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ORIGINAL ARTICLE

Sales forecasting in financial distribution: a comparison of quantitative forecasting methods

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Abstract

This paper deals with the issue of forecastability of sales activities of independent financial advisers (agents). Employing the most common quantitative methods on a diverse sample of timelines from multiple advisory companies, we have found that under most settings, these methods offer sub-par performance with high relative errors and no statistical differences between them. When a more granular approach is applied (reflecting sales unit size), ARIMA and the simple moving average emerge as significantly less accurate. This outcome is true for all sales units regardless of their size, when relative error is concerned. Thus, our analysis confirms the difficult forecastability of financial sales, speaking against the utilisation of more sophisticated forecasting methods, which mostly fail when compared to their much simpler and less costly counterparts.

Keywords Financial sales · Sales forecasting · Quantitative forecasting · Mean absolute percentage error (MAPE) · Linear model with mixed effects

Introduction

Sales forecasts represent crucial input for management planning and decision making in any distribution system (Merrilees and Fam 1999; Ali and Boylan 2010). One of its main application elements is centred within the effectiveness of different methods used in creating forecasts, in terms of their predictive accuracy. Is the more sophisticated method more accurate, and therefore worth investing in? Or should we stick with its less sophisticated counterparts? These questions are being regularly asked by professionals from nearly every country and industry, as illustrated by Mentzer and Kahn (1995), Gordon (2010) or Goodwin (2011) papers. For marketing decisions, the role of sales forecasting is even more important. As early as in 1970 s, most companies considered sales forecasts as the most critical aspect of their marketing success (Dalrymple 1975) and utilised formal, i.e. quantitative methods to prepare them (Dalrymple 1987). As evinced by Hofer et al. (2015) recent study, the methodological pattern continues to incorporate quantitative methods at large. Furthermore, sales forecasting remains one of the most important business success parameters, determining the effectiveness of integrated marketing-sales functions (Peterson et al. 2015; Madhani 2016). This puts even stronger pressure on accuracy of sales predictions and, thus, on performance as well as suitability of methods utilised to produce those.

Forecasting methods themselves have undergone tremendous development in past decades, particularly concerning quantitative applications. While in the late 1980 s Dalrymple (1987)[1] reported that the most frequent methods consisted of naïve extrapolation (30.6% of respondents), the moving average (20.9%) and the percentage rate of change (19.4%), less than 10 years later Mentzer and Kahn (1995)[2] found that the top three techniques utilised in business forecasting were almost totally different: simple regression (36% of the respondents), trend line analysis (28%) and the moving average (22%). The trend towards more sophisticated and complex methods is suggested by more recent studies on the topic, such as McCarthy et al. (2006) or Green and Armstrong (2015). Particularly, Box–Jenkins and the exponential smoothing techniques exhibit a gradually increasing popularity, followed by traditional and less sophisticated methods, such as the moving average or simple regression.

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[1] Total sample $n=134$ US companies.

[2] Results for 3-month–2-year forecasting horizon, total sample $n=186$ US companies.

From an accuracy perspective, early fundamental efforts to compare methods in a unified set-up were undertaken by Makridakis et al. (1982) in his well-known M-competition, which sparked fierce discussion and was followed by another two instalments (see Makridakis and Hibon 2000 for details). Numerous studies continued in different industry and situational contexts (for example, Chu and Zhang 2003; Lee et al. 2012; Chen 2011; Syntetos et al. 2015 and others) with highly diverse results, mostly iterating popular methods such as regression, Box–Jenkins ARIMA, exponential smoothing or the simple moving average among the most accurate. The important common trait, however, is that despite the growing complexity of most business applications, empirical evidence increasingly points to an unfavourable pay-off in terms of forecasting accuracy. As suggested by Green and Armstrong (2015) meta-analysis, there is an intangible break-even point, where the increasing complexity of the forecasting model does not only contribute to higher accuracy, but in most cases leads to a notable accuracy downfall. This phenomenon is of high concern to business forecasters and will be examined in this paper as well.

The distribution of financial products represents a special category of sales, with many similarities and dissimilarities to regular retailing. In its context, very little empirical literature on the sales forecasting topic is available. Apart from dated papers, such as O'Grady (1965) or Dalrymple (1987), Kaltenbacher and Decker (2014) analysis on new insurance products forecasting seems to be the only tangible evidence present. Developing a single causal model, the paper indicates that a more sophisticated approach to insurance-sales forecasting is desirable. Otherwise, we are left in the dark, moreover so in the European milieu. As evinced by Reifner et al. (2012) study, nevertheless, sales planning plays a central role in agent-based distribution networks. Setting minimum (benchmark) production levels, especially when multi-level marketing schemes are involved, relies heavily on both aggregate and individual sales forecasts. These are, however, impeded by the deficiency of historical data caused by high fluctuation and low retention of salespeople. Such discord is in sharp contrast with the lack of empirical evidence on forecasting methodology being used, as well as its performance under specific, short-series settings. Lack of accurate sales forecast can jeopardise whole marketing strategy of agent-based distribution network, particularly when it comes to marketing plan and its execution (i.e. over-staffing or over-investment). In this context, there is a strong need of performance evaluation of most prolific forecasting methods which up-to-date literature fails to offer. This creates an important research opportunity.

This paper seeks to fill the above-mentioned gap by comparing the predictive accuracy of the most common forecasting methods in the financial advice sales context. In the first part, selected forecasting methods and error measures are defined. Subsequently, a set of experiments with real data of financial advice sales is undertaken, featuring different set-ups (30 scenarios in total), and raw forecasting accuracy of year-ahead prediction is recorded. Finally, statistical differences between the accuracy measures of different methods are tested using linear models with mixed effects, and the outcomes of the experiment are discussed. By analysing the predictability of individual sales structures, we also indirectly tackle the question of whether the whole financial advice industry's activity can be forecast at all, which, given the market share it has in some sectors like insurance, can have almost macroeconomic consequences.

Data

Data sample

For the proposed analysis, we use sales data provided by a total number of eight financial advice companies (agents) operating in the Central-Eastern European region with a focus on the Czech Republic (Table 1). All of them provide commission-based advice and intermediation sales in the key retail product areas, such as investment funds, life and non-life insurance, pension savings and mortgage credits. As evinced by two selected sales indicators (life insurance and investment funds), the subsequent sample represents a major part of the target market:

The data we obtained represent aggregated sales across all product categories, transformed into generic common units (points), which represent monetary value of the sale. Such a system is the key performance metric across all surveyed countries and represents the main criterion in the evaluation of individual advisers (agents), as well as whole sales units and their managers. Different companies use different values of the point, however, meaning we have to deal with timelines representing different units. We have collected a total number of 43 timelines spanning from 1994 to 2017, providing annual data on 24 years of operations under diverse market/macroeconomic conditions. The sample was further divided into three categories of business units:

- Big sales units—over 100 individual advisers (18 timelines)
- Medium sales units—between 100 and 10 individual advisers (15 timelines)
- Small sales units—less than ten individual advisers (10 timelines).

All of the data were cross-checked for potential inconsistencies, with all potential outliers factually verified and missing items supplemented. The final dataset totalled 373

Table 1 Study sample. *Source*: own research

Company	Area of operations[a]	Organisational model	No. of individual agents (2015)	No. of new life insurance contracts[b] sold (2015)	Market share in life insurance[b]—IFA market (2015) (%)	No. of new investment funds contracts sold (2015)	Market share in investment funds[b]—IFA market (2015) (%)
A	CZ, DE, AU, SK	MLM	4692	66,744	27.153	37,808	19.105
C	CZ	Broker pool	1784	29,672	12.071	17,780	8.984
B	CZ, SK	MLM	886	30,232	12.299	20,472	10.345
D	CZ, SW, AU, DE	MLM	370	7292	2.967	14,844	7.501
E	CZ	MLM	95	3488	1.419	916	0.463
H	CZ	MLM	28	292	0.119	324	0.164
G	CZ	Flat	13	468	0.190	160	0.081
F	CZ	Flat	5	47	0.019	21	0.011
Sample total	–	–	7873	138,235	56.237	92,325	46.652

[a]*CZ* Czech Republic, *DE* Germany, *AU* Austria, *SK* Slovakia, *SW* Switzerland

[b]Regularly paid contracts, Czech market

observations and will be provided for verification purposes by the author upon request.

Method

Forecasting methods evaluated

Following the popularity and accuracy review undertaken earlier, a total number of six quantitative forecasting methods will be compared. Given the lack of specific literature on financial sales forecasting, we utilise their basic form as defined in the baseline literature (e.g. Hyndman and Athanasopoulos 2018), without further add-ons or methodological adjustments:

- in-sample naïve forecast (last year value)
- last trend analysis
- linear regression
- last change of selected macro-indicators
- official predictions of selected macro-indicators
- simple moving average
- Box–Jenkins ARIMA
- exponential smoothing.

As predictors, we used a set of macroeconomic indicators composed of real GDP growth (MF 2018), unemployment rate (CZSO 2018a), inflation rate (CNB 2018a), nominal and real wage growth (CZSO 2018b) and two-week repo interest rate (CNB 2018b). Aside from the (past) indicators themselves, we also utilised forecasts of some of them, as another predictor (forecasts published by the source institution by the end of the preceding year[3]). This is consistent with research conducted by Salomon and Shaver (2005) and would enable us to compare two different approaches to time series forecasting, enlarging a set of tested method variants to fifteen.

In terms of accuracy measurement, we used MAPE (mean absolute percentage error) as our primary error metric.[4] By operating with the naïve forecast, however, we are indirectly assessing relative accuracy as well. Thus, the evaluation framework is consistent with guidelines provided by Hyndman and Athanasopoulos (2018) and comparable with recent studies such as Lee et al. (2012) or Ramos et al. (2015). We utilised error formulas defined by Hyndman and Koehler (2006), while running two ways of simulation for every time series in our sample:

- *classical simulation* based on forecasting the last year of the sample (in our case 2016)
- simulation based on a *rolling forecasting origin*,[5] with minimum training set size (k parameter), set to the minimum value required by each method of prediction.

Subsequently, final error measures were calculated across the training sets, as a simple average for every defined forecasting experiment.

[3] Autumn annual prediction, published usually by November of the previous year.

[4] Scale dependent measures such as MAE or RMSE are disqualified by different units among the timelines.

[5] See Hyndman and Athanasopoulos (2018), chapter Time series cross-validation for details on this technique.

Table 2 Forecastability assessment results. *Source*: own calculations

Indicator[a]	Whole sample	Big sales units	Medium sales units	Small sales units
Coefficient of variation (CV)	0.527	0.487	0.547	0.562
Approximate entropy (ApEn)	0.219	0.198	0.210	0.278
Improvement potential over naïve benchmark (1—ApEn)	0.781	0.802	0.790	0.722
Naïve forecast (MAPE error)	0.232	0.132	0.233	0.422

[a]Average values for the sample and sub-samples

Experiments

We conducted a total number of 30 forecasting exercises (15 classical + 15 rolling origin), evaluating selected methods' accuracy on a 1-year-ahead forecasting horizon (annual sales). It needs to be noted that each rolling origin exercise is de facto a sequence of several predictions, making the real number even higher. Every simulation was modelled for the total sample and tested for different categories of sales units separately (big, medium, small), in order to capture potential differences between diverse sizes of business structure.

After calculating all of the accuracy measures for each of the experiments, aside from visual comparison, statistical testing of differences was carried out. Linear models with mixed effects were used for this purpose.

Results

Data attributes and forecastability

In accordance with Reifner et al. (2012) findings, surveyed companies provided for most sales units a much shorter time series, than their corporate history. Average length was 8.7 years,[6] with an average sample company lifespan over 18.7 years. This supports the thesis of low internal stability, which represents a potential challenge for the forecasting process.

In order to assess inherent forecastability of the data, we adopted a three-pronged approach. Firstly, we calculated the coefficient of variation over the individual time series,[7] as proposed by Gilliland (2010). Then, the approximate entropy (normalised—ApEn) indicator was composed as an alternative, following recommendations of Catt (2009). Finally, we used the simple naïve forecast (one step ahead) as a basis for subsequent improvement potential benchmarking, in accordance with the definition provided by Green et al. (2009). The results of these procedures are outlined in Table 2.

The assessment suggests we have a difficult forecasting task ahead. As implied by the coefficient of variation, sales production embodied in individual timelines is rather volatile, with standard deviation reaching over 50% of the mean with small and medium sales units. On the other hand, (1—ApEn) value indicates a strong possibility of naïve forecast error reduction, when a more sophisticated method is used. Last but not least, naïve forecast itself performed in a very diverse way, from strongly inaccurate (small units) to a more accurate level (big units). All in all, our forecastability evaluation supports expectations raised by the literature. Forecasting sales activity among financial agents is very challenging.

Accuracy errors

After assessing the forecastability of the data, we have progressed to the forecasting experiments themselves. Table 3 summarises the error values we got from both angles of the simulation:

Going through the numbers, we can observe two main findings. Firstly, the rolling forecasting origin technique visibly induced higher forecasting inaccuracy, as the length of time series used (the k parameter), was much shorter than in the classical way (whole timeline). ARIMA and the simple moving average methods are particularly sensitive to this. Then, relating the relative rankings, macro-indicators seem to be somehow better predictors than pure trend (time)-based methods, but not significantly. The third result is not related to the previous table and comes from a diverse unit size. We have found notable differences in this regard, with average MAPE across the set ranging from 0.19 to 0.48 (Table 4):

Testing statistical differences

The critical question is, are some of the above findings statistically significant? Table 5 summarises the answers we found.

When both criteria, the method used and the size of the unit being forecast, are taken into account, suddenly the accuracy differs significantly. Through post hoc testing, we

[6] In detail: 10.2 years for big units, 7.9 for medium units and 5.2 for small units.

[7] Other common variation metrics (mean, standard deviation) are not usable because of different units used by individual time series.

Table 3 Forecasting error—methods. *Source*: own research

Method	Classical simulation MAPE	Rolling forecasting origin MAPE
Naïve forecast	0.237	0.347
Trend analysis	0.229	0.401
Linear regression (time)	0.345	0.422
Simple moving average	0.290	0.472
ARIMA	0.381	0.562
Exponential smoothing	0.287	0.391
Linear regression (GDP growth forecast)	0.238	0.345
Linear regression (GDP growth past values)	0.239	0.344
Linear regression (unemployment forecast)	0.241	0.339
Linear regression (unemployment past values)	0.240	0.346
Linear regression (inflation forecast)	0.237	0.340
Linear regression (inflation past values)	0.237	0.347
Linear regression (nominal wages growth past values)	0.239	0.348
Linear regression (real wages growth past values)	0.239	0.348
Linear regression (two-week repo past values)	0.237	0.345
Average MAPE across the set	0.261	0.380

Table 4 Forecasting error—unit sizes. *Source*: own research

Unit size	Classical simulation MAPE	Rolling forecasting origin MAPE
Small sales units	0.402	0.484
Medium sales units	0.242	0.387
Big sales units	0.190	0.337

have identified methods and settings that make this difference (see Tables 6, 7, 8, 9 in "Appendix" for full details). It was revealed that ARIMA and the simple moving average consistently offer significantly lower accuracy over other methods, independently on unit size. The rest of the set, nevertheless, all falls into one group without any statistically viable deviation in this regard. This seemingly indicates a simple recommendation for business users, which is but a tricky one, as will be discussed further.

Discussion

Our results put up two main touching points with current empirical knowledge. Firstly, almost a universal lack of accuracy differences among forecasting methods confirms observations made by Reifner et al. (2012) regarding low internal stability and thus limited forecastability of financial agents' business. This clearly distinguishes financial distribution from other common sales industries such as retail (Chu and Zhang 2003) or tourism (Chen 2011). Yet this implication is not total. We have found that for all settings, certain methods (ARIMA and SMA) offer lower accuracy. On a general level, this mostly corresponds with industrial, as well as complex evaluations, for example with the said M-competition (Makridakis and Hibon 2000). Both methods in question require longer timelines to predict accurately, which is not fulfilled in surveyed environment.

From a practical perspective, however, this outcome comes with severe limitations. As evinced by forecasting research (Hyndman and Kostenko 2007), ARIMA and SMA methods rely on an adequate length of time series at hand. If this is not provided, the accuracy goes down quickly and agent-based financial distribution will mostly be the case.

Table 5 Statistical test results—forecasting method and size (linear model w. mixed effects). *Source*: own research

Classical simulation	Sum Sq	Mean Sq	Num DF	DenDF	F value	Pr(>|z|)
Forecasting method	1.185	0.085	14.000	569.028	7.943	0.000
Size of the sales unit	0.091	0.045	2.000	39.979	4.262	0.021
Rolling forecasting origin						
Forecasting method	6.568	0.469	14.000	4871.438	10.865	0.000
Size of the sales unit	0.452	0.226	2.000	41.404	5.231	0.009

Also, one cannot miss the cost–benefit perspective. If we look back at the values of the average forecasting error, it is obvious that the absolute value added of the ARIMA/SMA method would be rather limited. All for direct and indirect costs that would be notable, especially with smaller businesses (IT systems, data streams, etc.). This all supports scepticism raised by Goodwin (2011), which further increases, when we monetise our problem. Sales forecasts usually transcripts into revenues forecast and then the company budget—these management tools are mostly resilient to all but great shocks. Improvement here would arguably yield tangible financial effect only when substantial in size, or when projected on the biggest of businesses. The cost–benefit perspective, in line with Green and Armstrong (2015), therefore remains crucial here.

Conclusions

Put bluntly, this paper sought to answer a question, whether the financial agents' sales are forecastable at all and if so, how. We have identified the following main outcomes:

- Concerning the absolute value of the forecasting error, our analysis reveals that the answer to the crucial title question tends to be rather negative. MAPE values for individual methods reach from 0.22 to 0.56, representing 22–56% deviation of forecast from the real value (!). This is hardly acceptable from the management perspective, moreover so in comparison with simple naïve benchmark performance.
- When size of the sales units is taken into account, significant accuracy deviations between tested forecasting methods emerge, indicating that ARIMA and the simple moving average methods yield significantly lower accuracy in medium size units. Under these settings, forecasters should prefer rest of the set over these two methods. The remaining models, nevertheless, remained in the homogenous no significant differences zone, indicating low deviations among them.
- Our outcomes both on a general and granular level fully supported the thesis of financial sales low predictability. In this regard, the literature expectations and indications of our pre-experiment assessment of forecastability were confirmed. Arguably, (low) stability and internal effects can in mostly multi-level marketing sales networks shadow out even the strongest external factors, such as general macro-conditions (GDP growth, unemployment, inflation, etc.). Last but not least, this also makes the whole sector much less predictable from the macro-prudential perspective.

From practitioner's perspective, financial advice companies can benefit from our results in three basic ways. Firstly, our research implies it does not make sense to invest into more complex and sophisticated forecasting methods, accuracy wise. These fail to produce better results. Secondly, sales in the financial advice industry are not necessarily tied to macroeconomic development and should not be predicted as derived variable. This confirms old sales force saying "when times are good, the sales go up, when times are bad, easier recruiting will make for it". Finally, our results confirm overall low forecastability of financial sales, moreover so in the context of traditional quantitative methods. With this in mind, financial advice companies should tailor their own forecasting model on individual basis, possibly incorporating qualitative methods on larger scale, for example through sales force interviews. This, however, remains an outline for future research.

Our research was bounded by two main limitations. First of all, we tested only the performance of quantitative methods, omitting possible subjective adjustments. While their benefits remain controversial, experts' judgment could greatly improve accuracy when domain knowledge (concerning given sales unit) is concerned. Secondly, our experiments did work with aggregate sales production, not distinguishing between individual categories such as insurance or investments. While this does not affect the behaviour of individual agents (remuneration is based on aggregate sales abstracted into points), it prevents deeper dissemination of potential external effects on different product areas. Both these limitations represent opportunities for further research, which would be likely constructed as iteration of the current exercise, but based on expert judgment and detailed product settings. This way, even further practical implications can be expected.

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Appendix

See Tables 6, 7, 8 and 9.

Table 6 Post hoc tests—sales unit size (classical simulation). *Source*: own research

Unit size	Estimate	Std. error	z value	Pr(>|z|)
Medium–small	0.158	0.071	2.227	0.066
Big–small	0.206	0.072	2.864	**0.012**
Big–medium	0.048	0.062	0.766	0.723

Significant values at p = 0.05 in bold

Table 7 Post hoc tests—forecasting methods (classical simulation). *Source*: own research

Forecasting methods tested	Estimate	Std. error	z value	Pr(>|z|)
Trend analysis—naive forecast	−0.013	0.023	−0.580	1.000
Linear regression (time)—naive forecast	−0.119	0.023	−5.294	0.000
Simple moving average—naive forecast	−0.116	0.023	−4.946	0.000
ARIMA—naive forecast	−0.104	0.024	−4.394	**0.001**
Exponential smoothing—naive forecast	−0.064	0.022	−2.863	0.214
GDP growth forecast—naive forecast	−0.001	0.022	−0.035	1.000
GDP growth—naive forecast	−0.002	0.022	−0.096	1.000
Unemployment forecast—naive forecast	−0.003	0.022	−0.130	1.000
Unemployment—naive forecast	−0.002	0.022	−0.102	1.000
Inflation forecast—naive forecast	0.000	0.022	−0.005	1.000
Inflation—naive forecast	0.000	0.022	0.002	1.000
Nominal wages growth—naive forecast	−0.002	0.022	−0.079	1.000
Real wages growth—naive forecast	−0.002	0.022	−0.076	1.000
Two-week repo—naive forecast	0.000	0.022	0.000	1.000
Linear regression (time)—trend analysis	−0.106	0.023	−4.663	**0.000**
Simple moving average—trend analysis	−0.103	0.024	−4.343	**0.001**
ARIMA—trend analysis	−0.091	0.024	−3.793	**0.012**
Exponential smoothing—trend analysis	−0.051	0.023	−2.246	0.630
GDP growth forecast—trend analysis	0.012	0.023	0.546	1.000
GDP growth—trend analysis	0.011	0.023	0.485	1.000
Unemployment forecast—trend analysis	0.010	0.023	0.452	1.000
Unemployment—trend analysis	0.011	0.023	0.479	1.000
Inflation forecast—trend analysis	0.013	0.023	0.575	1.000
Inflation—trend analysis	0.013	0.023	0.582	1.000
Nominal wages growth—trend analysis	0.011	0.023	0.502	1.000
Real wages growth—trend analysis	0.011	0.023	0.505	1.000
Two-week repo—trend analysis	0.013	0.023	0.580	1.000
Simple moving average—linear regression (time)	0.004	0.024	0.156	1.000
ARIMA—linear regression (time)	0.016	0.024	0.661	1.000
Exponential smoothing—linear regression (time)	0.056	0.023	2.468	0.463
GDP growth forecast—linear regression (time)	0.119	0.023	5.260	**0.000**
GDP growth—linear regression (time)	0.117	0.023	5.199	**0.000**
Unemployment forecast—linear regression (time)	0.117	0.023	5.166	**0.000**
unemployment—linear regression (time)	0.117	0.023	5.193	**0.000**
Inflation forecast—linear regression (time)	0.119	0.023	5.289	**0.000**
Inflation—linear regression (time)	0.119	0.023	5.296	**0.000**
Nominal wages growth—linear regression (time)	0.118	0.023	5.216	**0.000**
Real wages growth—linear regression (time)	0.118	0.023	5.219	**0.000**
Two-week repo—linear regression (time)	0.119	0.023	5.294	**0.000**
ARIMA—simple moving average	0.012	0.025	0.489	1.000
Exponential smoothing—simple moving average	0.052	0.023	2.222	0.649
GDP growth forecast—simple moving average	0.115	0.023	4.913	**0.000**
GDP growth—simple moving average	0.114	0.023	4.854	**0.000**
Unemployment forecast—simple moving average	0.113	0.023	4.822	**0.000**
Unemployment—simple moving average	0.113	0.023	4.848	**0.000**
Inflation forecast—simple moving average	0.116	0.023	4.941	**0.000**
Inflation—simple moving average	0.116	0.023	4.948	**0.000**
Nominal wages growth—simple moving average	0.114	0.023	4.871	**0.000**
Real wages growth—simple moving average	0.114	0.023	4.873	**0.000**
Two-week repo—simple moving average	0.116	0.023	4.946	**0.000**
Exponential smoothing—ARIMA	0.040	0.024	1.692	0.936

Table 7 (continued)

Forecasting methods tested	Estimate	Std. error	z value	Pr(>|z|)
GDP growth forecast—ARIMA	0.103	0.024	4.361	**0.001**
GDP growth—ARIMA	0.101	0.024	4.303	**0.002**
Unemployment forecast—ARIMA	0.101	0.024	4.272	**0.002**
Unemployment—ARIMA	0.101	0.024	4.297	**0.002**
Inflation forecast—ARIMA	0.104	0.024	4.389	**0.001**
Inflation—ARIMA	0.104	0.024	4.396	**0.001**
Nominal wages growth—ARIMA	0.102	0.024	4.319	**0.002**
Real wages growth—ARIMA	0.102	0.024	4.322	**0.001**
Two-week repo—ARIMA	0.104	0.024	4.394	**0.001**
GDP growth forecast—exponential smoothing	0.063	0.022	2.828	0.231
GDP growth—exponential smoothing	0.062	0.022	2.766	0.265
Unemployment forecast—exponential smoothing	0.061	0.022	2.733	0.283
Unemployment——exponential smoothing	0.061	0.022	2.760	0.269
Inflation forecast—exponential smoothing	0.064	0.022	2.858	0.217
Inflation—exponential smoothing	0.064	0.022	2.865	0.212
Nominal wages growth—exponential smoothing	0.062	0.022	2.784	0.254
Real wages growth—exponential smoothing	0.062	0.022	2.787	0.253
Two-week repo—exponential smoothing	0.064	0.022	2.863	0.213
GDP growth—GDP growth forecast	− 0.001	0.022	− 0.062	1.000
Unemployment forecast—GDP growth forecast	− 0.002	0.022	− 0.095	1.000
Unemployment—GDP growth forecast	− 0.002	0.022	− 0.068	1.000
Inflation forecast—GDP growth forecast	0.001	0.022	0.030	1.000
Inflation—GDP growth forecast	0.001	0.022	0.037	1.000
Nominal wages growth—GDP growth forecast	− 0.001	0.022	− 0.044	1.000
Real wages growth—GDP growth forecast	− 0.001	0.022	− 0.041	1.000
Two-week repo—GDP growth forecast	0.001	0.022	0.035	1.000
Unemployment forecast—GDP growth	− 0.001	0.022	− 0.033	1.000
Unemployment—GDP growth	0.000	0.022	− 0.006	1.000
Inflation forecast—GDP growth	0.002	0.022	0.091	1.000
Inflation—GDP growth	0.002	0.022	0.099	1.000
Nominal wages growth—GDP growth	0.000	0.022	0.017	1.000
Real wages growth—GDP growth	0.000	0.022	0.020	1.000
Two-week repo—GDP growth	0.002	0.022	0.097	1.000
Unemployment—unemployment forecast	0.001	0.022	0.027	1.000
Inflation forecast—unemployment forecast	0.003	0.022	0.124	1.000
Inflation—unemployment forecast	0.003	0.022	0.132	1.000
Nominal wages growth—unemployment forecast	0.001	0.022	0.051	1.000
Real wages growth—unemployment forecast	0.001	0.022	0.054	1.000
Two-week repo—unemployment forecast	0.003	0.022	0.130	1.000
Inflation forecast—unemployment	0.002	0.022	0.097	1.000
Inflation—unemployment	0.002	0.022	0.105	1.000
Nominal wages growth—unemployment	0.001	0.022	0.023	1.000
Real wages growth—unemployment	0.001	0.022	0.026	1.000
Two-week repo—unemployment	0.002	0.022	0.103	1.000
Inflation—inflation forecast	0.000	0.022	0.008	1.000
Nominal wages growth—inflation forecast	− 0.002	0.022	− 0.074	1.000
Real wages growth—inflation forecast	− 0.002	0.022	− 0.071	1.000
Two-week repo—inflation forecast	0.000	0.022	0.005	1.000
Nominal wages growth—inflation	− 0.002	0.022	− 0.081	1.000
Real wages growth—inflation	− 0.002	0.022	− 0.079	1.000
Two-week repo—inflation	0.000	0.022	− 0.002	1.000

Table 7 (continued)

Forecasting methods tested	Estimate	Std. error	z value	Pr(>|z|)
Real wages growth—nominal wages growth	0.000	0.022	0.003	1.000
Two-week repo—nominal wages growth	0.002	0.022	0.079	1.000
Two-week repo—real wages growth	0.002	0.022	0.076	1.000

Significant values at p = 0.05 in bold

Table 8 Post hoc tests—sales unit size (rolling origin simulation). *Source*: own research

Unit size	Estimate	Std. error	z value	Pr(>|z|)
Medium–small	0.081	0.042	1.909	0.135
Big–small	0.135	0.042	3.228	**0.004**
Big–medium	0.054	0.036	1.520	0.280

Significant values at p = 0.05 in bold

Table 9 Post hoc tests—forecasting methods (rolling origin simulation). *Source*: own research

Forecasting methods tested	Estimate	Std. error	z value	Pr(>|z|)
Trend analysis—naive forecast	− 0.007	0.016	− 0.408	1.000
Linear regression (time)—naive forecast	− 0.037	0.016	− 2.265	0.617
Simple moving average—naive forecast	− 0.081	0.017	− 4.742	**0.000**
ARIMA—naive forecast	− 0.131	0.017	− 7.908	**0.000**
Exponential smoothing—naive forecast	− 0.017	0.016	− 1.086	0.999
GDP growth forecast—naive forecast	0.005	0.016	0.302	1.000
GDP growth—naive forecast	0.005	0.016	0.323	1.000
Unemployment forecast—naive forecast	0.014	0.016	0.852	1.000
Unemployment—naive forecast	0.008	0.016	0.510	1.000
Inflation forecast—naive forecast	0.009	0.016	0.537	1.000
Inflation—naive forecast	0.003	0.016	0.220	1.000
Nominal wages growth—naive forecast	0.004	0.016	0.264	1.000
Real wages growth—naive forecast	0.001	0.016	0.063	1.000
Two-week repo—naive forecast	0.003	0.016	0.167	1.000
Linear regression (time)—trend analysis	− 0.030	0.017	− 1.795	0.900
Simple moving average—trend analysis	− 0.075	0.018	**− 4.223**	**0.003**
ARIMA—trend analysis	− 0.125	0.017	**− 7.260**	**0.000**
Exponential smoothing—trend analysis	− 0.010	0.016	− 0.640	1.000
GDP growth forecast—trend analysis	0.011	0.016	0.699	1.000
GDP growth—trend analysis	0.012	0.016	0.720	1.000
Unemployment forecast—trend analysis	0.020	0.016	1.227	0.997
Unemployment—trend analysis	0.015	0.016	0.900	1.000
Inflation forecast—trend analysis	0.015	0.016	0.924	1.000
Inflation—trend analysis	0.010	0.016	0.621	1.000
Nominal wages growth—trend analysis	0.011	0.016	0.663	1.000
Real wages growth—trend analysis	0.008	0.016	0.469	1.000
Two-week repo—trend analysis	0.009	0.016	0.569	1.000
Simple moving average—linear regression (time)	− 0.044	0.018	− 2.502	0.438
ARIMA—linear regression (time)	− 0.094	0.017	− 5.488	**0.000**
Exponential smoothing—linear regression (time)	0.020	0.016	1.215	0.997
GDP growth forecast—linear regression (time)	0.042	0.016	2.553	0.401
GDP growth—linear regression (time)	0.042	0.016	2.576	0.386

Table 9 (continued)

Forecasting methods tested	Estimate	Std. error	z value	Pr(> |z|)
Unemployment forecast—linear regression (time)	0.051	0.016	3.073	0.126
Unemployment—linear regression (time)	0.045	0.016	2.757	0.271
Inflation forecast—linear regression (time)	0.046	0.016	2.770	0.263
Inflation—linear regression (time)	0.041	0.016	2.477	0.456
Nominal wages growth—linear regression (time)	0.041	0.016	2.520	0.426
Real wages growth—linear regression (time)	0.038	0.016	2.325	0.571
Two-week repo—linear regression (time)	0.040	0.016	2.424	0.496
ARIMA—simple moving average	− 0.050	0.018	− 2.793	0.250
Exponential smoothing—simple moving average	0.064	0.017	3.738	**0.015**
GDP growth forecast—simple moving average	0.086	0.017	5.014	**0.000**
GDP growth—simple moving average	0.086	0.017	5.040	**0.000**
Unemployment forecast—simple moving average	0.095	0.017	5.503	**0.000**
Unemployment—simple moving average	0.089	0.017	5.212	**0.000**
Inflation forecast—simple moving average	0.090	0.017	5.213	**0.000**
Inflation—simple moving average	0.085	0.017	4.945	**0.000**
Nominal wages growth—simple moving average	0.085	0.017	4.986	**0.000**
Real wages growth—simple moving average	0.082	0.017	4.800	**0.000**
Two-week repo—simple moving average	0.084	0.017	4.893	**0.000**
Exponential smoothing—ARIMA	0.114	0.017	6.869	**0.000**
GDP growth forecast—ARIMA	0.136	0.017	8.185	**0.000**
GDP growth—ARIMA	0.136	0.017	8.216	**0.000**
Unemployment forecast—ARIMA	0.145	0.017	8.677	**0.000**
Unemployment—ARIMA	0.139	0.017	8.394	**0.000**
Inflation forecast—ARIMA	0.140	0.017	8.378	**0.000**
Inflation—ARIMA	0.135	0.017	8.118	**0.000**
Nominal wages growth—ARIMA	0.135	0.017	8.160	**0.000**
Real wages growth—ARIMA	0.132	0.017	7.968	**0.000**
Two-week repo—ARIMA	0.134	0.017	8.062	**0.000**
GDP growth forecast—exponential smoothing	0.022	0.016	1.386	0.989
GDP growth—exponential smoothing	0.022	0.016	1.409	0.987
Unemployment forecast—exponential smoothing	0.031	0.016	1.931	0.837
Unemployment—exponential smoothing	0.025	0.016	1.596	0.959
Inflation forecast—exponential smoothing	0.026	0.016	1.617	0.956
Inflation—exponential smoothing	0.021	0.016	1.306	0.994
Nominal wages growth—exponential smoothing	0.021	0.016	1.350	0.991
Real wages growth—exponential smoothing	0.018	0.016	1.149	0.998
Two-week repo—exponential smoothing	0.020	0.016	1.252	0.996
GDP growth—GDP growth forecast	0.000	0.016	0.021	1.000
Unemployment forecast—GDP growth forecast	0.009	0.016	0.550	1.000
Unemployment—GDP growth forecast	0.003	0.016	0.208	1.000
Inflation forecast—GDP growth forecast	0.004	0.016	0.236	1.000
Inflation—GDP growth forecast	−0.001	0.016	−0.082	1.000
Nominal wages growth—GDP growth forecast	−0.001	0.016	−0.038	1.000
Real wages growth—GDP growth forecast	−0.004	0.016	−0.240	1.000
Two-week repo—GDP growth forecast	−0.002	0.016	−0.135	1.000
Unemployment forecast—GDP growth	0.008	0.016	0.530	1.000
Unemployment—GDP growth	0.003	0.016	0.187	1.000
Inflation forecast—GDP growth	0.003	0.016	0.216	1.000
Inflation—GDP growth	−0.002	0.016	−0.103	1.000
Nominal wages growth—GDP growth	−0.001	0.016	−0.059	1.000

Table 9 (continued)

Forecasting methods tested	Estimate	Std. error	z value	Pr(>|z|)
Real wages growth—GDP growth	−0.004	0.016	−0.261	1.000
Two-week repo—GDP growth	−0.002	0.016	−0.156	1.000
Unemployment—unemployment forecast	−0.005	0.016	−0.344	1.000
Inflation forecast—unemployment forecast	−0.005	0.016	−0.313	1.000
Inflation—unemployment forecast	−0.010	0.016	−0.632	1.000
Nominal wages growth—unemployment forecast	−0.009	0.016	−0.589	1.000
Real wages growth—unemployment forecast	−0.013	0.016	−0.789	1.000
Two-week repo—unemployment forecast	−0.011	0.016	−0.685	1.000
Inflation forecast—unemployment	0.000	0.016	0.030	1.000
Inflation—unemployment	−0.005	0.016	−0.290	1.000
Nominal wages growth—unemployment	−0.004	0.016	−0.246	1.000
Real wages growth—unemployment	−0.007	0.016	−0.448	1.000
Two-week repo—unemployment	−0.005	0.016	−0.343	1.000
Inflation—inflation forecast	−0.005	0.016	−0.318	1.000
Nominal wages growth—inflation forecast	−0.004	0.016	−0.274	1.000
Real wages growth—inflation forecast	−0.008	0.016	−0.475	1.000
Two-week repo—inflation forecast	−0.006	0.016	−0.371	1.000
Nominal wages growth—inflation	0.001	0.016	0.044	1.000
Real wages growth—inflation	−0.002	0.016	−0.158	1.000
Two-week repo—inflation	−0.001	0.016	−0.053	1.000
Real wages growth—nominal wages growth	−0.003	0.016	−0.202	1.000
Two-week repo—nominal wages growth	−0.002	0.016	−0.097	1.000
Two-week repo—real wages growth	0.002	0.016	0.105	1.000

Significant values at $p=0.05$ in bold

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