

FORECASTING SYSTEM AT THE NATIONAL BANK OF KAZAKHSTAN: SURVEY-BASED NOWCASTING

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Forecasting System at the National Bank of Kazakhstan: Survey-Based Nowcasting

Kamila Mekenbayeva¹ and Karel Musil²

Abstract

Macroeconomic performance is one of the most monitored and analyzed area of many institutions, including central banks. However, proper handling of real economic development and business dynamics from the point of nowcasting is a challenging task. One of possible ways to solve these problems is using the business tendency survey data, as it is shown on the Kazakh economy case in this paper. We introduce two techniques to exploit the survey: (i) utilizing all available information by a factor model and (ii) a simple and intuition-driven model based on a single equation regression. Despite pros and cons of both approaches, they offer comparable and robust results which can be practically applied; they significantly contribute and improve the forecasting and policy analyzing system at the National Bank of Kazakhstan for monetary policy decisions. Additionally, the paper briefly documents the used forecasting system at the National Bank and concisely summarizes the Kazakh business cycle.

JEL codes: C53, E32, E37, E52, E58, O11, P24

Keywords: nowcasting, business tendency survey, output gap, GDP, monetary policy, Kazakhstan

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1. Introduction

To effectively support monetary policy decisions and analyses, it is useful to introduce and develop a well-defined system that allows a systematic evaluation of new information and provides regular policy analyses and updates to macroeconomic forecasts.³ Developing such a system is a challenging task that requires coordination among teams with highly specified skills, establishing and maintaining techniques combining model-based approach, experts' views, and processes in order to ensure an efficient communication and benefit from available information and data.

Among many elements of the system, the core one is centered around technical tools used for short- and medium-term forecasting. The short-term analyses and projections are usually incorporated into the medium-term view and form together a consistent and integrated macrostory. The area of analyzing the current situation in the economy and predicting the very near future is a near-term forecasting (NTF) field. Although sometimes the NTF is referred as nowcasting, see e.g. Banbura et al. (2010), the exact difference in literature is not precise, especially for the real economy. We will not distinguish between them and use usually the nowcasting for analyses and projection of very recent past up to the current period or several quarters ahead.

The motivation for running the NTF and nowcasting is simple - many macroeconomic statistics and data are released with a substantial lag and thus the nowcasting is an important part, and logically also the initial phase, for forecasting or analyzing. This means that nowcasting is relevant especially for data available on low frequencies: quarterly or annual. So the main task of nowcasting is to use up-to-day information to predict more recent but so far unobserved values – either using higher frequency data or data that are released more timely.

Additionally, an important part of the forecasting process is the evaluation of the overall economic climate and the description of the state of the economy. From this point, the core interest is centered around real economic activity, particularly real gross domestic product (GDP). The forecast of economic performance is closely monitored not only by authorities (ministries of finance, central banks and international institutions), but also by private sector and international trading partners. Moreover, the GDP nowcast is usually used as an input for the whole

³ This system is usually referred as the Forecasting and Policy Analysis System (FPAS). However, the goal of this paper is not to introduce this system in details and discuss its pros and cons; see e.g. Coats et al. (2003) for its practical implementation on the Czech Republic case and for further references.

forecasting system and can be incorporated into the core projection model, forming together an integrated forecast.

The paper proposes and discusses several econometric approaches for nowcasting real GDP and its cyclical component in particular. Among available approaches business survey data are utilized and simple econometric techniques on quarterly data are used and applied on the case of Kazakh economy. The real-time Kazakh data covers a period of almost 10 years, constrained only by its historical availability.

The reason behind the application on the Kazakh economy is three-fold. First, the central monetary authority, the National Bank of Kazakhstan, has recently switched to the inflation targeting regime and established a forecasting system for policy analysis, and the near-term forecasting and nowcasting are fundamental elements of this system. The paper, as a one of its goals, briefly describes and documents this system. Second, data availability and quality constraints push for utilizing any available information for nowcasting. In this situation the business survey is a valuable source that should be effectively utilized. Finally, the analyses of the nowcasted GDP and business cycle position of the economy can significantly contribute to the assessment of the overall recent macroeconomic situation in the country. As it will become clear later, the obtained results from our analyses confirm the usefulness of the introduced approaches and can serve as an input for both the follow-up technical analyses (near- and medium-term) and policy discussions. Throughout the whole paper we focus mainly on the output gap because of its relevance for policy makers and its unchangeable position for follow-up near-term calculations and medium-term projections (to cross-check a consistency with its identification from a core projection model). To better understand the overall story behind output gap development, the paper also focuses on Kazakh business cycle overview and specifics.

Although the paper will concentrate on the discussion around GDP and its cyclical component, the presented ideas can be applied on nowcasting any variable. For this purpose and to complete the overall picture about nowcasting the real economic activity, the paper briefly discusses other alternative approaches (using higher frequency information or more timely observed data) in a theoretical framework. However, the paper does not pretend to be a theoretical textbook in nowcasting and to completely describe all the aspects related.⁴ It tries to organize

⁴ Despite frequent revisions of the national accounts by a statistical office, as a one of the major issues related to GDP data, the paper does not handle this fact either. It only uses the latest available data. This means that after any historical revision, the results are highly recommended to be reviewed and analyzed with all the consequences. In

the main and sometimes neglected essences of nowcasting and to highlight the value added of the business surveys on assessment of the economic environment. Additionally, the paper makes use of existing tools, available for improving the insight into the likely path of the economy in the near future, and designs a functioning tool for practical usage as the main task.⁵

To offer a general picture of the nowcasting and the research already covered, the next section provides a brief introduction and summary of this particular area. As the paper is applied on the Kazakh data and economy, the following part describes basic features of the used data, the available business survey in particular, and the current situation about the forecasting system at the National Bank of Kazakhstan. The core of the paper is devoted to the business cycle nowcasting. The last part concludes and appendices provide supplementary information and econometric results in technical details.

2. GDP Nowcasting

Various decision makers and institutions, such as central banks, governments, financial markets or business, ground their decisions on understanding the state of the economic activity. In the aggregate view, this framework is usually based on quarterly real GDP data which is the most comprehensive and broadest measure. However, GDP data is released with considerable delays, usually with several months lag after the end of the reference quarter. The regular forecasting exercises and extensive analyses in this particular area are not motivated only by the usefulness of GDP nowcast due to delays in its releasing, but also due to several rounds of historical revisions usually taken by statistical offices before the final release and noisiness of the provided data as well.

For monetary policy making purposes, a comprehensible understanding of the state of macroeconomic activity is highly desirable and need to be produced in real time. In other words, the policy issue is where the economy stands and where it is heading, especially in the short run. Thus central banks spend a considerable amount of resources to track current-quarter GDP estimation - the GDP nowcast -

general, the historical revision topic is another big course of study of the near-term forecasting. This problem, from the point of near-term forecasting view, is elaborated in more details for example in case of Ireland (Irish GDP estimates are extraordinary for their volatility and the degree of revision which occurs between initial and latest GDP estimates) in D'Agostino et al. (2008) or Liebermann (2012).

⁵ The near-term forecasting models used for practical application usually capture the elemental aspects of the data, are typically designed to be small (capturing only a particular sector of the economy), easy to estimate, operate and maintain. Throughout the paper we will follow this approach as well.

before the final numbers are released. The reason behind is not only to cover a more precise assessment of the overall situation in the economy in real time, but such an estimation is also used very often as an input for central bank's medium-term model-based forecasting round.

Besides the already mentioned problems related to GDP data and analyses additional issues are inherited. Among many of them it is useful to highlight the following ones to complete the overall picture and indicate the complexity of this area.

First of all, the GDP nowcast is based on both quantitative methods and qualitative expert judgments and relies on a large amount of information. Whenever new information becomes available, the nowcast should be adjusted. In principle any release (either preliminary estimations of GDP⁶ or any other time series related, especially business surveys) potentially affects reference-quarter estimates of GDP and its precision. This means that the NTF team should analyze any new information and economic news and reassess the nowcast.

Considering the relevance, one of the most valuable sources for an improved estimation of GDP are business surveys. Their obvious value added is reflected by their more timely release compared to the GDP final estimation. More timely information has not only survey data (usually referred as a soft or qualitative indicators), which are released within or just few days after the reference period, but also high frequency indicators (hard or quantitative indicators), such as monthly industrial indices, retail sales and the unemployment rate.⁷ Contrary to the indicators, the surveys provide qualitative assessments reflecting sentiment and/or expectations, but have a looser link than the hard data with the state of the economy. According to Gayer et al. (2014) the business and financial survey data are mostly ignored, but they exhibit a solid predictive power and several engaging features. Besides their timeliness, they are:

- subject to no or only minor revisions,
- broad sectoral coverage of the economy, and
- including respondents' views on future developments expectations.

⁶ For example for the euro area, the first (flash) estimate of GDP for a reference quarter is released six weeks after the end of the respective quarter.

⁷ In general, there exists a trade-off between the timeliness of a possible GDP predictor and the precision of the signal delivered by the predictor. For example an industrial production index, which frequently enters the GDP calculation directly, is usually highly correlated and thus constitutes essential ingredients for GDP nowcasts. For more details in case of Eurozone see e.g. Gayer et al (2014).

We will check these properties later on the surveys available in the Kazakh economy.

Requiring actual view about the economy, as discussed earlier, all available information and both types of high- and low-frequency data are usually used to construct an estimate of GDP. However, this is not a simple task - to make use of monthly or even higher frequency data (for example, daily financial data), the nowcast handles (i) mixed frequencies issue (monthly data for nowcasting quarterly GDP) and (ii) the econometric problem of jagged edges: variables usually have missing points at the end of the sample reflecting their different publication dates – the multivariate datasets form unbalanced samples, see Wallis (1996). These two challenges are handled under the method of bridge equations and the Kalman filter.

Recalling the previous discussion, another challenge about the GDP nowcasting is the inapplicability of the standard simple regression models as these are unable to handle a large number of explanatory/predictive variables.⁸ This problem is known as the "curse of dimensionality". On top of that most time series for nowcasting GDP are weakly correlated which means that the traditional univariate ARIMA models also tend not to be very useful. It should be beneficial to turn to some available alternatives. Besides the indicated bridge equations, a principal component analysis can be used (and it is employed in this paper as one of the options).

Additionally, the nowcast of GDP itself is not sufficient for policy makers. They require knowing at which growth rate the economy is expanding or contracting, i.e. which phase of a business cycle the economy is going through and what are the sources of this movement. In other words, this fundamental information is linked to the estimation of output gap as a percentage deviation of the actual GDP from its potential product. However, significant and (usually expost identified) extraordinary swings in the dynamics and structural changes bring additional complications to the process of nowcasting and estimating the economic activity from the point of output gap.

To conclude, based on the previous discussion, computing the GDP nowcast in real time is not straightforward and faces many issues. Thus one of the main

⁸ Higgins (2014) classifies possible approaches to GDP nowcasting into three groups. The first group is related to the single regression models, but all these models are dated back to the 1990s advocating their out-of-dateness. The second group is related to the medium-data and data-rich methods without component forecasting (GDP forecasting based on bridge equations, factor models, Bayesian of mixed-frequency vector autoregression among others) and the last one on bridge equation and tracking models used for forecasting of GDP components aggregated up to a GDP forecast by various methods.

goals of the responsible team is to produce a consistent story about the recent economic development with numerical scenario centered around a point-estimate of GDP and output gap. This particularly means that the NTF team is required to provide detailed data analysis, economic insight and intuition at the same time. This challenging task is therefore one of the priority within the forecasting process and calls for several rounds of discussions among involved experts.

Reflecting the previously highlighted points (and many other related issues), it is logical that there is a large literature on nowcasting GDP and methods aimed at handling the problems. The following part briefly reviews and classifies the related studies, bringing the survey-related ones into focus.

3. Importance of Survey Data for Nowcasting: Literature Review

There is an expanding list of literature dealing with problems of nowcasting (or short-term forecasting in general). Although this part tries to provide a comprehensive overview of the recent advances in the GDP nowcasting (particularly focused on business survey) in the literature, it does not pretend to be completely exhaustive. All the models are rather described in a simple way to offer basic intuition behind and consequences for the approaches used later in this paper.

In general, there are two research domains related. The first one tries to find out what are the contribution and value added of surveys for nowcasting. The second area of research tries to shed light on the methods used for processing information from surveys (or high frequency data) for GDP nowcasts. Although there is no unambiguous conclusion and unique consensus, some general conclusions can be identified.

Godbout and Jacob (2010) and Lombardi and Maier (2011) among others show that surveys have a broad forecasting power for GDP in the euro area. In line with their findings, Kenney et al. (2012) adds that surveys (or in more general soft data) are mainly useful at the beginning of the forecasting period, when no hard data for the reference quarter is available at all. However, when hard data for the quarter are released (by the end of the reference quarter) less weight should be put on the soft data. The same view is also expressed by Angelini et al (2008): the contribution of the soft data releases is large at the beginning of the quarter and small at the end while the opposite is true for hard data. This is confirmed also by Giannone et al (2006) emphasizing that both timeliness and quality of the soft data release matter for decreasing uncertainty. Gayer et al (2014) evaluates the impact of new releases of various range of soft data on GDP nowcasting in Euroarea. They conclude that surveys (i) are essential to improve forecasts, (ii) carry valuable informational content, and (iii) are beneficial in GDP nowcasting because of their broad sectoral coverage and (sometimes) forward-looking nature.

Believing, in line with the previous conclusions, that survey data and other soft information can be valuable for nowcasting, there are several methods how to process and utilize them for nowcasting and predicting. Although one can suggest that the nowcasting can heavily depend on judgments of a reseacher and soft data can contain high noise, Winter (2011) advocates to a completely opposite conclusion. He found that an appropriately designed model (in his case a dynamic factor model) is more efficient at processing new information comparing other linear statistical methods. The factor model also beats professional business forecasters in case of Dutch economy (even during financial crises at the beginning and the end of the 2000s in the Netherlands). This can indicate that it is optimal to generate the GDP nowcast by statistical methods and their augmentation by expert judgments has only limited value added.

Regarding technical methods for processing surveys towards the GDP nowcast in general, Barhoumi et al. (2008) provides an overview and comparison of available methods for short-term GDP nowcasting applied on the euro area. One of their findings states that methods using monthly data releases outperform techniques based on purely quarterly data. Among them, handling monthly data and facing the unbalanced sample, factor models based on the Kalman smoother seem to perform outstandingly. This is confirmed also by Arnostova et al. (2011) although the paper shows that this conclusion is not general and is not valid for countries newly entering the European Union in 2004 – Hungary, Poland and Lithuania as an example. This leads to a simple inference that it is difficult to draw some general conclusion about proper methods and the authors usually recommend to simultaneously using several competing methods and models.

One of the possible methods, the dynamic factor model (FM) based on the Kalman smoother, was introduced in Giannone et al. (2006). The core of this technique is formed by factor analysis which has been proved to be one of the powerful tools used in exploiting the large data set. This was applied, for example, by Aestveit and Trovik (2010) to estimate a current quarter GDP in Norway by a panel of almost 150 mainly financial market data, Porshakov et al. (2015) to study nowcasting for Russian GDP applying a large scale dynamic FM, or to use a business tendency survey and stock market data consisting of 562 monthly

indicators for nowcasting quarterly GDP in Switzerland by Siliverstovs and Kholodilin (2010)⁹. The last mentioned paper confirmed that the factor model offers an appropriate forecast accuracy of GDP growth rates at all forecast horizons and all data vintages. Additionally, the largest forecast accuracy is achieved when GDP nowcast for an actual quarter is prepared about three months ahead of the official data release. This point is valid for almost all the referred papers and thus can be considered as a general conclusion: all the nowcasting methods should be used up to two quarters.

Although using the same technique, the previous papers deliver contradictory conclusions about blocks of variables that have the largest impact on GDP forecast accuracy. Asking which indicators are important for nowcasting, Giannone et al. (2008) conclude that the Philadelphia Federal Bank surveys as well as the report on the employment situation contribute the most to an increase in forecast accuracy, whereas the impact of financial variables (including stock market indices) is found to be negligible. Contrary, Aastveit and Trovik (2007) find that the stock market variables are an important factor in reducing forecast uncertainty, but they do not include surveys in the their factor model due to a mixed frequency problem. Siliverstovs and Kholodilin (2010) document that both business tendency surveys and stock market indices possess the largest informational content for GDP nowcasting although their ranking depends on the method of transformation of monthly indicators used for the calculation.

However, using a big data sample is not the only way of GDP nowcasting. Contrary to the previous approaches, some studies even do not confirm the findings that complex dynamic models with disaggregated data outperform simple static approaches or the most parsimonious models relying on lower number of observations, see e.g. Barhoumi et al (2009) or Marcellino and Schumacher (2007) in case of France and Germany, respectively. We will focus and elaborate on this disagreement in the second part of the paper as well.

The preference of the parsimonious approach is also clear from Yiu and Chow (2011). The paper suggests to nowcast Chinese quarterly real GDP growth from the regression on the two underlying common factors only. An alternative specification suggests including lagged values of quarterly GDP growth as a

⁹ The FM technique applied by the Bank of Russia by Porshakov et al. (2015) and by Siliverstovs and Kholodilin (2010) directly use the approach introduced in Giannone et al. (2008) and Doz et al. (2011), which follow the original paper by Giannone et al. (2006). The methodology in Giannone et al (2008) has a number of desirable features and it offers a parsimonious solution for the inclusion of a rich information set.

dependent variable, which improves the model's ability to capture dynamics in quarterly GDP growth.¹⁰

Although all the previous papers offer several ways how to handle the GDP nowcasting¹¹, it is important to note that it is a country specific problem. For example, Lebeouf and Morel (2014) used an unrestricted mixed-data sampling model for short term forecasting of real GDP for Japan and Euro area.¹² Whilst the Purchasing Managers Index is one of the best-performing indicators for the forecasting in the Euro area, consumption indicators and business surveys are the most predictive for Japan.

To conclude, the literature review reveals that not much empirical and theoretical research on GDP nowcasting and potential output estimation for Kazakh economy was undertaken compared to other countries with transition economies. Konurbayeva (2006) evaluates different approaches to forecast potential GDP in Kazakhstan for the period 1996 – 2005. The author uses Hodrick-Prescott (HP) filtration and constructs two production functions and finally obtaining similar results. Polyakova (2011) conducted empirical assessment of Okun's law for Kazakh economy for 2000 - 2008 time period. Similarly with the previous research the author constructs the Cobb-Douglas production function to estimate potential product of Kazakhstan. The paper incorporates expenditures on education and research and development as an additional factor of production. The results conclude that potential GDP growth in Kazakhstan has not changed sharply over the analyzed time period and the economy stayed around its potential. More structured approach is used by Agambayeva et al (2010). The paper develops a small macroeconomic model of Kazakhstan in order to produce medium-term forecasts of the main macroeconomic variables, including potential output and output gap by applying the Cobb-Douglas production function. Consequently, the existing literature verifies that the production approach has been widely applied to estimate potential output in Kazakhstan so far. In this regard, this paper, which employs survey data, contributes significantly to the analysis of the economy of Kazakhstan, estimating its potential product and forecasting main macroeconomic variables in a different approach.

¹⁰ Even a simpler approach using a univariate regression model for GDP forecast based on nine years of quarterly real-time survey data in Sweden offers Osterholm (2013).

¹¹ To complete the picture, a general review of available methods is documented in Camacho and Perez-Quiros (2013) or Banbura et al. (2010).

¹² The model relates low-frequency variables, quarterly real GDP growth, to lags of high-frequency variables, such as monthly, weekly or daily indicators.

4. Situation of Kazakhstan

Before we start with a practical applications of the survey data in Kazakhstan, let's first overview some facts about the development of the economy and the National Bank's capability to reasonably handle the issue of real economy nowcasting.

4.1. Macroeconomic Development in Kazakhstan

Given all the previous comments, it is clear that analyzing and/or nowcasting GDP is not a mechanical matter. Real development of the economy is necessary to put into context of the overall economic development, long-term dynamics and temporal developments. All these factors together form an overall fundamental macroeconomic story as a cornerstone. Let's first learn some basic lessons from the past development of the Kazakh economy and include them into the discussion about the GDP nowcast later on.

After declaring its independence in 1991, Kazakhstan started the process of significant structural reforms, transforming its political and economic systems from centrally planned to market-oriented. In this regard, domestic economy has undergone fundamental restructuring processes including privatization, establishing free entrepreneurship, introducing its own currency (Kazakhstani Tenge), transforming country's financial system by establishing private commercial banks and creating conditions to attract foreign investment among others. This period of reforms and restructuring lasted until the late 1990s and was accompanied with high inflation and downturn of economic activity, which was further deteriorated by financial crises in Asia and Russia in 1998. During that period the economy was running below its potential, which helped to dampen inflation to single digit numbers in the second half of the 1990s. However, stagnation of economic activity led to decrease in investment activity and loss of competitiveness of domestic producers. By the end of the 1990s most of institutional and structural reforms necessary for further development of the economy in free market conditions were largely in place which significantly improved the overall situation in the follow-up periods. Figure 1 presents the dynamics of GDP growth rates and inflation over the last twenty years in Kazakhstan.



Figure 1: CPI Inflation and Growth Rates of GDP in Kazakhstan, y-o-y

The structure of the Kazakh economy by sectors is showed in Figure 2. Whilst economic performance in the 1990s was more or less evenly spread among all the major industries, the situation completely changed in the next decade. The first half of the 2000s was a period of prominent economic growth that was driven by a sharp increase in industrial production, particularly mining sector. It attracted most of the foreign investment coming to the country during the 1990s. The sector helped to increase Kazakhstani exports (oil, gas, metals) and contributed to the rapid improvement in the banking sector and financial services. Increase in the real income of households combined with growth of consumer credits positively enhanced domestic demand. The Kazakh economy grew robustly at average annual rate of 10.3% between 2000 and 2006.



Source: Committee on Statistics of the Republic of Kazakhstan, author's calculations Figure 2: Real GDP Growth and Contributions of Sectors (sectoral decomposition of GDP by production methods), y-o-y

During the "economic boom" period the economy was growing at higher rates than its estimated potential. This slight overheating of the economy generates mild inflationary pressures which were compensated by low imported prices and favorable development of commodity and food prices. As a result, overall inflation did not accelerate. The economic growth was partially driven also by monetary easing – monetary regulations aimed at supporting economic growth increased the level of bank credits by 17 times from 2000 to 2006. At the same time, the credit growth, largely based on significant external borrowing of domestic banks, led to increased vulnerability of Kazakhstan to external economic shocks.¹³ All in all, combined with unfavorable external development, this finally resulted in the acceleration of inflationary processes in the country and annual inflation rate amounted to 18.8% by the end of 2007.

Further macroeconomic development of Kazakhstan was affected by the global financial crisis to a great extent. With the break out of the crisis foreign markets were closed for funding and domestic banks experienced shortage of liquidity, which initially led to the crisis in the financial sector and then in the real sector of economy. The situation deteriorated in the second half of 2008 when world prices of main Kazakhstani exports suddenly dropped. Growth rate of real GDP slowed down to 1.2% in 2009, the lowest level since 1998. The actual GDP fell below its slow-downing potential that resulted in negative output gap caused

¹³ For more details see Monetary Policy of the Republic of Kazakhstan to 2020, <u>http://www.nationalbank.kz/cont/publish305261_28968.pdf</u>

by a slump in domestic demand and investments. Not only was the industrial sector hit, but also the construction and service industries suffered.

Measures taken by the government during the crisis were among main factors to stabilize the economy, supported the financial sector and improved the liquidity situation in the banking sector. A single-step devaluation of Kazakhstani Tenge was carried out in order to save the NBK's foreign exchange reserves and maintain competitiveness of domestic producers. In the meantime, the recovery of the world economy, improved terms of trade and gradual growth resumption of demand for Kazakhstani exports contributed to the improvement of domestic economy and annual GDP growth was recorded at 7.5% in 2011.

Nevertheless, being a small open economy heavily dependent on oil exports, which compile the largest share in export revenues of the country, Kazakhstan was severely hit by the drop in world oil prices in mid-2014. Additionally, slowing economic development in China and negative economic situation in Russia, which are among the main trading partners of Kazakhstan, adversely affected the Kazakh economy. Depreciation of the Russian ruble at the end of 2014 led to the loss of competitiveness of domestic producers and to the switch of the domestic demand towards comparably cheaper imported goods from Russia.

Additionally to the worsening of the external economic conditions, high level of dollarization of Kazakh economy prevented monetary authorities from persuasion of an effective monetary policy. In order to follow the fixed exchange rate monetary policy regime and to maintain exchange rate at the established level, the NBK disposed a considerable amount of its foreign exchange reserves in 2014 and in the first half of 2015. To renew an external balance, enhance the price competitiveness of nonoil exports and improve the overall economic performance, the NBK decided to ease its monetary policy stance by nominal depreciation in a response to challenging external environment. Later on, on August 20th, 2015 the Government and the NBK released a Joint Statement "On Transition to a New Economic Policy: to Reforms in the Real Economy and New Monetary Policy Regime"¹⁴, whereby the NBK adopted an inflation targeting regime and pegging exchange rate was abandoned. The new monetary policy framework was aimed at strengthening the interest rate channel and ensuring a more predictable and stable path of inflation.

¹⁴Available through <u>http://www.nationalbank.kz/cont/publish420901_29263.pdf</u>

4.2. The FPAS and the NTF Team at the NBK

The adoption of the inflation targeting regime was not the only change that happened during that period. The NBK had implemented various stages necessary for the transition to a new monetary policy framework and established the system for forecasting and policy analysis (FPAS) to support policy decision-making. In essence, the FPAS is a system that promotes a systematic evaluation of new information and provides regular policy analyses and updates to macroeconomic forecast and alternative policy scenario. The FPAS at the NBK was established under the technical assistance mission of the IMF. The implementation of the system involved formation of the centralized database of main macroeconomic variables, establishment of forecasting teams and assurance that the forecasts are based on all relevant information and the process itself is internally consistent.

The system comprises two main teams - one is responsible for developing near-term nowcasts and forecasts of the economy (NTF team), and the second one (QPM team) develops and operates the code projection model, and simulates alternative scenarios that are generated to highlight and quantify possible risks related to the baseline forecast (for more details see e.g. Laxton et al (2009)). The medium-term forecasting (QPM) team employs semi-structural quarterly projection model to produce medium-term forecasts for the period of up to 1.5 year (6 quarters) which corresponds to the monetary policy horizon. To support the QPM team, which applies structural macroeconomic models, that are based on theoretical economic links and fundamentals, the NTF team also incorporates statistical and econometric models that utilize mainly empirical links in a large volume of all available data. Currently, both teams are well established, functioning and effectively handling their responsibilities.

At the initial stage of establishing the FPAS at the NBK, the NTF was focused mainly on data analyses and interpretation on expert judgments and intuition. This generated a solid basis for its further development. Later the NTF was enriched by introducing a bulk set of econometric models and technical tools to conduct forecasts of domestic macroeconomic indicators under concern, such as GDP, inflation, fiscal variables as well as macroeconomic indicators of main trading partners. Moreover, the NTF team prepares general assessment of external conditions and commodity prices and their forecasts for the medium term. Inside the NTF team each forecaster is assigned with a task of monitoring particular sector in line with national accounts (GDP calculated by production approach and GDP calculated by expenditure approach), balance of payments, prices and inflation, government budget and transfers from the National Oil Fund¹⁵, external conditions and other important parts of the Kazakh economy. Such an arrangement using both technical and judgmental views of the NTF experts ensures effective framework for analyzing, nowcasting, forecasting and future development of the unit.

One of the agenda of the NTF team covers the real economic activity sector of the Kazakh economy. Considering substantial lag of the official release of statistical data for the national accounts and limited availability and quality of other real economic data and indicators, nowcasting GDP and evaluating its business cycle position still remain a challenging task.

In order to effectively operate the national accounts area, the NTF expert is required to assess all the available information in a systematic and complex way. Hence, business tendency surveys (BTS), conducted by different institutions all over the world proved to be very valuable, these surveys are very useful also for Kazakhstan¹⁶.

5. Survey-Based Nowcasting of Kazakh Economic Development

This second part of the paper is finally aimed at a practical usage of the survey data. After the introduction of the Kazakh business tendency survey, two methods of its processing towards the identification of the real economy situation are presented.

5.1. Data: Business Tendency Survey in Kazakhstan

Generally, the surveys are carried out on a regular basis to obtain information by asking company managers about the current situation of their business and their plans for the near future. Contrary to conventional statistical surveys, the BTS collect qualitative data based on the answers of respondents, which aim to receive their judgement on recent developments, an assessment of the current situation, or expectations for the near term future. The questionnaires are designed in a way to cover a wide range of variables and to give a complete picture of a particular industry and economy as a whole. These include multiple-choice questions on production, new orders, demand for output, inventories, exports,

¹⁵ The National Fund of the Republic of Kazakhstan was created in August 2000 as a stabilization fund that ensures the economy of the country will be stable against the price changes of oil and gas. It accumulates all types of taxes paid by oil and gas producing companies in the country. ¹⁶ For a general description of the BTS see OECD (2003).

imports, investments, prices and employment and many others. Given that one of the main advantages of the BTS is its timeliness, the questionnaires generally consist of no more than 3 pages and are designed in a straightforward way. The questions are clear, unambiguous and phrased in a plain and non-technical language. For example, respondents might be asked to assign qualities to the value of their order books such as "higher than normal", "normal" or "below normal" (OECD, 2003). Therefore, the questionnaires can be completed quickly and the results of the survey can be published much sooner than the official statistical data are released.

The survey results are not subject to revisions unlike most statistical data, which is another benefit of the business surveys. Moreover, by including questions on expectations of company managers regarding a particular issue, the survey allows to produce forecasts for one or two quarters ahead. The mechanism in place for carrying out regular business tendency surveys thus provides a flexible instrument for obtaining policy-relevant information in such situations (OECD, 2003).

The results of the survey obtained as answers on multiple-choice qualitative questions are transformed into a single time series by applying one of the two methods. The first method called "Net-Balances" is based on the calculation of the balance of opinions; the second one is constructing diffusion indices. For calculating balances, the reply options are previously converted into percentages and the net balance is then calculated by subtracting the (*down/below normal*) percentage from the (*up/above normal*) percentage, i.e. 20 - 50 = -30. Note that in the calculation of balances the (same/normal) replies are discarded. Balances can take values from -100 to +100 with midpoint at 0.

Meanwhile, the diffusion index is compiled using estimated percentages of favourable answers plus half of the fraction of no change answers. The diffusion indices range from 0 to 100 and have a turning point at 50. An index value above 50 indicates growth in the variable, and opposite for a value below 50. The index value of 50 indicates no change.

The NBK has been conducting business surveys since 2000 and closely follows all the points of the methodology as stated previously (in line with the OECD standards). In case of the NBK's BTS for Kazakhstan, the sample consists of almost 3000 companies of large, medium and small size representing all sectors of the domestic economy. Participation in the survey is voluntary and selected enterprises are encouraged to participate by sending them feedback analytical reports with emphasis on the competitive position of the company in the industry it operates and convincing them that the information they provide is very valuable for macroeconomic analysis. Such a broad and general basis of companies across the whole economy, together with a long historical tract, allows for a representative sample with very valuable data for further processing and analyzing.¹⁷

The questionnaires were designed in accordance with the best practices and compile questions to provide valuable information on business conditions and an overview of aggregate economic activity. Furthermore, since the survey was initiated and conducted by the NBK, it was decided to include questions on financial indicators, such as an assessment of credit conditions by company managers, interest rates and loan durations, deposits, existence of overdue loans and others. Progressively, the survey in Kazakhstan was also enlarged by adding special questions addressing economic conditions which are important for country's economy. These include, for example, managers' view on the impact of exchange rate devaluation. Considering high level of dollarization of Kazakh economy and large share of imported goods in consumer and investment goods, domestic producers are very sensitive to changes in the exchange rate and terms of trade.

The questionnaires are sent regularly to respondents by bank officers at the regional branches (14 regions and 2 big cities) on a particular date. The officers at branches are responsible for conducting the follow-ups and collecting all questionnaires before the deadline. Upon receiving, they enter the answers to the centralized system of data processing and the results are then used and applied for forecasting by the experts at the NBK headquarter. The results of the survey are usually available on the third week of the month following the reporting quarter, which is quite before the official release of the flash estimate of GDP for the reporting quarter¹⁸.

The results of the survey at the NBK are available in the form of diffusion indices and cover all important production and service sectors.

Although the establishment of the BTS at the NBK dates back to 2000, the data collection of the survey was started in 2005, as the period before was devoted to sample selection, establishing contact with selected enterprises, organizational,

¹⁷ Despite its voluntary character, the NBK gratefully thanks all the contributors of the BTS for their participation.

¹⁸ According to the official publication calendar of the Committee on Statistics of the Republic of Kazakhstan, the flash estimate of the quarterly GDP calculated by production approach is available on the 45th day after the end of the quarter.

regulatory and research issues. Since 2005 the content of questionnaires has been revised twice and each time new questions were introduced or a clarification of the existing ones was added. The last revision was undertaken in 2014-2015 and very worthwhile questions in terms of forecasting and analyses, such as capacity utilization level, change in inventories, sources of financing current and fixed assets, were extended. Although the time series of these indicators are short and could not be applied for empirical analysis at this moment, they are evaluated for making judgments over the general economic conditions. Thus, the implementation area of the BTS data could be extended in the future and the value added of survey results to forecasting process will increase substantially.

As it was previously mentioned, late publication of data on GDP is the main challenge to produce its accurate nowcast. GDP in Kazakhstan is calculated on quarterly and annual basis by the Committee on Statistics of the Ministry of National Economics using three different methods:

- Production method corresponds to the sum of value added by types of economic activity (sectors) and net taxes on products and imports. This method shows the sectoral structure of economic growth and provides useful information about the supply-side of an economy.
- Expenditure approach focuses on total expenditures on goods and services and represents total demand in the economy.
- Income approach concentrates on the payments to the factors of production involved in the production activities.



Source: Committee on Statistics of the Republic of Kazakhstan

Although GDP in Kazakhstan is measured by three approaches (and the core prediction model of the FPAS relies on the expenditure approach), the decision of using production method was drawn on several factors. Firstly, the income

Figure 3: Real GDP Growth by Production and Expenditure Approach, y-o-y

approach calculated GDP is released only in current prices but not in real terms (and thus is not appropriate for any kind of real economy analyses at all). Secondly, although the production and expenditure approaches calculated GDP is published in current and constant prices with corresponding growth rates, there is a substantial time lag between the publishing dates of these two approaches. The expenditure approach calculated GDP is released 3 months after the reported quarter, while production approach GDP data is available on the 45th day following the quarter. Whilst discrepancies between both methods are small recently, differences especially prior to 2006 are attributed to statistical discrepancies and changes in the methodology (Figure 3). Moreover, the final use GDP data is subject to historical revisions more often compared to value added GDP data due to revisions of the current account data and the methodology. Meanwhile, as a result of historically established practices the production approach remains a primary method for the GDP calculation. Thus we will use the production approach for further analysis in this paper.

Although the flash data on GDP is released with a 45-days lag, the Committee on Statistics publishes monthly indicators, which represent particular importance for nowcasting. These include industrial production index, manufacturing production volume, retail sales, volume of construction works, monthly indices of transportation and communication services and many others. These data along with information coming from business tendency survey of the NBK are utilized in producing quarterly nowcast for real GDP and its components.

To demonstrate the relevance of full information embodied in the BTS itself for the GDP nowcast, a factor analysis is introduced in the next part. Revealing that this approach is reasonably successful, we try to use only subset of information available from the BTS taking the advantage of parsimony. All the presented methods can be further extended by including other indicators and time series to improve prediction abilities of the models.

5.2. Factor Model Approach

To nowcast GDP, any release or news related to economic development may potentially affect the current quarter estimates of economic performance and their precision. This means that there is no reason to disregard any available information, no matter of frequency or time of availability. To follow this idea, we utilize the framework designed by Giannone et al. $(2006)^{19}$ and adjust it to specifics that we are facing with the Kazakh economy.

Assuming that large information sets help in forecasting, a factor analysis methodology, which follows the idea that the dynamics of a large set of time series are generally driven by a small number of common factors, seems to be appropriate. Giannone et al. (2006) introduced a statistical framework which extracts a signal from a large number of observations, accounts for asynchronous releases and bridges the monthly frequency with the quarterly GDP series. This means that by using a FM the method extracts common factors by a statistical principal component analysis first and then the common factors are extracted by the Kalman filter for the whole sample to use them for projecting the quarter-to-quarter GDP growth on the estimated factors.²⁰

The system of equations is set up by the following general state space representation

$$\dot{X}_t = \Lambda \dot{F}_t + \varepsilon_t,\tag{1}$$

$$\dot{F}_t = A\dot{F}_{t=1} + \eta_t, \tag{2}$$

$$Y_{t} = \alpha + \beta Y_{t-1} + BF_{t} + CF_{t-1} + \mu_{t},$$
(3)

where a dot over a variable refers to the variable in its original frequency. This means that \dot{X}_{t} is a matrix of observed indicators in their original frequency (usually monthly), \dot{F}_{t} and F_{t} is a matrix of identified latent factors (common factors) in their original (corresponding to the same frequency as for \dot{X}_{t}) and quarterly frequency respectively, Y_{t} is quarter-to-quarter real GDP growth, $\Lambda, A, B, C, \alpha, \beta$ are matrices of parameters and $\varepsilon_{t}, \eta_{t}, \mu_{t}$ are idiosyncratic error terms.

Equation (1) and (2) describe a FM. The second equation, assuming that the common factors follow a vector autoregressive process, allows to implement the Kalman filter in order to calculate recursively the missing observations of the common factors especially at the end of the sample (to handle the unbalanced panels which are characterized by ragged ends). The last equation suggests projecting GDP growth on a few unobserved common factors and its lagged value

¹⁹ The method was used by many practical applications on data, see for example Silverstovs et al (2010) or Porshakov et al (2015).

²⁰ The Kalman filter framework is not necessary to use to predict the factors and a simple BVAR can do this task.

in a regression whose parameters can be estimated by OLS.²¹ The procedure also assumes that there is a conversion of the original frequency of the common factors into the quarterly one.

Giannone et al. (2006) suggest to limit the maximum of extracted factors to two to keep the forecasting model parsimonious and avoid a possible problem of an overfitted model. However, in practice the number of the factors and final specification of equation (3) results from statistical tests, including information criteria, and analysis of data fit.

Because we are interested in cyclical development of the economy, output gap y_t instead of real GDP growth Y_t is used in equation (3). This means that the equation is equivalently specified as

$$y_t = \alpha + \beta y_{t-1} + BF_t + CF_{t-1} + \mu_t$$

Using the Kazakh BTS data, which are available only in a quarterly frequency, the whole set of equation does not face the mixed frequency problem and thus does not require using any bridge equations to link together variables with different frequencies.²² To estimate the common factors, the sample of 31 indices available within the business survey covering the period starting from 2006Q1 was utilized.²³ The sample finishes in 2015Q4 as the Kazakh economy went through significant changes and structural breaks in the second half of 2015; these include especially a change in monetary policy regime and an oil price drop. Despite this, more than 10 years of quarterly data per every time series is available and forms a sufficiently large data set for the factor analysis.

The estimated first ten common factors are presented in Figure 4. It reveals that each of the most important three factors covers more than 10 % of volatility and the first five factors explain more than 90 % of the total volatility of the BTS data.

 $^{^{21}}$ Notice that the state space representation uses only the common factor component and thus it is assumed to be predictable. Such a constraint does not form a significant loss of information because the common factors usually capture the main cross correlations in data. For details see Giannone et al. (2006) and Giannone et al. (2005). Additionally, the state space representation allows to easily calculate confidence bands and asses a contribution of major blocks of dataset to the forecast error.

²² This simply means that equation (1) and (2) are based on quarterly observation. Thus the common factors are also estimated at the same frequency and $\dot{F}_t = F_t$.

²³ All series, where required, are normalized prior to the estimation of the FM.



Figure 4: Estimated Common Factors from the Business Survey Data, authors' calculation.

The second step, in a general framework, suggests to specify a vector autoregressive process by using the identified common factors and to run the Kalman filter in order to fill the missing common factors at the end of the sample. However, the BTS provides a balanced panel as all the indices are collected every time. Thus there is no need to run the Kalman filtration in this case.

The common factors are then used for the nowcasting the Kazakh real economic activity. As all the survey data time series, and consistently also the common factors, are stationary, the GDP data are transformed in the same way. We run Hodrick-Prescott filtration first and use the output gap, as a percentage deviation of the actual output from its potential level, for the follow-up analysis – the gap is regressed on the identified common factors.

Besides the common factors, a lagged value of the output gap is used for the regression as well, reflecting its relatively high persistence exhibited by the data. In general the regression equation can be further manipulated by adding more lagged terms, but no significant improvement was gained in this case. By testing regression properties (statistical significance of estimated parameters and information criteria in particular), the number of common factors was set to two

without any lagged values in the final regression specification.²⁴ The regression, referred as equation (3) in a general notation, has the following form

$$y_t = 0.65 y_{t-1} + 0.22PCA1_t - 0.18PCA2_t + \mu_t,$$
(4)

where all the estimated parameters are statistically significant. Because all the variables used for the regression are of zero means, an intercept is not statistically significant and thus dropped out. The parsimonious model consists of only lagged output gap and two common factors; the lagged values of the factors with the combination of their current counterparts are not statistically significant. Despite its relatively simple specification, the equation performs quite strongly; R-squared is equal to 0.92. For more details about the statistical properties of the results see Appendix.

The results of the regression are presented in Figure 5. The picture reveals that the fitted values closely follow the actual value of the output gap including its business cycle dynamics. The dynamics is driven by the output gap persistence and by the first principal components (PCA 1) in particular as it is clear from the decomposition. The contribution of the second principal component (PCA 2) is rather minor but still significant.

²⁴ When calculating the standard errors of the standard errors for the statistical significance f the parameters, the fact that the factors used as regressors are estimated is not taken into account.



Figure 5: Output Gap Regression Results, authors' calculation.

The presented outcomes of the regression show that a combination of the PCA together with a single equation regression is able to offer an appropriate tool for Kazakh GDP nowcasting. Besides its powerfulness and robustness, the approach is general and can be easily modified and extended.

However, a possible drawback of the previous method is the end-point bias problem of the Hodrick Prescott filter which can significantly influence and possibly distort the output gap nowcast. This can be handled, for example, by a judgmental check and adjustment of residuals of the regression at the end of the sample – believing that the regression is correctly and robustly estimated within the sample, where the end-point bias problem does not appear. Another possible solution to this problem is to use a different filtration technique for the identification of the output gap.

As it is suggested in the previous case, the Kalman filter easily solves a problem of ragged ends and forecasting of the common factors. Moreover, it can be used for the identification of the output gap as well. By doing so, there is only one extra step in the whole process – the output gap is filtered out from the observed GDP time series by separating a potential growth of the economy from the observed real GDP growth. Additionally, the method produces not only a nowcast of the output gap, but also of the whole GDP because the potential product is a part of the Kalman filtration and forecasting.

To follow the previous idea and to preserve a simplicity and efficiency of the whole approach, the Kalman filter decomposes the observed GDP into its output gap and potential product components. The output gap dynamics is driven by the common factors identified from the PCA in the same way as it is defined by equation (4). Additionally, because the Kalman filter works with a state space representation of the model, the maximum likelihood estimation of the used parameters can be applied. In this case, the estimated equation for output gap has the following form

$$y_t = 0.58 y_{t-1} + 0.23PCA1_t - 0.28PCA2_t + \mu_t.$$
(5)

The difference in the estimated parameters with respect to equation (4), which is based on Hodrick Prescott gap filtration and OLS estimation, comes from the fact that the observed variables – in this case real GDP – is decomposed into its potential and gap component based on the model specification or, in other words, the output gap is not directly observed. Then the parameters of the equation are estimated.

To compare the outcomes, there is no big difference for the estimated parameters for the lagged gap and the coefficient for the first principal component (PCA 1), however, the coefficient for the second principal component is higher. This produces some differences. However despite this dissimilarities, the Kalman filter identified that the output gap exhibits almost identical dynamics as the one from the Hodrick Prescott filtration; see Figure 6.



Figure 6: Output Gap Filtration and Comparison, authors' calculation.

The picture also reveals that, given the uncertainties, the fitted values of output gaps in both cases are similar. The Kalman filter produces slightly more volatile gap, but still with the same business cycle properties. By comparing the contributions of explaining factors behind the output gap decomposition, the result is almost identical.

What is crucial and clear from this alternative approach is the fact that the end-point bias in Hodrick Prescott filtration of the output gap does not degrade the outcomes and does not cause a serious problem preventing from using this technique. Given the simplicity and streamlines of the approach based on Hodrick Prescott filtration, the results are valuable without a heavy end-point bias in this case. They can definitely serve as a first and quick benchmark for the policyrelevant discussion.

To further illustrate the advantages and correctness of these methods, a historical nowcast exercise was executed (in a form of in-sample simulations based on observed data from the BTC). Figure 7 presents the performance of the Kalman filter based on the maximum likelihood estimated equation, see equation (5), in terms of historical nowcast errors for the first two quarters. This covers the nowcast periods. The exercise, however, lacks judgment as a regular input into GDP nowcasting. Hence, the performance corresponds more to mechanical insample simulations and should not be confused with the nowcasts from historical prediction rounds.



Figure 7: Historical In-sample Simulations, authors' calculation.

The output gap and year-to-year GDP growth simulations are based on a nowcast of principal components (again mechanical and without any judgmental input). Although the output gap nowcasts indicate a gradual slowdown of the Kazakh economy during 2008 and 2009, there are some prediction errors coming mainly from difficulties connected to the turning points of the business cycle dynamics. This error is significantly lower for GDP growth. Once the economy started to gradually recover, the ex-post nowcasts begin to be much more accurate and closely follow not only the filtered output gap, but also the observed year-to-year GDP growth. Similar situation characterizes also economic slowdown at the beginning of 2015. However, based on the whole period covering past 10 years and even despite only a mechanical manner of the simulations, the specification of the model and the used method seem to provide a very powerful tool for the GDP nowcasting that can be utilized in practical forecasting exercises.

5.3. Regression Model Approach

The heretofore methods based on utilizing all the available information in the BTS provides relatively reasonable results but on the costs of a quite complicated technical framework. The subsequent approach tries to simplify it.

Using the fact that output gap identification by the HP-filter is very close to the multivariate approach by the Kalman filter, we will continue with the HPidentified output gap to keep the technical framework as simple as possible (but still without any significant impact on the results from the point of their practical usage). Additionally, we try to find only a limited subset of indices within the BTS to explain and nowcast the output gap by a simple single equation regression. In other words, the goal of an austerity with a clear intuition behind the results is of the prime importance of this section and it clearly prevails over the perfect accuracy of the estimation.

Therefore, a simple regression model based on the selected business survey indicators was developed at the NBK. The model allows for more up-to-date estimation of the business position of the economy in a noncomplicated way and crosschecks the FM and Kalman filter approach at the same time. The data used include indicators of demand for the output in main production sectors of country's economy and expected estimation of changes in demand for the particular businesses according to the managers of surveyed enterprises.²⁵ Figure 8 represents annual growth rates of real GDP and time series of the data employed in the model, particularly diffusion indices of changes in demand for output in mining, manufacturing, construction, wholesale and retail trade, transportation and storage and information and communication sectors of economy, which constitute approximately 60% of the country's GDP²⁶.

²⁵ Additionally, survey results give an overview about financial situation of the private sector, capacity utilization and changes in stocks. Although these data are not put into the model, they provide good basis for analysis of the changes in real sector.

²⁶ According to data on GDP for 2015 released by the Committee on Statistics these sectors compose 57% of total GDP. The selection of the indices does confirm not only the economic intuition and logical correctness, but also statistical significances and robustness of the specification tested during the phase of the model development.



*Figure 8: Demand for Output in Sectors (diffusion indices, seasonally adjusted*²⁷) *and Growth Rate of Real GDP*

In general, the figure reveals that the growth rate of real GDP closely follows the dynamics of diffusion indices. According to the survey results, companies in the mentioned sectors faced high demand for their output in the period of rapid economic growth, see, for example, the period prior to 2008. After the global financial crisis, demand has decreased considerably as a result of slowdown in economic activity. The demand for output has improved slightly following recovery of macroeconomic conditions in the country. The situation deteriorated in 2014, when sudden decrease in world oil prices occurred, followed by unfavorable economic situation in Russia (as one of the main trading partners of Kazakhstan) and depreciation of the Russian ruble. Most of the BTS contributors, particularly managers in the manufacturing industry, stressed a sharp decline in their demand for the output in the first quarter of 2015. They indicated increased fierce competition from foreign producers, particularly Russian companies. Devaluation of the Russian ruble led the imported goods from Russia to be than domestically produced ones. The percentage of comparably cheaper companies reporting increase in inventories has notably risen in the first quarter of 2015.

Therefore, the indicators of the survey reflect the general economic tendencies and are quite reliable for nowcasting. From the previous description, it is clear that some of the indicators have a great potential to explain the overall movement in the real economy. We try to utilize this characteristic.

²⁷ The seasonal adjusted series are the final seasonally adjusted data (D11 component) of X-12-ARIMA quarterly seasonal adjustment method developed by the U.S. Census Bureau.

The regression model employs GDP (production approach) in constant 2005 prices and a subset of diffusion indices covering the period from 2006 to 2015^{28} . All the seasonally adjusted time series are transformed by using logarithmic function and multiplied by 100, then the cyclical components of all indicators are obtained by applying Hodrick-Prescott filtration. The regression is estimated by an OLS method.

Equation (6) presents the specification of the regression equation together with the estimated value of parameters and Table 1 gives detailed description of the data employed.

VariableDescription
$$y_t$$
Output gap, % X_I Diffusion index of demand for output in mining industry X_2 Diffusion index of demand for output in manufacturing industry X_3 Diffusion index of demand for output in construction X_4 Aggregated diffusion index of demand for output in wholesale and retail trade, transport and storage and information and communication sectorsDDummy variable (equals 1 for 3Q 2013 and 3Q 2014, and 0 for other periods) u_t error term

$$y_t = 0.06 X_{1,t} + 0.09 X_{2,t-2} + 0.07 X_{3,t-4} + 0.03 X_{4,t-1} + 0.67 D + u_t$$
(6)

Table 1: Data Description

The coefficients of the estimated regression proved to be statistically significant at 95 % level. The dummy variable was introduced to the regression to capture the outliers in the residuals of the estimated regression, which were caused by extraordinary events during the particular periods. After applying the dummy variable, the remaining residuals show that the model captures the patterns in the data quite well. Positive signs of the coefficients suggest that increase in the demand for output of producers of mining, manufacturing, construction and service sectors would indicate improvements in the business activity and economic conditions. This in turn would determine the position of the cyclical component of the real output.²⁹

²⁸ More detailed information on the results of the BTS can be found in the quarterly reports published on the NBK's official website, available in Kazakh and Russian only (<u>http://www.nationalbank.kz/?docid=3341&switch=russian</u>). ²⁹ More details about the results of the estimation from Eviews are provided in Appendix.

Figure 9 shows the results of the fitted output gap from regression model (6) and obtained by the HP filtration. The results indicate that the model explains the cyclical component of the real output fair enough. However, a slightly worse fit of the model during 2006-2009 and 2012-2013 is explained by the dynamics of financial and insurance sector which is not covered by the business tendency survey. During 2006-2008 period Kazakh economy experienced a "boom", mainly driven by rapidly growing financial and insurance sector (annual average growth rate of the sector during that period accounts for 43%). Availability of external channels of borrowing for Kazakh banks and possibility of attracting considerable amounts of funds from foreign markets increased the vulnerability of Kazakh financial sector to external shocks. Thus, following the global financial crisis of 2008-2009 the financial and insurance sector contracted substantially and marked the beginning of economic slowdown in the country. During the post-crisis period the financial sector retrieved in response to the boost in consumer credits and positively contributed to the economic activity in 2012-2013.



Figure 9: Output Gap Dynamics, authors` calculations

The results of the previous regression can be compared with the outcomes of the factor models, obtained from equation (5). Figure 10 shows that the fitted values of output gap are close to each other. The differences are not out of the common uncertainty of output gap estimation and are attributed to the model specification of the second approach. Nevertheless, it is worth to note that the regression offers simplicity, clear intuition and comprehensible interpretation behind its results. Both methods exhibit comparable results and the same story about the business cycle position of the economy. Therefore they can be used simultaneously to crosscheck the outcomes.



Figure 10: Output Gap Comparison from Different Approaches

6. Conclusion

Real economic activity, measured either by the real GDP or the output gap, attracts a lot of attention not only among academics and researchers, but also among practitioners including monetary policy makers. Important inferences could be drawn about economic situation based on dynamics of business cycles in the past and the near future on the basis of the output gap indicators. In addition, taking into account the fact that the output gap is a measure of overheating or underproduction of the economy and has a direct relevance to monetary policy, proper real economy analyses are highly valuable and desirable.

However, there is a significant lag in the GDP data release by statistical offices, among many other issues related to this area. Thus producing an authentic view about the up-to-day development of the GDP is extremely challenging and there is no general approach solving all the problems related. Various methods handle different problems and usually require country specific attitude. The same conclusion is valid for the case of Kazakhstan. In this regards, nowcasting and near-term forecasting, as a key responsibility of the NTF team, forms a crucial input for the monetary policy analysis and macroeconomic forecasting. Analysts within the team have developed several models to support their expert view about the economic development. These models play an active role in the whole monetary policy forecasting system, which noticeably boosted analytical capacities and the overall potential of the team. On top of that, they enormously improved the quality of nowcasting.

In case of the GDP nowcasting at the NBK, fundamental information from the business tendency surveys is largely utilized. Although there is no general consensus among economists about the significance of the contribution of the surveys to the real economic forecasting, the Kazakh example completely removes

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any hesitation – the paper introduces several methods utilizing data from the BTS to effectively and relatively accurately nowcast the business cycle position of the Kazakh economy.

The paper describes two general approaches to utilize information from the BTS: using all available indices or only a subset of them to simplify the technical framework. These require different tools: factor models supported by the Kalman filtration and OLS regression accompanied by the univariate HP filtration. Although the former approach is more accurate, the regression offers simplicity, clear intuition and comprehensible interpretation behind its results. Both methods exhibit comparable results and can be used simultaneously to crosscheck the outcomes. However, this does not mean that they are perfect and can be mindlessly operated; the judgmental view of the experts at the NBK based on their experience and knowledge still remains in place.

The outlined approaches do not cover all the possible ways of nowcasting GDP or utilizing information from surveys. They rather serve as wonderful and practical examples of the facts that even data without extraordinary reliability and quality can be effectively used for analyses and that statistical offices are not the only source of an available data – the business survey data are valuable sources of information as well. Additionally, from the technical point of view, not only are super complicated tools the best option in all cases, but also simple methods based on intuition can deliver robust and comparable results. Altogether, it means that systematic and regular using of data can potentially improve analytical and prediction capacities, which has happened at the NBK during several past years.

Nevertheless, the economy is changing and developing throughout the time. This requires permanent checking and improving the used tools. On one hand, wider range of data sources should be potentially utilized for GDP analyzing and nowcasting; on the other hand, the business tendency survey potential has not been completely exploited. Permanent improvement of the BTS is also necessary precondition for its successful usage. Wider range of methods and ways of GDP nowcasting is worthwhile and beneficial as well. Taking into consideration all the previous, the scope for future activities is enormous and offers many opportunities for future applied research in this particular area in case of Kazakhstan.³⁰

³⁰ One of possible and practical extensions of this paper would be to investigate if surveys have additional information content to hard data for the Kazakh economy. This comparison could be done by estimating a factor model based on hard indicators (possibly including also financial variables), then estimating the same model including the survey data and comparing these two models.

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Appendix: Technical Details from Estimations

1. Regression output of the principal component analysis model based on a complete set of all business survey indicators

Dependent Variable: Y Method: Least Squares Date: 10/22/16 Time: 13:09 Sample: 2006Q1 2015Q4 Included observations: 40

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C Y(-1) PCA1 PCA2	0.097081 0.648925 0.213226 -0.179055	0.097046 0.053833 0.028657 0.040266	1.000368 12.05442 7.440634 -4.446865	0.3238 0.0000 0.0000 0.0001
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.922788 0.916353 0.607758 13.29729 -34.73116 143.4153 0.000000	Mean dependent var S.D. dependent var Akaike info criterion Schwarz criterion Hannan-Quinn criter. Durbin-Watson stat		0.260445 2.101384 1.936558 2.105446 1.997622 1.669515

2. Regression output of the model based on selected business survey indicators

Dependent Variable: Y Method: Least Squares Date: 13/02/17 Time: 16:33 Sample (adjusted): 2006Q1 2015Q4 Included observations: 40 after adjustments White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
X1	0.055800	0.012850	4.342582	0.0001
X2(-2)	0.087412	0.012032	7.264721	0.0000
X3(-4)	0.068913	0.017422	3.955460	0.0004
X4(-1)	0.033080	0.013063	2.532299	0.0161
D	0.674368	0.241018	2.798003	0.0084
С	0.280303	0.161276	1.738031	0.0913
R-squared	0.834200	Mean dependent var		0.370762
Adjusted R-squared	0.809818	S.D. dependent var		2.201038
S.E. of regression	0.959870	Akaike info criterion		2.893443
Sum squared resid	31.32590	Schwarz criterion		3.146775
Log likelihood	-51.86886	Hannan-Quinn criter.		2.985040
F-statistic	34.21332	Durbin-Watson stat		1.143871
Prob(F-statistic)	0.000000	Wald F-statistic		155.7643
Prob(Wald F-statistic)	0.000000			