurozone as well. Four areas are analyzed within them: industry, construction, trade and selected services. This data is then processed and the results are provided to government institutions, central banks or financial institutions. The conclusions drawn are not only for European institutions, but also for politicians or business leaders who can respond to the current and expected developments in the economy (Eurostat, 2018). Both the professional and non-professional public are interested not only in the quantitative data, but also in the qualitative data. In this case, results of the Business tendency survey (BTS) help. The BTS informs about the assessment of businesses – how the economic situation of a company will develop over the next three months (in the opinion of the respondents). The main advantage of the BTS is that the opinion comes directly from people working in industrial enterprises and results are subject to little revision (Cornec, 2014).

Industry has always been one of the key areas of the Czech economy. This is the main reason why the authors of this paper selected this area for analysis. The calculations will be based on two data sources: Short-term statistics in industry and the Business tendency survey. The authors have monthly data ranging from 2003 to 2016. In this case, 400 industrial companies will be analyzed. The number of companies was chosen by the means of the maximum number of the ones reporting continually during the time of interest. Authors will focus on two indicators: employment and sales.

The main question is: How accurately can companies predict their future? Answering the question, we tried to scale and categorize real data-based economic development, recorded by short-term business statistics, into categories corresponding within predictions, offered by Business tendency survey, such that the appropriate categories from the both sources correlate themselves enough. The categorization attempt is performed for real data of two economic indicators – employment and sales. If such categorization of real data offered by short-term statitics would be successful, it does mean that the Business tendency surveys published without any significant delay can provide sufficient and early idea about near future economic development.

This paper is divided into three chapters. The first one is a literature review about the Business tendency survey, short-term statistics and companies´analysis on microdata level. The second chapter describes the methods and data which are used in the analysis. The last chapter presents the most important results of the calculation.

2. Literature Review

Information about the quantitative indicator of economic activity is important for decision makers (e.g. policy makers) and for policy-orientated research. Unfortunately quantitative data are published with a significant time delay and on a low-frequency basis. Sometimes they need revisions. The Business tendency survey can help to mitigate the problem and close the gap of missing, readily available quantitative data (Bierbaumer-Polly, Hölzl, 2015). Despite numerous advantages of BTS some authors propose to change qualitative data to quantitative. Anderson (1951) suggests to convert quantitative measures of respondents´assesment and expection as difference between (weighed) percentages of positive and negative answers to the task of interest. This change describes "aggregated" view (e.g. cross-sectional average) of economic subjects of their economic environment and expectation (Erkel-Rouse, Minodier, 2009).

The behaviour of aggregates can be described thanks to the cross-sectional behaviour and characteristics of individual firms (Higson *et al.,* 2002). Clower (1998) warned that results achieved on the micro level (e.g. individual companies) can have a different interpretation of the same aggregate phenomena. It is important to be careful of making a conclusion on the macro level. Kaiser and Spitz (2000) have shown that the inclusion of firm-specific variables (regional and sectoral affiliation, firm size) decreases the inaccuracy of the standard error of the outcome variable of interest (sales growth). Firm-level, industry-specific and regional structural characteristics are important during definition model following Basile *et al.* (2014). Nieuwstad (2005) analyses the matching of production information (recent output and expectations) in the Netherlands. He found that roughly 20 percent of companies answer completely illogically. On the level of industry, the matching between the balance statistics and production data increases to more than 50 percent. Companies have better results in assessing the recent past than predicting the near future.

Thanks to German and U.S. business survey data, Bachmann, *et al.* (2012) analyse the dynamic relationship between uncertainty and economic activity. Ehrmann (2005) says that small companies which have little collateral and a lower value of assets react better to a tightening of funds than large firms. Bierbaumer-Polly, Hölz (2015) have published that the answers of companies to different questions (within the Business tendency survey) are the same at the microeconomic level. The best results were for order book levels, their current degree of capacity utilisation and their production predictions. Business tendency surveys are useful for finding information about business cycle conditions (current and predictions). Micro data can describe business cycle dynamics in a consistent way and are not influenced primarily by structural characteristics.

Siliverstovs (2014) provides information about the KOF Swiss Economic Institute which collects data for short-term prediction. Thanks to them, the KOF Employment Indicator is made, which is constructed on monthly and quarterly data. This indicator has better predictive ability for employment in Switzerland.

Jílek, Pecáková, and Vojta (2005) analyse situation in the Czech Republic. They found that unchanged development prevails (roughly 60%) in an enterprise´s predictions in the Czech Republic. In reality, the percentage of enterprises with stagnating development is about three or four percent. The authors have stated that the results of business surveys should only be used as supplementary information.

3. Methods

Data from two sources are used – Short-term statistics in the industry and the Business tendency survey. The Czech Statistical Office collects both types of data. Data from the short-term statistics carries a precise numeric character while the Business tendency survey offers only categorical data.

The Business tendency survey collects opinions from companies in the industry, construction, trade and selected services. Respondents (we focus only on industrial companies) answer questions about the future economic indicator of interest – i.e. production, trade, demand, supply, prices, loans or employment. The questions the companies are asked to answer deal with their estimates of the evolution of the next three months of each of the economic indicators of interest. The respondent does not quantify; he/she only asseses the asked change of the economic indicator during the following three months in terms of a "decrease", "stagnation", or "increase" of the current state. In other words, a respondent is asked at the beginning of month t to assess the progress of the economic indicator of interest in the next consecutive three months t, $t+1$, $t+2$, respectively, where t stands for an ordinal index of the month. For this article, a respondent's answer for only two economic indicators of interest are considered – employment and sales[1]. The respondent has to answer the following two questions, (i) “the number of employees will (in the next three months)” and (ii) “the number of sales will (in the next three months)”. The possible answers to both of them are

- “Increase”
- “Remain at the same level”
- “Decrease”.

Thus, we are able to find a value of opinion $o_{t,i,c}$ stands for a record of indicator i for a company c linked to the months t, $t+1$, $t+2$. It is clear that for $\forall c$, $\forall i$ and $\forall t$ is $o_{t,i,c} \in \{\text{decrease}, \text{stagnation}, \text{increase}\}$.

Short-term statistics in the industry collect precise quantitative data about industrial companies. We focus on:

- employment = the average number of employees of a company registered for a month. This indicator includes all permanent and temporary employees that have a contract of employment with the reporting company; irrespective of the activity they perform.
- sales = economic turnover of a company recorded for a month.

These two sources will be compared. Categories of the selected indicators of our interest, i.e. employment and sales, are collected via the Business tendency survey and, therefore, are fixed (their possible levels are “decrease”, “stagnation” and “increase”), whereas the categories of the indicators offered by the short-term statistics in industry are of a quantitative, numeric character. In order to make both mentioned sources comparable, we had to transform quantitative (numeric) data coming from the short-term statistics in industry in the following manner:

(i) transformation of absolute values of the indicators to relative ones.
(ii) categorization of the computed relative values from the previous step into three levels according to defined ratio *k* (see below).

Describing step (i) in greater detail, two metrics were defined to transform absolute values of the indicators (employment, sales) to relative ones.

- *mean to first*, $MTF_{t,i,c} \stackrel{\text{def}}{=}$ an average of values of indicator i linked to the consecutive months t, $t+1$, $t+2$, respectively, recorded by company c, divided by the value of indicator i linked to month t, recorded by company c, where t stands for an ordinal index of the month and i stands for one of the indicators of interest, $i \in \{\text{employment}, \text{sales}\}$.
- *last to first*, $LTF_{t,i,c} \stackrel{\text{def}}{=}$ the value of indicator i linked to month $t+2$, recorded by company c, divided by the value of indicator i linked to month t, recorded by company c, where t stands for an ordinal index of the month and i stands for one of the indicators of interest, $i \in \{\text{employment}, \text{sales}\}$.

Using both defined metrics, values of each of the indicators (employment, sales) for the first 400 companies[2] ordered by length of consecutive responding (in months) and for all of the available months, but always except for the last two[3], were transformed.

---

[1] Prediction of sales covers domestic and international sales.

[2] The number of companies was chosen by means of the maximum number of the ones reporting continually during the time of interest.

Going deeper into step (ii), for each of the named indicators, employment and sales, we defined an interval of ratios $k : k \in \langle 1.0; 5.0 \rangle$, such that all values of the indicator transformed according to step (i) greater than or equal to k are labeled as "increased", all values of the indicator transformed according to step (i) lower than $1/k$ are labeled as "decreased" and the remaining values of the indicator transformed according to step (i) greater than or equal to $1/k$ and lower than k are labeled as "stagnation". A value of indicator i transformed according to the metric *mean to first*, or *last to first* for a given company c and month t and labeled due to ratio k, as described above, is marked as $MTF_{t,i,c}(k)$, or $LTF_{t,i,c}(k)$, respectively.

The choice of the boundaries between categories $\{decrease, stagnation, increase\}$ as ratios of k (and 1), i. e. asymmetric, is preferred to alternative approaches such as a symmetric neighbourhood around 1.0. The approaches are equivalent and derivable one from another.

The procedure was performed for transformed data of both indicators of interest (employment, sales) according both the *mean to first* and *last to first* metrics, as defined before in step (i).

For a given ratio k, we are able to transform quantitative data originating from Short-term statistics in industry for both indicators (employment, sales), all considered companies and all months into qualitative data ("decrease", "stagnation", "increase"), as was described above.

After the categorization of the values for each of the indicators, we got tuples like $\left[o_{t,i,c}, MTF_{t,i,c}(k)\right]$ and $\left[o_{t,i,c}, LTF_{t,i,c}(k)\right]$, respectively.

As we stated before, for $\forall c$, $\forall i$ and $\forall t$ is $o_{t,i,c} \in \{\text{decrease, stagnation, increase}\}$. Similarly, for a given ratio k such that $k \in \langle 1.0; 5.0 \rangle$, each of the metrics *mean to first*, $MTF_{t,i,c}(k)$, and *last to first*, $LTF_{t,i,c}(k)$, could be exactly equal to one of the values $\{\text{decrease, stagnation, increase}\}$. Thus, we are able to construct cartesian product in the terms of

$$\begin{aligned} o_{t,i,c} \times MTF_{t,i,c}(k) \big| \forall t, i, c \in \\ &\in \{\text{decrease, stagnation, increase}\}_{predicted} \\ &\times \{\text{decrease, stagnation, increase}\}_{calculated} \end{aligned}$$

and

$$\begin{aligned} o_{t,i,c} \times LTF_{t,i,c}(k) \big| \forall t, i, c \in \\ &\in \{\text{decrease, stagnation, increase}\}_{predicted} \\ &\times \{\text{decrease, stagnation, increase}\}_{calculated} \end{aligned}$$

and, furthermore, we are able to construct a matrix $\boldsymbol{C}(k) = \{n_{jl}\}_{j,l \in \{\text{decrease, stagnation, increase}\}}$, where $n_{jl} \in \{0, 1, 2, 3, \dots\}$ for each $j, l \in \{decrease, stagnation, increase\}$ is a count of all companies c during the time of interest t which predicted j-th value of the indicator i of a set $\{decrease, stagnation, increase\}$ (so the $o_{t,i,c}$ is equal to j-th value of the set

[3] Nor $MTF_{t,i}$ neither $LTF_{t,i}$ could be calculated for the last two months because there are no values for the last two months presented in the dataset.

$\{decrease, stagnation, increase\}$ for each of the companies c), but – according to the given ratio k – the labeled value of indicator i of all companies c during the month of interest t was l-th value of the set $\{decrease, stagnation, increase\}$. When we fix i, we can sum up any n_{jl} of all such companies c during all the times of interest t. Let us call matrix $\boldsymbol{C}(k)$ *a confusion matrix*. The same approach is applicable for both *mean to first*, $MTF_{t,i,c}(k)$, and *last to first*, $LTF_{t,i,c}(k)$ metrics. Finally, for a given ratio k, using this line of thinking, we got exactly four confusion matrices $\boldsymbol{C}(k)$ for both $i \in \{\text{employment}, \text{sales}\}$ and both metrics $MTF_{t,i,c}(k)$, $LTF_{t,i,c}(k)$.

In case there is a match between predicted $o_{t,i,c}$ and the labeled value $MTF_{t,i,c}(k)$ or $LTF_{t,i,c}(k)$ of indicator i of all companies c during the month of interest t, one of the possible three diagonal values of matrix $\boldsymbol{C}(k)$ would increase by one. The higher the sum of diagonal values of the matrix $\boldsymbol{C}(k)$ (sometimes called a trace of a matrix and denoted as $\operatorname{tr}\boldsymbol{C}(k)$), divided by the sum of matrix $\boldsymbol{C}(k)$ (sometimes called a sum of a matrix and denoted as $\sum \boldsymbol{C}(k)$), the higher is the rate of match between predicted and labeled values of indicator i, i. e. the better (more accurate) predictions a company could make about its near future (whether we are focusing only on $i \in \{\text{employment}, \text{sales}\}$). Let the trace $\operatorname{tr}\boldsymbol{C}(k)$ of matrix $\boldsymbol{C}(k)$ divided by the sum $\sum \boldsymbol{C}(k)$ be called *accuracy*; we can easily see that the proportion $\frac{\operatorname{tr}\boldsymbol{C}(k)}{\sum \boldsymbol{C}(k)}$ is a point estimate of predictive accuracy of indicator $i \in \{\text{employment}, \text{sales}\}$ of a group of companies c during all the months of interest t (Gupta, 2015). In addition, it is clear that $0 \leq \frac{\operatorname{tr}\boldsymbol{C}(k)}{\sum \boldsymbol{C}(k)} \leq 1$.

Finally, we can reformulate the task as finding a ratio k maximizing $\frac{\operatorname{tr}\boldsymbol{C}(k)}{\sum \boldsymbol{C}(k)}$ for a given $i \in \{\text{employment}, \text{sales}\}$ and metrics *mean to first*, or *last to first*, respectively.

The larger is k the broader is interval $\left(\frac{1}{k}, k\right)$ used for the labeling values of the indicator i as "stagnation". It is not hard to realize that for any values of the ratio k larger than some uknown, but large enough constant k_0 are intervals $\left(0, \frac{1}{k_0}\right)$ and (k_0, ∞) hardly populated by values of an indicator i, since the first interval covers only very low values and in opposite, the second one covers unfeasibly large values, respectively. The labeled values of such indicator i contain only the value "stagnation". Thus, in that case the confusion matrix $\boldsymbol{C}(k) = \{n_{jl}\}_{j,l \in \{\text{decrease, stagnation, increase}\}}$ (for a definition of the matrix and more details see the paragraphs above) comes into its simple form of $\boldsymbol{C}(k) = \{n_{jl}\}_{j,l \in \{\text{stagnation}\}}$and tends to a constant value (below 1.0). Practically, we want to find a ratio k maximizing $\frac{\operatorname{tr}\boldsymbol{C}(k)}{\sum \boldsymbol{C}(k)}$ for a given $i \in \{\text{employment}, \text{sales}\}$ and metrics *mean to first*, or *last to first*, respectively, but in case more than one value of k is found, the lowest of them would be considered to be the k solving the problem. In fact, we search for k somewhere below k_0, but close to k_0.

The task could be considered as a nonlinear program where the mentioned proportion $\frac{\operatorname{tr}\boldsymbol{C}(k)}{\sum \boldsymbol{C}(k)}$ is a utility function and $k : k \in \langle 1.0; 5.0 \rangle$ is a constraint. We try to find the lowest possible k that maximizes the proportion $\frac{\operatorname{tr}\boldsymbol{C}(k)}{\sum \boldsymbol{C}(k)}$. Thus, in case we would find more values of the ratio k maximizing the proportion $\frac{\operatorname{tr}\boldsymbol{C}(k)}{\sum \boldsymbol{C}(k)}$, we will consider the lowest of them as a solution. The canonical form of the linear program is as follows:

$$\underset{k}{\operatorname{argmin}}\left\{\max\ \frac{\operatorname{tr}\boldsymbol{C}(k)}{\sum\boldsymbol{C}(k)}\right\}\quad s.t., \tag{1}$$

$$1.0\ \leq k\ \leq 5.0. \tag{2}$$

Trying to plot a dependency of the accuracy $\mathbf{max}\ \frac{\operatorname{tr}\boldsymbol{C(k)}}{\sum\boldsymbol{C(k)}}$ on the ratio $\boldsymbol{k}$ and taking into account the idea that for large values of $\boldsymbol{k}$ the accuracy asymptotically tends to some constant below 1.0, we could expect an increasing curve of the accuracy until the value of $\boldsymbol{k}$ is equaled to theoretical value of $\boldsymbol{k_0}$ from where the accuracy asymptotically tends to a consant below 1.0. The value of $\boldsymbol{k}$ solving the problem should be “close below” the value $\boldsymbol{k_0}$.

4. Results

There are 400 companies included in the sample; they reported their predictions between 2003 and 2016. A correct observation was considered when a company filled in values of the future indicator of interest for all three consecutive months. The sample seems to be adequately large in order to evaluate the predictive accuracy in the industry. The results were calculated in R.

4.1 Employment

The employment ($i =$ employment) indicator was evaluated first. The ratio $k = 1.555$ (approx.) maximizes the utility function (point estimate of predictive accuracy), as we can see in Figure 1. The confusion matrix for the calculated value of k has the following form – numerical values recalculated and labeled by the metrics *mean to first* and *last to first* are in the rows, companies’ predictions from the Business tendency survey are in the columns (Table 1). The prediction accuracy is about 0.741.

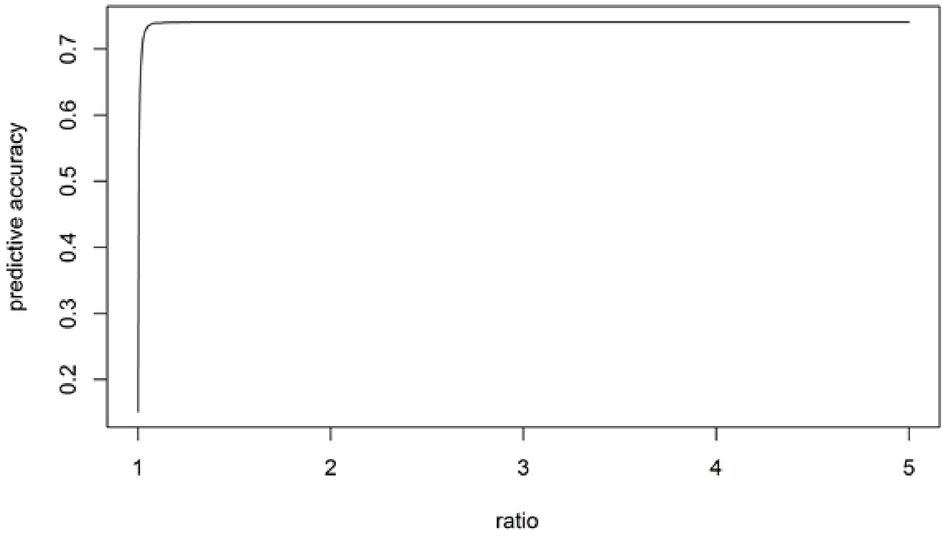
Table 1 Confusion matrix – employment – mean to first

	Decrease	**Stagnation**	**Growth**	**Sum**
Decrease	16	2	0	18
Stagnation	10212	47559	6424	64195
Growth	6	11	15	32
Sum	10234	47572	6439	64245

Source: data – Czech Statistical Office, own calculation

The calculations say that the ratio is $k = 1.555$ (approx.). If we look at the plot (Figure 1), we can see that the function reaches its „maximum“ for the first time approximately at $k = 1.1$ and then, for higher k, increases slowly as tends asymptotically to its (unknown) hypothetical maximum. As a result, we can see that respondents are able to realize relatively small changes in the employment – a change about only 10% of current employment status (i. e. when $k = 1.1$) is enough for them to predict other development than “stagnation” (due to consideration the intervals for labeling as proportions based on ratio k it is irrelevant whether “decrease”, or “increase”). In fact, this ratio has more sense than 1.555 (such ratio is, according to the opinion of the authors, unexpectedly high).

Figure 1 Employment – mean to first



Source: data – Czech Statistical Office, own calculation

For the second metric, *last to first*, the prediction accuracy is higher, 0.742. The ratio has a value $k = 1.750$, see Figure 2. In the confusion matrix (see Table 2), stagnation is the most numerous group once again.

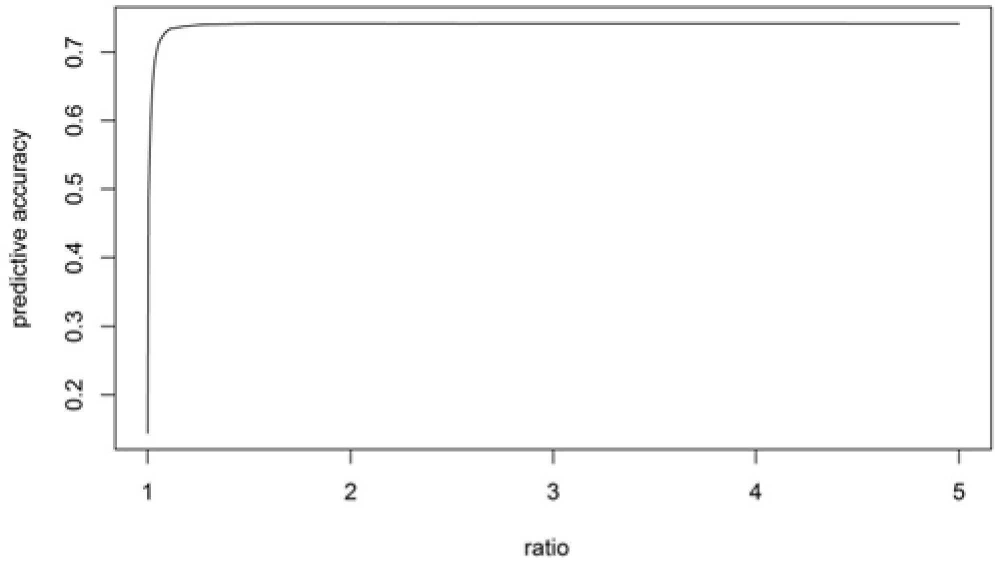
Table 2 Confusion matrix – employment – last to first

	Decrease	**Stagnation**	**Growth**	**Sum**
Decrease	47	22	1	70
Stagnation	10569	49711	6692	66972
Growth	16	18	17	51
Sum	10632	49751	6710	67093

Source: data – Czech Statistical Office, own calculation

Compared to a metric *mean to first*, the *last to first* metric gets higher value (Figure 2), which confirms the ratio calculations. From the Figure 2, a value of 1.2 could be indicated for the appropriate ratio.

Figure 2 Employment – last to first



Source: data – Czech Statistical Office, own calculation

4.2 Sales

The confusion matrix has a similar form as the one for employment.

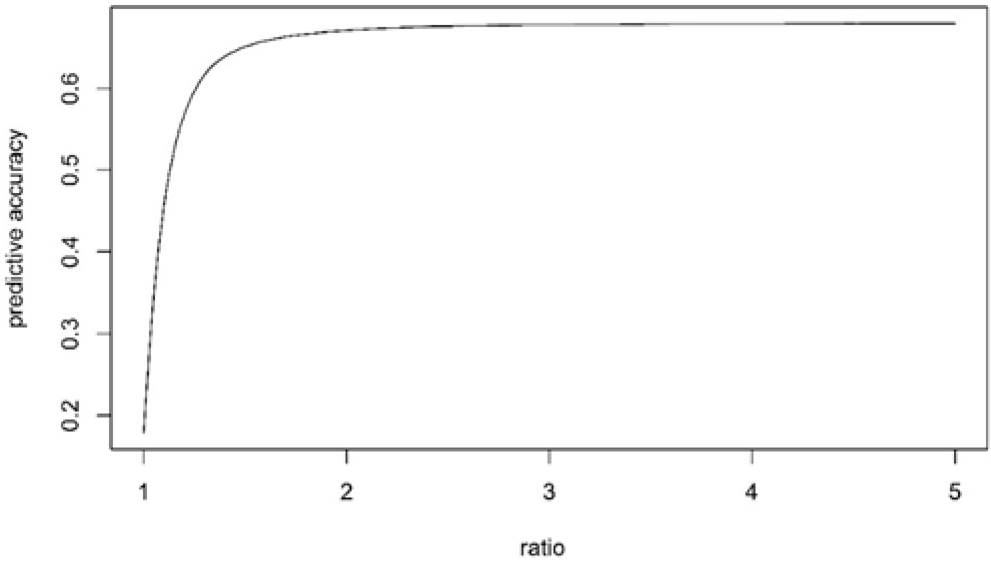
Table 3 Confusion matrix – sales – mean to first

	Decrease	**Stagnation**	**Growth**	**Sum**
Decrease	3	0	0	3
Stagnation	6033	43322	14244	63599
Growth	24	152	84	260
Sum	6060	43474	14328	63862

Source: data – Czech Statistical Office, own calculation

When we deal with the metric *mean to first*, the ratio maximizing the predictive accuracy, which is about 0.680, is $k = 4.975$. Figure 3 shows the relation between ratio k and predictive accuracy. We can say that value 1.6 is optimal ratio for the indicator sales and for metric *mean to first*.

Figure 3 Sales – mean to first



Source: data – Czech Statistical Office, own calculation

For the metric *last to first* the prediction accuracy is 0.677. The ratio has a value $k = 4.990$, see Figure 4.

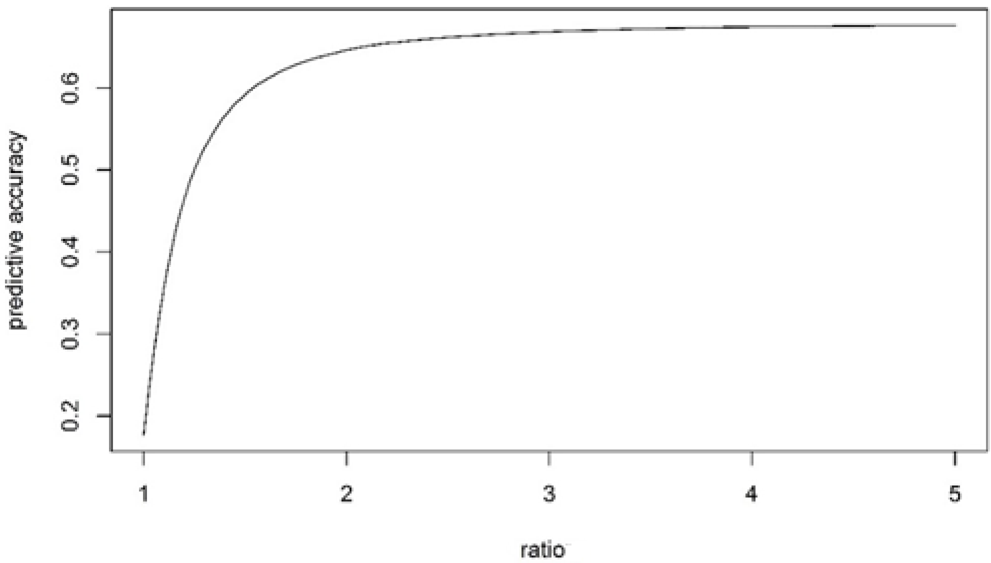
Table 4 Confusion matrix – sales – last to first

	Decrease	**Stagnation**	**Growth**	**Sum**
Decrease	85	285	106	476
Stagnation	6289	44910	14564	65763
Growth	38	280	131	449
Sum	6412	45475	14801	66688

Source: data – Czech Statistical Office, own calculation

The Figure 4 shows that the ratio (for the indicator sales and for metric *last to first*) is higher than the first metric (*mean to first*). The ratio is about 1.7.

Figure 4 Sales – last to first



Source: data – Czech Statistical Office, own calculation

The results could show that respondents are more sensitive to changes in the employment than to changes in sales, probably the changes in (integer) numbers of employees are more easily to assess than changes in (real) amounts of sales.

5. Conclusion

The results of the analysis are promising for further research and for discussion regarding the significance and benefits of the Business tendency survey. The analysis can be extended. Going further, we can conduct analysis on the NACE level or according to a companies' size. Ehrmann (2005) points out the reality that small companies evince better and more precise expectations of their funds than big companies.

Many authors warn about companies answering illogically. According to Nieuwstad (2005), this propotion is about 20% of companies. Jílek, Pecáková and Vojta (2005) calculated that over 60% of companies chose the option "the same level" in the Business tendency survey, although only three or four percents (!) of companies are stable in reality. The results of this paper show that both metrics return similar ratio (and therefore similar boundaries for real data categorization) for a given metric. The ratio k for employement is 1.555 (approx.), and 1.750 (approx.), respectively, and for the sales is 4.975 (approx.), 4.990 (approx.), respectively, given we transform real companies' data by *mean to first*, and *last to first* metrics, respectively. We can see the values of ratio k in plots, too. These values are lower (more realistic). According to the *mean to first,* the value is 1.1 (approx.) for the employment, it means: a change about only 10% of current employment status is enough for them to predict other development than "stagnation", for metric *last to first* the value is higher: 1.2 (approx.). The change for sales has to be higher for respondents to report change. According to the *mean to first,* the ratio is 1.6 (approx.), resp. to the *last to first* is 1.7 (approx.). Anyway, the calculated ratios can be used in recommendations for the respondents in methodology for BTS.

In any case, the human factor and subjectivity has a huge influence in the Business tendency survey. The answers to the question can be subjective and personally interpreted. In order to improve the analyses, the authors would need to know more information about respondents in Business tendency survey – e. g. their education, age and professional skills. This is the reason why "survey on survey" will be conducted in cooperation with the Czech Statistical Office. After that, discussion about the construction of the national individual business confidence indicators could begin. We use Switzerland as an inspiration. They constructed their own KOF Employment Indicator which has a better predictive ability (Siliverstov, 2014).

Acknowledgements

This paper has been prepared under the support of a project of the University of Economics, Prague – Internal Grant Agency, project No. F4/14/2018 "Business Tendency Survey in the Czech Republic and Possibilities of increasing its predictive ability".

References

[1] Anderson, O. 1951. Konjukturtest und Statistik. Möglichkeiten und Grenzen einer Quantifizierung von Testergebnissen. Allgemeines Statistisches Archiv, Vol. 35, pp.209-220.

[2] Bachmann, R., Elstner St. and Sims, E.R. 2012. Uncertainty and Economic Activity: Evidence from Business Survey Data, American Economic Journal, Macroeconomics, Vol. 5(2), pp. 217-49.

[3] Basile, R., de Nardis, S. and Pappalardo, C. 2014. Firm heterogeneity and regional business cycle differentials', Journal of Economic Geography , Vol. 14(6), pp. 1087–1115.

[4] Bierbaumer-Polly, J., Hölzl, W. 2015. Business Cycle Dynamics and Firm Heterogeneity Evidence for Austria Using Survey Data. WIFO Working Papers, No. 504

[5] Clower, R.W. 1998. Three Centuries of Demand and Supply. Journal of the History of Economic Thought, Vol. 20(4), pp. 397-410.

[6] Cornec, M. 2014. Constructing a conditional GDP fan chart with an application to French business survey data. *OECD* Journal: Journal of Business Cycle Measurement and Analysis. https://doi.org/10.1787/jbcma-2013-5jz417xzw931

[7] Ehrmann, M. 2005. Firm Size and Monetary Policy Transmission - Evidence from German Business Survey Data, Ifo Survey Data in Business Cycle and Monetary Policy Analysis, pp. 145-172.

[8] Erkel-Rousse, H., Minodier, D. 2009. Do business tendency surveys in industry and services help in forecasting GDP growth? A real-time analysis on French data, Documents de Travail de la DESE-Working Papers of the DESE, INSEE.

[9] Eurostat. 2018. Short-term business statistics (STS) in brief [cit. 06-06-2018] http://ec.europa.eu/eurostat/web/short-term-business-statistics/overview/sts-in-brief

[10] Gupta A. 2015. Learning Apache Mahout Classification. Birmingham: Packt Publishing Ltd. ISBN 978-78355-459-9.

[11] Higson, C., Holly, S. and Kattuman, P. 2002. The cross-sectional dynamics of the US business cycle: 1950–1999, Journal of Economic Dynamics and Control, Vol. 26(9), pp. 1539-1555.

[12] Jílek, J., Pecáková, I., Vojta, M. 2005. Konjukturální průzkumy ČSÚ a predikce. Statistika, 5.

[13] Kaiser, U., Spitz, A. 2000. Quantification of Qualitative Data Using Ordered Probit Models with and Application to a Business Survey in the German Service Sector. Economic Surveys and Data Analysis CIRET Conference Proceedings, Paris 2000 Statistics. Retrieved from www.oecd.org

[14] Nieuwstad, C.H. 2005. A comparison on the company level of Manufacturing Business Sentiment Survey data and Realized Turnover, Statistics Netherland, Discussion Paper, No. 05007.

[15] Siliverstovs, B. 2014. Do business tendency surveys help in forecasting employment?. OECD Journal: Journal of Business Cycle Measurement and Analysis. https://doi.org/10.1787/jbcma-2013-5k4bxlxjkd32