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Sentiment Indicators Based on a Short Business Tendency Survey[1]

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מדדי הסנטימנט מבוססי סדרות קצרות של סקר מגמות בעסקים

טניה סוחוי ודניאל רואש

תקציר

בתקופה שאחרי משבר 2008-09, השונות המחזורית של הצמיחה ירדה ותוכן המידע הנמצא בסקרי עסקים איכותניים השתנה. במאמר זה אנו מדווחים על ניסיון לבחון את כושר הניבוי של סקר מגמות בעסקים שנערך מידי חודש על ידי הלמ"ס החל מ-2011, ואת תרומתו הפוטנציאלית ל"חיזוי ההווה" (Nowcasting).

ברמת הפירמה, בדקנו את הקשר בין תשובות איכותניות (soft data) לבין נתונים כמותיים (hard data) באמצעות רגרסיה לוגיסטית עם אפקט אקראי של החברה; זאת בהתבסס על מיזוג בין נתוני הסקר המתארים את ההערכות האיכותניות של חברות לגבי המכירות (בדיעבד) בשוק המקומי לבין נתוני הפדיון שלהן שנאספו ממקורות אדמיניסטרטיביים. אנו מתעדים שיפור בטיב ההסבר מאז שחל שינוי בניסוח השאלון והוא התמקד בהערכות "חודש מול חודש קודם". על פי האפקטים השוליים שנאמדו, ההסתברויות לדווח לסקר על "שיפור" בפעילות הושפעו במידה הרבה ביותר משינוי הניסוח. התוצאות מראות גם שהקשר בין נתונים איכותניים וכמותיים מושפע מהטרוגניות של החברות ואפקט זה בולט במיוחד בענף השירותים.

ברמת המאקרו, אנו מנסים לשקלל את מאזני הנטו הסקטוריאליים של התשובות במשקולות מבוססות רגרסיה המאפשרת להפיק אומדני תוצר מוקדמים בתדירות חודשית. הקשרים ההדדיים בין המשתנים ברגרסיה זאת מטופלים באמצעות שיטת-PLS וסינון משתני הסבר על בסיס סטטיסטיקות של חשיבות יחסית. אינדיקטור סנטימנט הנובע מתהליך זה מסביר בין 21 ל-48 אחוזים משונות התוצר במדגם, ומקיים גם התאמה סבירה מחוץ למדגם - אם משתנה המטרה הוא האומדן הראשון של שיעור הצמיחה. לגבי האומדן הסופי של הצמיחה, המודל לא מראה טיב תחזית טוב יותר משימוש בהנחה פשוטה של צמיחה ממוצעת במהלך תקופת הבדיקה בין 2016 ל -2019.

Sentiment Indicators Based on a Short Business Tendency Survey

Daniel Roash and Tanya Suhoy

Abstract

In the post 2008-09 crisis period the variance of real growth has declined and the information content of qualitative surveys has changed. We report on a recent attempt to assess the reliability of the Business Tendency Survey, conducted in Israel since 2011, and its usefulness for nowcasting.

At the firm level, the relationship between soft and hard data has been explored through logistic regression with firms' random effects, based on matched datasets that merge firms' qualitative evaluations of past sales with their revenue, collected from administrative sources. We document an improvement in the reliability of qualitative responses since the questionnaire was focused on month-over-month evaluation. Estimated marginal effects show that the probabilities of the "Up" response have been influenced the most. Our results suggest a significant effect of intra-sectoral firms' heterogeneity, particularly in Services.

On a macro level, we aggregate sectoral balances of opinions with monthly updated regression-based weights, thus enabling early estimates of underlying monthly GDP growth. Mutual correlations between survey covariates are handled through PLS-regression and variable selection based on relative importance scores. This Sentiment indicator explains between 21 and 48 percent of in-sample GDP-variance and suggests a reasonable out-of-sample fit, if we target the first GDP estimate. Regarding final GDP estimates, the model does not outperform an assumption of average growth over the test period between 2016 and 2019.

Keywords: Business-tendency survey, Sentiment indicator, Partial Least Squares, Monthly GDP

JEL: E32, E37

1. Introduction

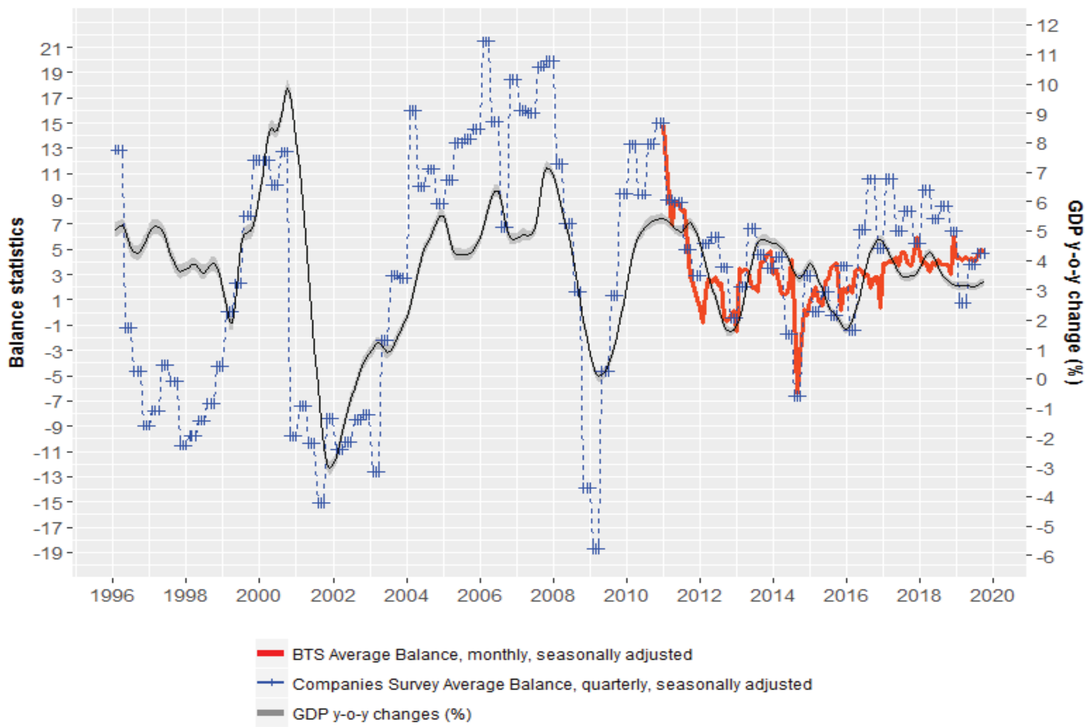
We investigate the relationship between the qualitative ("soft") data, drawn from the monthly Business Tendency Survey (BTS) and their quantitative ("hard") data counterparts in the post 2008-09 crisis period in order to evaluate underlying sentiment in terms of monthly GDP growth. As they are published before GDP data and most macroeconomic indicators, qualitative responses converted into the balance statistic (i.e., the difference between proportions of firms reporting an increase and a decrease in their activity) provide policymakers with new information about the state of economic growth (IFC, 2009; Matheson, 2010). Empirical evidence of the predictive ability of monthly survey indicators gave rise to nowcasting with "ragged-edge" data trough mixed-frequency equations (Baffigi et al., 2004; Banbura et al., 2013; Marcellino and Schumacher, 2010; Ferrara et al., 2010), as well as dynamic factor models that exploit the comovement structure of hard and soft data (Hansson et al. 2005; Banbura and Rünstler, 2011; Österholm, 2014; Kaufmann and Scheufele, 2017; Mogliani, et al. 2017). In view of our purpose, it is worth paying special attention to models providing early estimates of GDP growth at monthly frequency, thus enabling intra-quarter cyclical monitoring (Mittnik and Zadrozny (2004); Mitchell, et al. (2005); Frale, et al. (2010); Mariano and Murasawa, 2010).

In contrast to the quarterly survey of companies conducted by the Bank of Israel on a voluntary basis since 1983, in 2011 the Central Bureau of Statistics (CBS) launched a monthly compulsory survey that meets OECD methodological requirements and has the advantage of sectoral representativeness, timeliness, and high response rate. The BTS sample is a sub-sample of the Job Vacancy Survey and includes about 1,400 firms in Manufacturing, Construction, Trade, Hotels and Services. The firms have been asked to assess on a five-point Likert scale—from "marked decrease" to "marked increase"—the changes in the company's main indices such as output, domestic and export sales, employment, and prices. Beside retrospective questions, the firms have been also asked about expected changes[1]. Figure 1 depicts total balances of opinions derived from both surveys over time alongside year-over-year GDP growth.

In the aftermath of the 2008–09 crisis, cyclical variance has greatly declined and the balance statistics have become less correlated with macroeconomic variables that used to be viewed as cyclical

[1] We refer to the CBS site: https://old.cbs.gov.il/reader/?MIval=cw_usr_view_SHTML&ID=915 for questionnaires' description, details on sampling strategy and methodology of balance statistics.

Figure 1. Total Balances[a], calculated from the (long) quarterly Companies Survey and from the (short) monthly BTS alongside year-over-year GDP growth [b]



[a] For the Companies Survey this is an average of sectoral balances of sales/revenue assessments, weighted according to GDP industrial composition and seasonally adjusted; for the BTS retrospective and prospective balances of opinions are, first, reconstructed over the sample with eliminated level/variance shift, caused by the change in the questionnaire, then averaged into contemporaneous sectoral components and seasonally adjusted; the latter are summarized in the total balance using industrial composition weights (Appendix A).

[b] Based on quarterly seasonally adjusted GDP levels, monthly interpolated and bootstrapped.

references.[2] This non-linearity, also noted in the Eurozone (Malgarini, 2011; Tresor-Economics, No 125, 2014; Bruno, et al. 2016), was documented along with a high degree of uncertainty in the survey as about 60% of firms were reporting "No change". To make answers less vague and more precise, the wording of the questionnaire was changed in 2015 and since then it has been focused on a specific month and not on a three-month assessment, as before.

We study survey performance using firm-level and macro (time-series) data.

[2] According to our estimates, the standard deviation of the trend-cycle component, extracted from month-over-month changes of the industrial production index through X-12-Arima procedure have decreased, in average, from 0.68 percent in the period 2001–10 to 0.23 percent in 2011–19; for the quarterly GDP percent changes the corresponding numbers are 1.05 percent and 0.53 percent, respectively.

First, we construct firm-level datasets that merge firms' categorical assessments of their past sales with revenue data collected from CBS industrial surveys and administrative records. Using these matched datasets, we evaluate the logistic link between qualitative and quantitative data as well as the effect of the questionnaire change on this relationship. Estimated Marginal Probability Effects indicate an improvement in survey consistency since the change, while individual random effects are taken into account (Carriere et al., 2006). Our results confirm empirical findings that intra-sectoral firm's heterogeneity affects the relationship between the soft and hard data over the cycle (Basile et al., 2014; Hölzl, 2015) and remain significant—especially in the Services sector—after controlling for observable firm-specific characteristics (firm size, sub-industry affiliation, reporting mode).

Next, we proceed with macro-level data seeking to nowcast monthly GDP growth by one or more common factors, extracted from mutually correlated sectoral balances. Here we apply the Partial Least Squares (PLS) method which, in contrast to principal components or factor models, assigns factor loading with respect to the target variable. Hence, some survey covariates may be selected or unselected according to their relative importance in the sense of explained variance (Wold, 1993; Chong and Jun, 2005). The PLS method for the construction of the European Economic Sentiment Indicator was suggested by Gelper and Croux (2011) as a statistically-based alternative to the official European Commission indicator constructed with ad-hoc weights.

In view of short data span of the survey we preserve monthly-frequency framework rather than mixed-frequency (MIDAS) model and treat dependent quarterly GDP rates as a monthly series with missing observations, replaced with interpolated and repeatedly bootstrapped values obtained through the bagging method (Bergmeir et al., 2016). Keeping in mind that the monthly GDP variable is unobservable and assuming its inter-dependence with other cyclical variables observed at monthly frequency, we augment the response by inclusion of either the industrial production or the total revenue index, both measured on a monthly basis and seasonally adjusted. Further identification of intra-quarterly GDP lag structure is done through covariance between survey variables and past values of monthly cyclical variable introduced in the right side.

As monthly GDP changes projected by this regression are mainly driven by survey variables, we called them "Sentiment" although past values of hard indicators have also been taken into account. Cyclical variables—industrial production and revenue indexes—perform in a very similar way with respect to latent monthly GDP changes and share up to 25 percent of the Sentiment variance.

The Sentiment Index obtained on the basis of this model provides a range of real time estimates for the monthly GDP growth rates based on survey sectoral balances, and is found to be more correlated with actual GDP growth than the total balance, compiled with fixed industrial composition weights.

Among the three alternative target variables considered - total GDP, business sector product, and GDP adjusted for import taxes, the latter shows a higher coefficient of determination, since it skips fluctuations caused by the volatility of consumer imports, caused, as a rule by bringing forward vehicle purchases and not captured in the survey content.

The out-of-sample checks of the Sentiment are still preliminary, as the test sample from 2016:01 to 2019:06 was very short and the underlying GDP growth was rather flat. There is some evidence that monthly GDP estimates obtained from the Sentiment model outperform an assumption of the average growth with regard to the first GDP estimate. In contrast, the out-of-sample errors calculated relative to revised GDP data are much larger due to significant updates made to the 2016 National Accounts data and the model fails to outperform the baseline assumption for this short period.

The rest of the paper is organized as follows. Section 2 deals with the information content of firm-level data. Section 3 deals with a macro-level Sentiment index, derived from sectoral balances of opinions with respect to latent month GDP growth. Section 4 concludes.

2. Firm-level aspect

2.1. The model

We estimate the relationship between the firms' categorical responses and actual quantitative data using the following logistic regression with individual random effects:

$$\log\left[\frac{\Pr(Y_{it} = j)}{\Pr(Y_{it} = "No\ change")}\right] = \alpha_j + \beta_j \Delta_{it} + \gamma_j (\Delta_{it} * dum_{it}^{new}) + \sum_k \delta_{jk}\, z_{ik} + u_{it} \quad (1)$$

where

Y_{it} – is a response given by firm i in month t and encoded as $j = "Up"$ (“Increase" or “Great increase"), $j = "Down"$ (“Decrease" or “Great decrease") and $j = "No\ change"$, assigned as the reference category;

Δ_{it} - is a revenue change of firm i in month t, compiled in log-difference terms.

dum_{it}^{new} - is a dummy variable which takes on value 1 if the firm responded by the new questionnaire format and 0 otherwise.

z_k - are dummy variables controlling for firms' characteristics (sub-industry, size group, grade of export intensity and partnership reporting[3]) assumed to be time-invariant in the sample;

u_{it} – is a composite random error term, which includes time-varying random effects of $i - th$ firm and time-invariant noise component.

$\beta_j, \gamma_j, \delta_{jk}$ – are parameters to be estimated.

The marginal probability effect (MPE) of the transition to the new questionnaire is calculated as follows:

$$\frac{\partial \hat{P}_j}{\partial x^{(2)}} = \hat{P}_j[\widehat{\widetilde{\gamma}}_j - \sum_{m=1}^{2} \hat{P}_m \widehat{\widetilde{\gamma}}_m]$$

where

$\widehat{\mathrm{P}}_{\mathrm{j}} = \{\widehat{\mathrm{p}}_{\mathrm{jit}\}}$ - are fitted probabilities of response $j = \text{"Up"}, \text{"Down"}, \text{"No change"}$ based on vector of covariates X and parameters B estimated under the generalized logit link, specified above, as follows:

$$\hat{P}_j = \exp(X'B_j)/\sum_{m=1}^{2}(\exp(X'B_m)) \qquad (2)$$

$x^{(2)} = \Delta * dum^{new}$ - is an interaction term in (1) which specifies the transition to the new questionnaire.

2.2. Firm-level data

Our firm-level panel datasets were constructed for Manufacturing, Retail Trade, and Services sectors that cover more than 85% of the business-sector activity in Israel[4] and include firms that provided qualitative assessments of past domestic sales for the survey between 2013 and 2018. These answers

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[3] In manufacturing sector sub-industry differences are less significant than technology-level division (high, medium-high, medium-low and low). In services, sub-industry division of the BTS was used, i.e., banking and insurance, business services, food and accommodations, IT-services, transportation and storage and other. Size classification, as defined in the BTS, are firms with 5–9 employed, 10–49, 49–100, 100–250 and more than 250. Export intensity, categorized as "low", "medium" or "high" was categorized based on firms' distribution by export share in past two-year revenue (according to 25-th and 50-th percentiles). An additional dummy variable was assigned to firms in Services and Trade sectors reporting to the tax authority through partnership.

[4] According to GDP industrial composition.

were merged—by firm and referenced month—with quantitative data collected from CBS industrial surveys and administrative records.

Initially, the Manufacturing dataset included 579 different firms reporting by the old questionnaire format (between 2013 and 2014) and 588 by the new one (2016–18 data), the Retail trade—193 and 314, respectively, and Services—564 and 833, respectively. The change in the questionnaire was conveyed by a follow-up experiment in 2015, which required a split of the survey sample into two groups: firms that received a questionnaire in a new format and firms that continued to respond in a previous format. Thus, the 2015 data are made up from control/treatment sub-samples including 254/321 firms in Manufacturing, 76/97 in Trade and 253/195 in Services.

Categorization of qualitative responses originally given by a 5-point scale was narrowed down to three categories: "Up" – from "Great increase and "Increase", "No-change", and "Down" – from "Decrease and "Great decrease".

Quantitative data on the revenue in the Manufacturing sector are taken from the monthly CBS survey of the industrial production index, which is closely monitored and provides data of highest accuracy. The revenue data in the Retail and Service sectors are taken from the Business Register—an administrative source established by the CBS and updated on a daily basis by the tax authorities. Using this source, we also complete missing data for manufacturing firms sampled in the BTS but not in the quantitative monthly Industrial Survey. However, administrative data should be handled with caution in cases where sample units represent multiple partnerships: in these cases recorded revenue may be biased. Such cases were extensively searched and partly removed from the panel.

It is worth noting significant seasonality detected in qualitative data and amplified since the transition to the new questionnaire format. Thus, a relationship between qualitative and quantitative data may be overestimated due to seasonal co-movements. In order to account for this issue, we processed seasonal adjustment of each firm's revenue series based on its historical data over the longest possible span. Firms for which at least a three-year continuous revenue series were not found were removed from the panel.

We end up with matched datasets with the number of firms reduced by 11–20 percent compared to initial sectoral samples. Table 1 provides descriptive statistics of these panels. Monthly seasonally adjusted changes in revenue matched to qualitative answers are winsorized between the 2.5 and 97.5 percentiles. The panels are unbalanced because of sample rotation, non-response (varying between 1 percent and 6 percent) and limited availability of quantitative (original or seasonally adjusted) data.

Table 1. Descriptive statistics of matched datasets: number of firms[a], proportion of firms providing each category of response and mean percent change in revenue[b], corresponding to each response, by sector and questionnaire version[c] (2013:1-2018:12)

	Response	Proportion of responses: Matched dataset	Proportion of responses: Survey	Mean [std dev] of monthly change in revenue (%)
Panel A. Manufacturing				
Old questionnaire	"Up"	0.158	0.152	1.349 [0.888]
	"No change"	0.580	0.596	-0.675 [0.560]
	"Down"	0.261	0.252	-3.695 [0.829]
Number of firms		**470**	**579**	
New questionnaire	"Up"	0.228	0.218	2.250 [0.612]
	"No change"	0.565	0.589	-0.902 [0.511]
	"Down"	0.207	0.193	-3.333 [0.337]
Number of firms		**524**	**588**	
Retail Trade				
Old questionnaire	"Up"	0.184	0.191	2.612 [1.264]
	"No change"	0.544	0.515	-1.527 [0.577]
	"Down"	0.273	0.293	-8.054 [0.984]
Number of firms		**183**	**193**	
New questionnaire	"Up"	0.294	0.306	3.744 [1.012]
	"No change"	0.504	0.452	-0.474 [0.593]
	"Down"	0.202	0.242	-3.688 [0.902]
Number of firms		**228**	**314**	
Services				
Old questionnaire	"Up"	0.178	0.166	2.756 [0.777]
	"No change"	0.667	0.648	-0.082 [0.400]
	"Down"	0.155	0.187	-0.345 [0.768]
Number of firms		**456**	**564**	
New questionnaire	"Up"	0.218	0.231	2.892 [0.827]
	"No change"	0.628	0.600	-0.193 [0.704]
	"Down"	0.154	0.169	-0.906 [0.574]
Number of firms		**666**	**833**	

[a] Compared to the BTS sample. The matched panels are unbalanced and include firms for which monthly revenue data of at least 3-year-length were available.

[b] Calculated as mean monthly percent change in revenue, by response category; standard deviation of the mean is given in brackets.

c Change in the questionnaire wording made in 2015 was conveyed by a follow-up experiment that required a split of the BTS sample into treatment and control sub-groups. "Old questionnaire" denotes responses given between 2013 and 2015 in a previous format, "New questionnaire" denotes responses given between 2015 and 2017 in a new format.

2.3. Estimation results

Table 2 reports parameters of logistic relationship (1) estimated by maximum-likelihood[5] method.

As shown, slope parameters β relating to the period before the change in the questionnaire format are not statistically significant for the Services and Trade sectors, as estimated by seasonally adjusted revenue data. As expected, they are more significant while estimated by unadjusted data. For all three sectors, parameter γ indicates a strengthened relationship between qualitative and quantitative data since the transition to the new questionnaire format.

Figure 2 provides more visualization with fitted values of probabilities for each response category, obtained from the model.

Estimated slopes and coefficients of determination, shown in Table 2 indicate that qualitative evaluations in the Manufacturing sector are more closely related to revenue data than in Trade and Services. Note too, that standard deviations of individual random terms, shown in Table 2 in bold, provide evidence of statistically significant firms` heterogeneity within each sector, which is of greater extent in Services.

Table 3 reports marginal effects of the transition to the new questionnaire, by sectors and response categories. In average, probabilities of providing an "Up" response have greatly increased, especially in the Trade sector. The results suggest also a significant reduction in the likelihood of providing a "No-change" response in Services sector, which contributes to greater accuracy of the balance statistics.

Table 3: MPE x 100 of the transition to the new questionnaire

Response	**Manufacturing**		**Retail Trade**		**Services**	
	Mean	St.dev	Mean	St.dev	Mean	St.dev
"Up"	3.96	0.263	5.423	0.561	3.973	0.531
"Down"	-2.483	0.121	1.827	0.127	-3.311	0.634
"No change"	-1.506	0.321	-3.233	0.892	-1.667	0.424

[5] Parameters δ of dummy variables controlling for firms' characteristics are not shown.

Table 2. Parameters of the logistic regression[a] estimated over the period 2013:1–2018:12 (monthly firm-level data), by sector and specification of quantitative data (unadjusted/seasonally adjusted)

		Unadjusted revenue changes			Seas.adjusted revenue changes		
Parameter	Response	Estmate	StErr	P-value	Estmate	StErr	P-value
Panel A. Manufacturing							
α_{up}	*"Up"*	-1.327	0.175	<0.0001	-1.351	0.197	<0.0001
α_{down}	*"Down"*	-1.245	0.179	<0.0001	-1.393	0.182	<0.0001
β_{up}	*"Up"*	0.202	0.061	0.001	0.152	0.069	0.002
β_{down}	*"Down"*	-0.194	0.06	0.001	-0.252	0.068	0.001
γ_{up}	*"Up"*	0.518	0.078	<0.0001	0.389	0.069	<0.0001
γ_{down}	*"Down"*	-0.406	0.075	<0.0001	-0.183	0.064	0.051
$\sigma(u)$		**1.597**	0.119	<0.0001	**1.622**	0.059	<0.0001
N		24549					
Cox-Snell R^2		0.415			0.316		
Panel B. Retail Trade							
α_{up}	*"Up"*	-0.980	0.0159	<0.0001	-0.449	0.051	<0.0001
α_{down}	*"Down"*	-0.794	0.0148	<0.0001	-0.949	0.063	<0.0001
β_{up}	*"Up"*	0.183	0.0635	0.0786	0.130	0.035	0.001
β_{down}	*"Down"*	-0.076	0.0541	0.2386	-0.719	0.051	<0.0001
γ_{up}	*"Up"*	0.711	0.1227	<0.0001	0.695	0.151	<0.0001
γ_{down}	*"Down"*	-0.489	0.1088	<0.0001	0.355	0.131	0.013
$\sigma(u)$		**1.412**	0.102	<0.0001	**1.350**	0.086	<0.0001
N		8493					
Cox-Snell R^2		0.351			0.237		
Panel C. Services							
α_{up}	*"Up"*	-1.988	0.094	<0.0001	-1.336	0.097	<0.0001
α_{down}	*"Down"*	-2.633	0.109	<0.0001	-2.221	0.082	<0.0001
β_{up}	*"Up"*	0.092	0.063	0.239	0.131	0.059	0.016
β_{down}	*"Down"*	0.003	0.062	0.857	-0.069	0.051	0.223
γ_{up}	*"Up"*	0.239	0.054	<0.0001	0.269	0.069	<0.0001
γ_{down}	*"Down"*	-0.695	0.051	<0.0001	-0.329	0.054	<0.0001
$\sigma(u)$		**3.934**	0.215	<0.0001	**4.097**	0.235	<0.0001
N		27714					
Cox-Snell R^2		0.204			0.139		

[a] See parameter notations in equation (1). Standard deviations of random effect denoted by $\sigma(u)$ indicate the extent of unobservable intra-sectoral firms` heterogeneity. Parameters $\delta$ of dummies controlling for firms` characteristics (sub-industry, size group, export profile, reporting mode) are omitted to save space.

Cox-Snell R^2 is the coefficient of determination compiled as $1-(L_0/L_M)^{(\frac{2}{N})}$, where L_0/L_M are values of the likelihood function estimated without/with explanatory variables, N is the number of observations.

3. Macro-level aspect

3.1. PLS-based Sentiment index

At the macro level, we are looking for an aggregation of sectoral (seasonally adjusted) balances with regression-based weights, which would translate survey information into projected monthly rates of GDP growth.

Like the principal component regression, the PLS-method constructs uncorrelated linear combinations of the predictors via eigenvalue-decomposition of the correlation matrix. The difference is that the PLS-regression identifies each new combination of the original predictors with respect to the target (GDP) variable. For the formal description of the PLS-method, we refer to Wold, et al. (1993).

To obtain historical GDP data at monthly frequency, we perform linear-spline interpolation of quarterly seasonally adjusted GDP levels, while assigning the known GDP level to the first month of the quarter and missing values to the remaining months. Then, we apply the bagging procedure suggested in Bergmeir, Hyndman and Benítez (2016) which derives the trend component, bootstraps the remainder, and adds it back. To ensure enough observations for bootstrapping, we have used the GDP series since 1995.

We allow the left side of the PLS-regression be univariate or bivariate: in the first case we regress monthly GDP changes $\{y_t\}$ by survey-based variables $\{x_{1t}, x_{2t}, \dots x_{pt}\}$; in the second case we specify a vector of two dependent variables $\{y_t\ , c_{t-1}\}$, which exploits mutual correlation between the GDP and monthly observed another cyclical variable (industrial production or revenue index) and projects GDP rates using their predicted loadings. In the latter case the explanatory set becomes $\{x_{1t}, x_{2t}, \dots x_{pt}, c_{t-2}, c_{t-3}\}$, i.e., augmented by two additional lags of hard data.

Of the total of M bagged GDP series (in log-difference terms) the regression produces M different forecasts for the month of interest t, some of which, say $\left\{y_t^{(1)}, y_t^{(2)}, \dots y_t^{(M_{val})}\right\}$, $(M_{val} < M)$ have passed the test set validation[6], thus enabling supervised median forecast $\hat{y}_t$, as well as the 5th and 95th percentiles of the forecast distribution for setting confidence limits.

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[6] The number of extracted factors is supervised through test set validation: the optimal h is determined through the minimization of the predicted residual error sum of squares (PRESS), calculated as $\sum_{j=1}^{n} u_{h,j}^2$, where $u_{h,j}$ denotes the prediction error for y_j obtained by the model of h factors, while y_j is excluded. The test ensures

As the model fit largely depends on the explanatory set and the number of survey-based covariates is large, since it includes retrospective and prospective balances of opinions on multiple aspects of firms' activity in each sector, we handle selection of variables, based on their relative importance scores[7]. After permutations in the explanatory set and screening we end up with a limited number of specifications that run (Section 3.3).

3.2. Survey-based explanatory series

The main issue of the suggested approach is a discontinuity in the series of survey balances caused by a change in the wording of the questionnaire. Since the questionnaire has focused on the specific month, we document an upward shift in the balances, smaller variance and amplified seasonality. To handle the break, we use parallel data from the treatment and control sub-samples, surveyed in the follow-up experiment during 2015.[8] First, we recalculate new questionnaire balances in terms of a 3-month moving average with decreasing weights of 0.5, 0.3, and 0.2; next, we evaluate parameters of level shift and standard deviation ratio over the follow-up period and apply them to the old

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that the forecast outperforms (in terms of out-of-sample mean squared error) the benchmark of the mean growth, calculated as a conditional mean of the dependent variable with deleted observation to be predicted, as follows:

$$\bar{y}_{\in j} = \left(\sum_{k=1,k\neq j}^{n} y_k\right)/(n-1)$$

To avoid overfitting we limit the number of extracted factors by three. If for all possible h we get

$\sum_{j=1}^{n} u_{h,j}^2 \geq \sum_{j=1}^{n}(y_j - \bar{y}_{\in j})$, the given GDP-simulation is filtered out.

As shown in https://robjhyndman.com/papers/cv-wp.pdf this procedure is valid if the residuals of the model are uncorrelated.

[7] The relative importance score of the $i-th$ covariate is calculated as follows:

$$VIP_i = \sqrt{\frac{p}{\sum_{m=1}^{h} SS(b_m T_m)} \sum_{m=1}^{h} w_{mi}^2 SS(b_m T_m)}$$

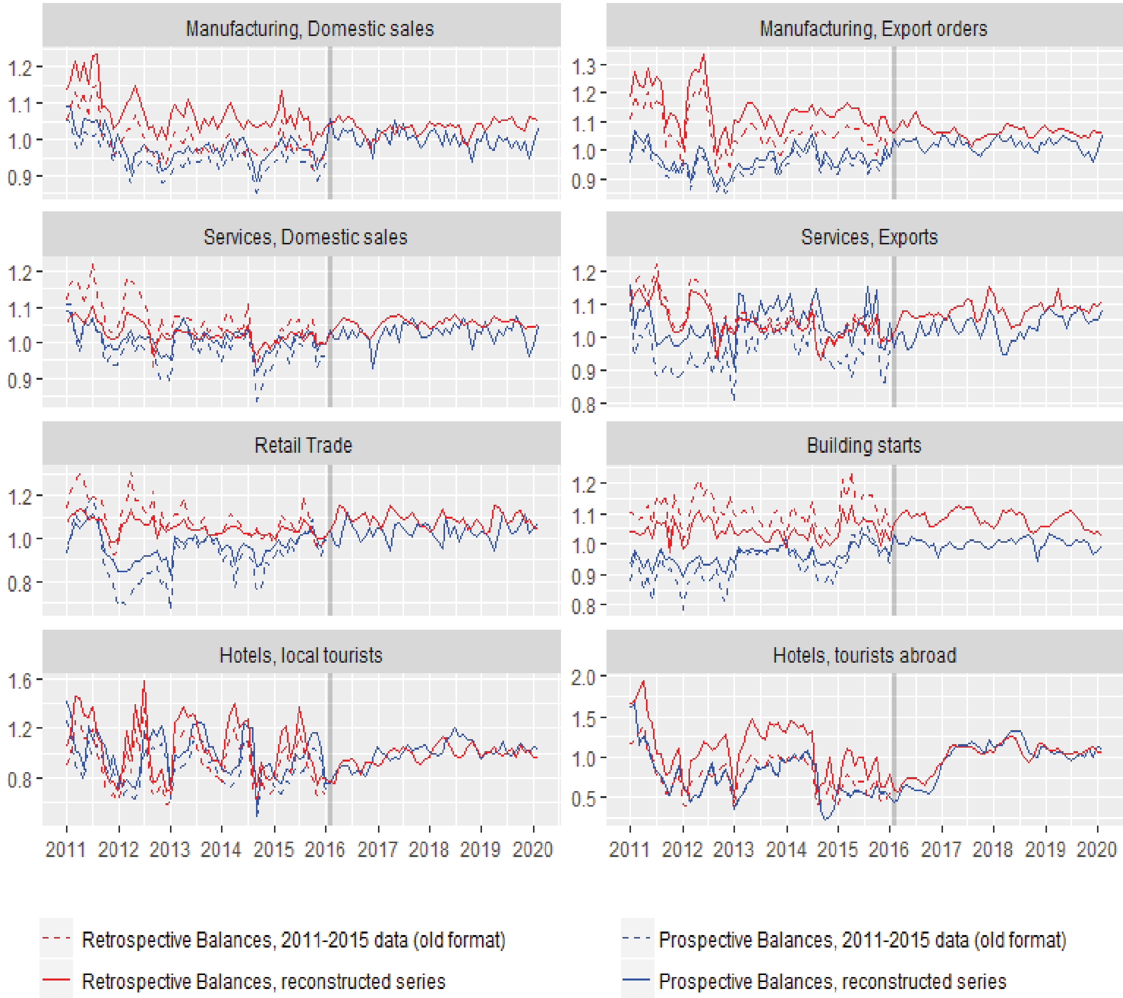
where p is the number of covariates, h is the number of extracted factors; w_{mi} is the loading of the standardized explanatory variable X_i $(i = 1, \dots p)$ on the common T_m $(m = 1, .. h)$;

$SS(b_m T_m) = b_m^2 T_m` T_m$ - is the share of variance of the dependent variable y explained by the factor T_m .
Using Chong and Jun (2005) results, we filter out covariates which VIP scores are below 0.76 in 50 percent of simulations.

[8] An additional break could have occurred due to the transition from a 3 to 5-point response scale introduced in 2013 for Services, Retail trade and Construction, whereas earlier it was used for only the Manufacturing and Hotels industries. Since the wording of the questionnaire remained the same and we do not have overlapping data to assess the shift, the data between 2012 and 2013 were concatenated. Regression analysis was done including and excluding 2011–12 data, to ensure the robustness of results.

questionnaire series. Figure 3 depicts retrospective and prospective balances, available by the old format and reconciled over the whole period. Our final step is seasonal adjustment of reconstructed balances.

Figure 3. Retrospective and Prospective Balances available by the Old questionnaire format (2011:01-2015:12, dashed) and reconstructed over the period 2011:01-2020:01 (solid), by sector and activity aspect [a]



[a] Vertical reference line denotes the questionnaire change.

3.3. Estimation results

Appendix B reports parameters of PLS-regressions, estimated with respect to total GDP (B-1), GDP excluding import taxes (B-2) and Business-sector product (B-3) growth rates. All specifications presented are supported by cross-validation tests and include explanatory series selected according to their VIP-scores. Each panel presents a specification with univariate dependent GDP series and three specifications with a bivariate outcome, including—besides GDP series—either industrial production or total revenue index (seasonally adjusted and log-differenced). Regression parameters obtained with respect to additional monthly cyclical variable are not shown.

The results suggest positive and significant weights of retrospective balances when the corresponding prospective balance is not included in the regression. Otherwise, high collinearity between retrospective and prospective evaluations relating to the same aspect of activity leads to redundancy and switching of the sign; in this case one of the two is excluded. Balances of the hotel industry are filtered out due to low VIP-scores, as well as prospective balances of employment, of domestic sales in Manufacturing and of overall building activity; retrospective balances of building starts are positively significant. We do not have a clear interpretation for negative coefficients obtained for retrospective balances of employment: it may indicate either redundancy or lagged dynamics of employment relative to the cycle and requires further investigation. Regressions that control for hard data (i.e., past industrial production or revenue) deliver positive/negative coefficients for the second/third lag of the revenue index, and mostly negative for the industrial production lags, thus reproducing the autocorrelation structure (the "saw" shape) of monthly cyclical indicators.

Table 4 summarizes VIP-scores of survey-based covariates, evaluated with respect to different target GDP variables (total GDP, GDP excluding import taxes and business-sector product), while the balances are grouped by sector, time aspect and domestic/export activity. As seen, inclusion of hard data reduces relative importance of survey variables but the corresponding VIP-scores remain above the threshold of 0.76. According to their relative importance, cyclical variables share 20.7–25.1 percent of the explained GDP variance. The upper panel provides evidence of high relative importance of Retail Trade balances, although the industrial weight of this sector is relatively low (Appendix A). Depending on model specification, retrospective survey balances share 49.8–52.9 percent, and prospective ones—between 21.1 percent and 26.4 percent. The bottom panel shows relatively high importance of export balances. Depending on model specification, export evaluations (either retrospective or prospective) share between 18 percent and 25 percent of the Sentiment variance.

Figure 4 depicts in-sample fit of the sentiment indicator, evaluated through the PLS-method with regard to GDP and business-sector product growth rates. As seen in Appendix B, survey information explains between 21 percent and 48 percent of the variance of underlying monthly GDP growth, depending on model specification and simulation. In contrast, the Total balance, which aggregates sectoral balances with fixed weights of industrial composition (Figure 1) is weakly correlated with GDP growth over the survey period; the corresponding correlation is 0.14 and not significant.

Table 4. Mean VIP-scores of survey balances [a], evaluated with respect to different dependent GDP variables and summarized by sector, domestic/export activity and time aspect (retrospective/prospective) over the period 2011:01-2019:12

	Total GDP		GDP excl import taxes		Business-sector product	
	No hard data	With hard data	No hard data	With hard data	No hard data	With hard data
Panel A. By sector						
Manufacturing	1.169	0.848	1.172	0.883	1.201	1.109
	(0.268)	(0.156)	(0.243)	(0.158)	(0.153)	(0.193)
Retail Trade	0.835	0.809	0.865	0.837	0.871	0.829
	(0.212)	(0.134)	(0.167)	(0.156)	(0.185)	(0.161)
Services	0.901	0.846	0.907	0.851	1.121	0.905
	(0.267)	(0.201)	(0.248)	(0.200)	(0.126)	(0.135)
Construction	0.804	0.812	0.798	0.801	0.872	0.819
	(0.171)	(0.149)	(0.164)	(0.141)	(0.151)	(0.148)
Panel B. By time aspect						
Retrospective	1.027	0.883	0.983	0.856	1.310	1.141
	(0.237)	(0.215)	(0.223)	(0.203)	(0.376)	(0.315)
Prospective	0.898	0.821	0.849	0.789	1.012	0.902
	(0.281)	(0.188)	(0.176)	(0.163)	(0.302)	(0.200)
Panel C. By Domestic/Export activity						
Domestic	0.888	0.833	0.851	0.809	0.888	0.833
	(0.357)	(0.233)	(0.307)	(0.193)	(0.357)	(0.233)
Exports	0.816	0.783	0.831	0.791	0.816	0.783
	(0.269)	(0.194)	(0.267)	(0.198)	(0.269)	(0.194)

[a] Corresponding standard deviations are shown in parentheses. VIP-scores of hard variables (lagged changes in industrial production or revenue indices) vary between 0.90 and 1.30 and are not shown.

At this time, it is still slightly early to judge the out-of-sample performance of the model, since the test period is short (2015:01-2019:06) and the dynamics of GDP over this period were rather flat. This is even more challenging because of unusually large revisions made in National Accounts data for 2016.

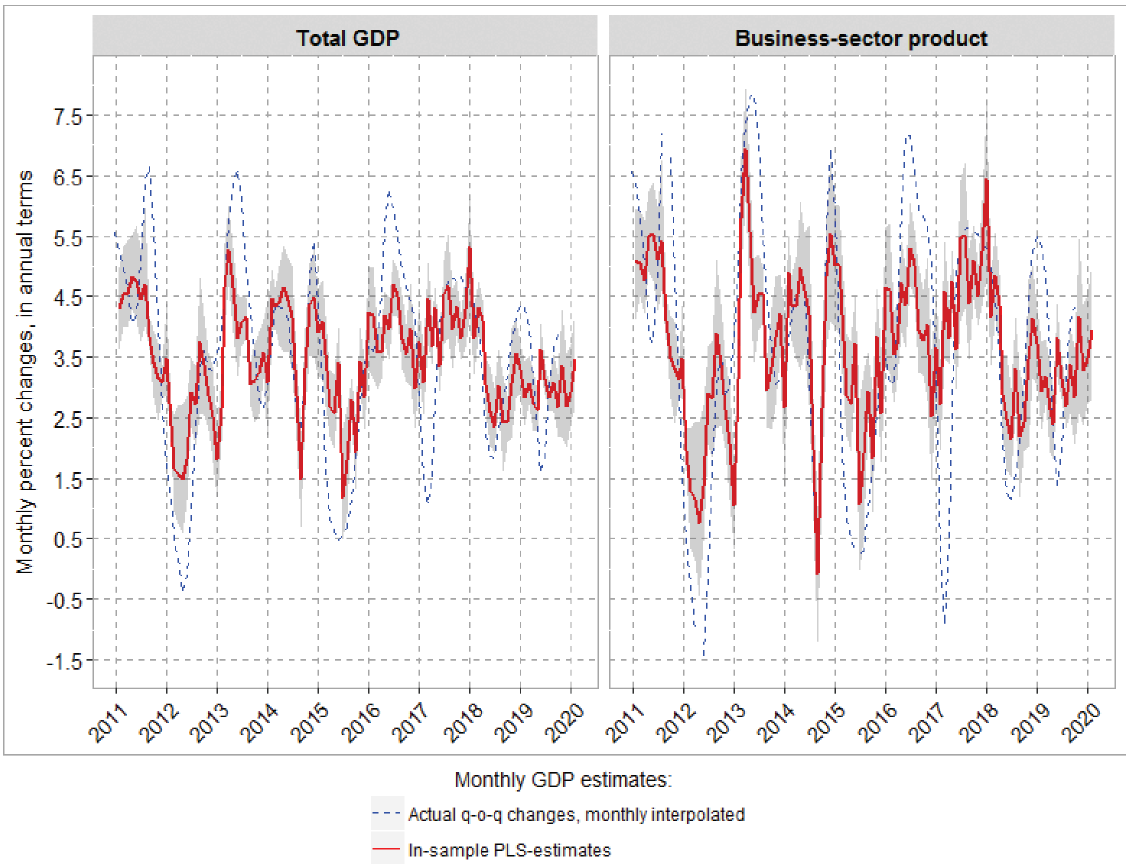
Table 5 summarizes out-of-sample errors, obtained (at monthly frequency) using the sentiment-projected GDP growth compared with the simple assumption of mean growth, calculated in real-time over a rolling window of 52 quarters.

Due to different data frequency and unsynchronized publications of the Business Tendency Survey and National Accounts, the forecast horizon in our PLS-equations varies from two to four months:

the maximum forecast horizon occurs in February, May, August and November as the survey data are published 10–12 days earlier than the first GDP estimate of a new quarter.

In contrast, in March, June, September and December, the model provides forecasts for up to two months. Another result is that sequential vintages of our out-of-sample forecasts produced at monthly frequency are partly overlapping. The upper panel of Table 5 refers to the first vintage of monthly GDP estimates, the bottom panel—to the most updated, available in real time. Reference series for the upper and bottom panels are first and revised (four quarters later) National Accounts estimates of quarterly GDP growth rates (in annual terms) spread uniformly at monthly frequency. The mean

Figure 4. Monthly In-Sample PLS-Estimates [a] of GDP[b] and Business Sector Product (2011:01-2019:12)



[a] The red line denotes median in-sample forecasts calculated over all cross-validated simulations obtained through specifications shown in Appendix B; the bootstrapping band is set between the 5% and 95% percentiles of the corresponding distribution.

[b] Calculated over in-sample forecasts of GDP and GDP, adjusted for import taxes.

growth, calculated as a baseline forecast over a rolling window of 52-quarters has been calculated from real-time GDP vintages and uniformly spread over the quarter.

As seen, the sentiment indicator outperforms the baseline assumption of average growth with respect to the first GDP vintage. In the context of revised GDP data, it delivers similar MAE and RMSE-statistics and does not outperform the average growth assumption for a given test period.

Table 5. Mean out-of-sample forecast errors [a] of the PLS-model compared to the baseline average-growth assumption and corresponding MDM-statistics [b]

	Average revision in growth rates[c]	MAE		RMSE		MDM
		Baseline	PLS	Baseline	PLS	PLS/Baseline
Panel A.Relative to the first estimate						
Total GDP		1.25	1.08	1.56	1.29	-1.72 *
GDP excl.import taxes		1.12	0.83	1.48	1.11	-1.90 **
Business-sector product		1.83	1.23	2.24	1.92	-2.15 **
Panel B.Relative to the revised estimate						
Total GDP	1.18	0.97	1.03	1.22	1.36	0.25
GDP excl.import taxes	0.96	1.15	1.11	1.21	1.19	-0.03
Business-sector product	1.48	1.32	1.56	1.83	2.01	0.45

[a] Denoted as MAE (mean absolute forecast error) and RMSE (root mean squared forecast error) and calculated over the test period between 2015:11 and 2019:05, in annual terms.

[b] The MDM-statistic (Harvey et al., 1997) enables a modified Diebold-Mariano test in small samples; it is negative, if the first model outperforms the second one; * and ** indicate significance at the 10% and 5% levels, respectively.

[c] Calculated as the absolute difference between National Accounts quarterly growth rates (in annual terms), released for the first time and revised after four quarters.

4. Conclusions

The Sentiment Indicator builds on the reliability of soft data, provided by the BTS and its timeliness.

Firm-level data provide evidence that the accuracy of qualitative assessments has significantly improved since the transition to the new questionnaire format, focused on month-over-month evaluation. The estimated logistic link between soft and hard data suggests a significant marginal effect of this change, while the probabilities of providing the "Up" response have been influenced the most. Our results suggest that the relationship between soft and hard data depends on intra-sectoral firms' heterogeneity, particularly in the Service industry; this effect remains significant after observable firms' characteristics are controlled for.

At the macro level, the BTS provides new information for monthly nowcasting through retrospective and prospective balances of opinions, related to specific aspects of business activity. The Sentiment model with monthly updated weights of explanatory balances produces reasonable real-time estimates of underlying monthly GDP growth with regard to the first GDP estimate, available about 45 days later. Regarding final GDP estimates, the model is not found superior to the baseline assumption of average GDP growth over three last years, possible due to large revisions in 2016 data. We document also better performance of the Sentiment indicator, calculated with respect to GDP, adjusted for imports taxes.

Bibliography

"Are Business Surveys Equally Successful to Forecast Economic Activity in France?", Tresor-Economics, 2014, No 125.

Baffigi, A., R. Golinelli, and G. Parigi (2004). "Bridge Models to Forecast the Euro Area GDP", *International Journal of Forecasting*, 20(3), 447–460

Banbura, M. and Rünstler, G. (2011). "A Look into the Factor Model Black Box: Publication Lags and the Role of Hard and Soft Data in Forecasting GDP", *International Journal of Forecasting*, 27, 333–46.

Bańbura, M., D. Giannone, M. Modugno and L. Reichlin (2013). "Now-casting and the Real-Time Data Flow", ECB Working Paper Series No 1564 / July 2013.

Basile R., de Nardis S. and C. Pappalardo (2014). "Firm Heterogeneity and Regional Business Cycles Differentials", *Journal of Economic Geography*, 14(6), 1087-1115.

Bergmeir, C., R. J. Hyndman, and J. M. Benitez (2016). "Bagging Exponential Smoothing Methods using STL Decomposition and Box-Cox Transformation", *International Journal of Forecasting,* 32, 303-312.

Bruno G., L. Crosilla and P. Margani (2016). "Inspecting the Relationship between Business Confidence and Industrial Production: Evidence Based on Italian Survey Data", ISTAT, Italy. URL: *https://ec.europa.eu/info/sites/info/files/file_import/g1_istat_it_new_normal_ciret2016_0.pdf*

Carriere I. and J. Bouyer (2006). "Random-Effect Models for Ordinal Responses: Application to Self-Reported Disability among Older Persons", *Epidemiology and Public Health*, 2006, 54, 61-72.

Chong, I. and C. Jun (2005). "Performance of Some Variable Selection Methods When Multicollinearity is Present", *Chemometrics and Intelligent Laboratory Systems*, 78 (2005), 103-112.

Ferrara L., D. Guegan and P. Rakotomarolahy (2010). "GDP Nowcasting with Ragged-Edge Data: A Semi-parametric Modelling", *Journal of Forecasting*, Wiley, 2010, 29 (1-2), 86-199.

Frale, C., M. Marcellino, G.L.Mazzi and T.Proietti (2010). "Survey Data as Coincident or Leading Indicators", *Journal of Forecasting*, 2010, vol. 29, issue 1-2, 109-131.

Gelper, S. and C. Croux (2010). “On the Construction of the European Economic Sentiment Indicator”, Oxford Bulletin of Economics and Statistics, 72.1 (2010) 0305–9049.

Hansson, J., Jansson, P. and Löf, M. (2005). “Business Survey Data: Do They Help in Forecasting GDP Growth?”- *International Journal of Forecasting*, 21, 377–89.

Harvey, D.L., S.J. Leybourne and P. Newbold (1998). "Tests for Forecast Encompassing", *Journal of Business and Economic Statistic,* Vol.16, No 2, 254-259.

Hölzl, W. (2015). “Business Cycle Dynamics and Firm Heterogeneity. Evidence for Austria Using Survey Data”, Working Paper, December 2015, Austrian Institute of Economic Research.

Kaufmann, D. and Scheufele, R. (2017). “Business Tendency Surveys and Macroeconomic Fluctuations”, *International Journal of Forecasting*, vol. 33(4), p.p. 878-893.

Malgarini M. (2011). “Industrial Production and Confidence after the Crisis: What’s Going On?”, Fifth Joint EU-OECD Workshop on International Developments of Business and Consumer Tendency Surveys.

Marcellino, M. and C. Schumacher (2010). “Factor MIDAS for Nowcasting and Forecasting with Ragged-Edge Data: A Model Comparison for German GDP”, *Oxford Bulletin of Economics and Statistics*, 2010, 72(4), 518-550

Mariano, R.S. and Y. Murasawa (2010). “A Coincident Index, Common Factors, and Monthly Real GDP”, *Oxford Bulletin of Economics and Statistics*, 2010, 72(1), 27-46.

Mitchell J., R.J. Smith, M.R. Weale, S.Wright and E.L. Salazar (2005). "An Indicator of Monthly GDP and an Early Estimate of Quarterly GDP Growth", *The Economic Journal*, 155 (February), F108-F129.

Mittnik, S. and P. Zadrozny (2004). "Forecasting Quarterly German GDP at Monthly Intervals Using Monthly IFO Business Condition Data”, CESifo Working Paper no 1203.

Mogliani, M., O. Darne and B. Pluyaud (2017). "The New MIBA Model: Real-time Nowcasting of French GDP Using the Banque de France's Monthly Business Survey", *Economic Modelling*, 64 (2017), 26-39.

Österholm, P. (2014). “Survey Data and Short-Term Forecasts of Swedish GDP Growth”, *Applied Economics Letters*, Vol.21, 2014 - Issue 2, p.p.135-139.

Matheson, T. (2011). “New Indicators for Tracking Growth in Real Time”, IMF Working Papers 11/43.

"The Use of Surveys by Central Banks", *IFC Bulletin*, No 30, 2009 – URL:*bis.org/ifc/publ/ifcb30e.pdf*

Wold, S., Johansson A, Cochi M (editors) (1993). “PLS-Partial Least Squares Projections to Latent Structures”, Leiden: ESCOM Science Publishers; 1993, p.p. 523-550.

Appendix A. Industrial composition weights used in Total balance of opinions

Sector	Aspect of business activity	Share in GDP[a]	Intra-sectoral division[b]	Component weight
Manufacturing	Domestic sales		80%	17.9%
Manufacturing	Export orders	22.4%	20%	4.5%
Retail Trade	Total sales	6.5%	-	6.5%
Services	Domestic sales		80%	47.3%
Services	Exports	59.1%	20%	11.8%
Construction	Building activity	10.3%	-	10.3%
Hotels[c]	Local tourists		50%	0.9%
Hotels	Foreign tourists	1.7%	50%	0.9%

[a] The industrial composition of business-sector GDP is given in the "Statistical Abstract of Israel" (2018, Table 18.1), URL: https://old.cbs.gov.il/reader/shnaton/templ_shnaton_e.html?num_tab=st18_01x&CYear=2018

Since not all sectors of the business sector are covered by the Business Tendency Survey and some are partly covered (for example, manufacturing does not include mining and quarrying, commerce is represented by only retail trade, business services do not include education etc.) and the hotels are represented separately from the services industry, although originally it is a part of the food and accommodation sub-industry), the composition was adjusted according to VAT sources.

[a] Exports shares are calculated according to perennial VAT composition.

[c] The hotels are covered by the survey as a separate sector, although they are a part of the services industry (the food and accommodation sub-industry) according to industrial CBS classification. The weight of this sector was calculated from the VAT sources.

Appendix B-1. PLS-parameters [a], estimated for regression of monthly GDP growth by survey-based variables, by selected specifications (sample: 2013:01-2019:12)

Sector	Activity aspect	Evaluation	Spec.1 No hard data	Spec.2	Spec.3	Spec.4
Panel A. With past values of revenue index						
Manufacturing	Domestic sales	Retrospective	0.180 [0.085]	0.175 [0.071]	0.162 [0.056]	0.153 [0.060]
	Export orders	Retrospective	0.098 [0.070]		0.109 [0.046]	
		Prospective		0.093 [0.054]		0.107 [0.059]
	Output	Retrospective				
		Prospective	0.094 [0.063]			
Retail Trade	Sales	Retrospective	0.117 [0.068]	0.135 [0.067]	0.145 [0.056]	
		Prospective				0.075 [0.057]
Services	Domestic sales	Retrospective	0.117 [0.070]		0.173 [0.059]	0.180 [0.066]
		Prospective		0.162 [0.075]		
	Exports	Retrospective		0.125 [0.088]		0.182 [0.065]
		Prospective	0.230 [0.094]		0.136 [0.076]	
	Employment [b]	Retrospective	-0.280 [0.070]		-0.201 [0.060]	-0.210 [0.067]
Construction	Building starts	Retrospective	0.119 [0.095]	0.081 [0.058]		
Revenue index	Hard data [c]	Second lag		0.105 [0.058]	0.095 [0.055]	0.111 [0.056]
Revenue index	Hard data [c]	Third lag		-0.031 [0.054]	0.031 [0.051]	-0.013 [0.053]
Number of accepted simulations (out of 350)			**384**	**240**	**123**	**85**
Sentiment Mean and Standard deviation [d]			**3.53%** [0.88%]	**3.52%** [0.86%]	**3.51%** [0.76%]	**3.52%** [0.82%]
Average Correlation with interpolated GDP growth			**0.521** (<0.0001)	**0.567** (<0.0001)	**0.547** (<0.0001)	**0.513** (<0.0001)
Panel C. With past values of industrial production index						
Manufacturing	Domestic sales	Retrospective		0.216 [0.073]	0.099 [0.076]	0.095 [0.070]
	Export orders	Retrospective			-0.098 [0.058]	-0.083 [0.067]
		Prospective		0.103 [0.065]		0.029 [0.082]
	Output	Retrospective				
		Prospective				
Retail Trade	Sales	Retrospective		0.138 [0.068]	0.105 [0.052]	
		Prospective				0.061 [0.059]
Services	Domestic sales	Retrospective			0.162 [0.078]	0.153 [0.087]
		Prospective		0.144 [0.079]		
	Exports	Retrospective				0.234 [0.123]
		Prospective		0.170 [0.075]	0.141 [0.070]	
	Employment [b]	Retrospective			-0.195 [0.071]	-0.187 [0.073]
Construction	Building starts	Retrospective		0.075 [0.052]		
Industrial production	Hard data [c]	Second lag		-0.101 [0.069]	-0.109 [0.080]	-0.105 [0.071]
Industrial production	Hard data [c]	Third lag		-0.039 [0.065]	-0.018 [0.077]	-0.038 [0.075]
Number of accepted simulations (out of 350)				**221**	**92**	**50**
Sentiment Mean and Standard deviation [d]				**3.55%** [0.71%]	**3.51%** [0.77%]	**3.52%** [0.73%]
Average Correlation with interpolated GDP growth				**0.493** (<0.0001)	**0.536** (<0.0001)	**0.541** (<0.0001)

[a] The parameters are given for standardized variables. The number in brackets is standard deviation of the parameter over simulations accepted by cross-validation. Estimates over the sample 2011:01-2019:12 are quite similar.

[b] Compiled as mean balance of employment in Manufacturing and Services sectors.

[c] Seasonally adjusted and log-differenced CBS monthly index.

[d] Actual average of monthly interpolated series is 3.55% (in annual growth terms), standard deviation is 1.67%.

Appendix B-2. PLS-parameters [a], estimated for regression of monthly GDP adjusted for import taxes by survey-based variables, by selected specifications (sample: 2013:01-2019:12)

Sector	Activity aspect	Evaluation	Spec.1 No hard data	Spec.2	Spec.3	Spec.4
Panel A. With past values of revenue index						
Manufacturing	Domestic sales	Retrospective	0.229 [0.078]	0.269 [0.061]	0.230 [0.055]	0.246 [0.043]
	Export orders	Retrospective	0.116 [0.063]		0.112 [0.047]	
		Prospective		0.110 [0.052]		0.197 [0.049]
	Output	Retrospective				
		Prospective	0.147 [0.079]			
Retail Trade	Sales	Retrospective	0.106 [0.057]	0.154 [0.076]	0.111 [0.050]	
		Prospective				0.083 [0.051]
Services	Domestic sales	Retrospective	0.203 [0.078]		0.219 [0.056]	0.243 [0.055]
		Prospective		0.172 [0.069]		
	Exports	Retrospective		0.274 [0.101]		0.217 [0.082]
		Prospective	0.290 [0.096]		0.131 [0.096]	
	Employment [b]	Retrospective	-0.294 [0.061]		-0.202 [0.064]	-0.222 [0.066]
Construction	Building starts	Retrospective	0.133 [0.092]	0.140 [0.082]		
Revenue index	Hard data [c]	Second lag		0.127 [0.061]	0.091 [0.064]	0.114 [0.060]
Revenue index	Hard data [c]	Third lag		-0.032 [0.081]	0.051 [0.072]	-0.015 [0.066]
Number of accepted simulations (out of 350)			**329**	**281**	**239**	**181**
Sentiment Mean and Standard deviation [d]			**3.80%** [1.24%]	**3.79%** [1.21%]	**3.78%** [1.06%]	**3.78%** [1.14%]
Average Correlation with interpolated GDP growth			**0.522** (<0.0001)	**0.572** (<0.0001)	**0.521** (<0.0001)	**0.556** (<0.0001)
Panel C. With past values of industrial production index						
Manufacturing	Domestic sales	Retrospective		0.245 [0.085]	0.253 [0.066]	0.235 [0.066]
	Export orders	Retrospective			0.124 [0.062]	
		Prospective		0.162 [0.070]		0.192 [0.061]
	Output	Retrospective				
		Prospective				
Retail Trade	Sales	Retrospective		0.056 [0.058]	0.107 [0.056]	
		Prospective				0.091 [0.066]
Services	Domestic sales	Retrospective			0.236 [0.071]	0.259 [0.087]
		Prospective		0.135 [0.056]		
	Exports	Retrospective		0.303 [0.106]		0.209 [0.103]
		Prospective			0.123 [0.081]	
	Employment [b]	Retrospective			-0.148 [0.065]	-0.174 [0.088]
Construction	Building starts	Retrospective		0.140 [0.082]		
Industrial production	Hard data [c]	Second lag		-0.127 [0.070]	-0.123 [0.082]	-0.113 [0.107]
Industrial production	Hard data [c]	Third lag		-0.046 [0.062]	-0.014 [0.065]	-0.020 [0.090]
Number of accepted simulations (out of 350)				**294**	**219**	**133**
Sentiment Mean and Standard deviation [d]				**3.83%** [1.08%]	**3.79%** **[** 1.11%]	**3.78%** [1.18%]
Average Correlation with interpolated GDP growth				**0.639** (<0.0001)	**0.539** (<0.0001)	**0.565** (<0.0001)

[a] The parameters are given for standardized variables. The number in brackets is standard deviation of the parameter over simulations accepted by cross-validation. Estimates over the sample 2011:01-2019:12 are quite similar.

[b] Compiled as mean balance of employment in Manufacturing and Services sectors.

[c] Seasonally adjusted and log-differenced CBS monthly index.

[d] Actual average of monthly interpolated series is 3.62% (in annual growth terms), standard deviation is 1.44%.

Appendix B-3. PLS-parameters [a], estimated for regression of monthly business-sector product growth by survey-based variables, by selected specifications (sample: 2013:01-2019:12)

Sector	Activity aspect	Evaluation	Spec.1 No hard data	Spec.2	Spec.3	Spec.4
Panel A. With past values of revenue index						
Manufacturing	Domestic sales	Retrospective	0.211 [0.072]	0.244 [0.076]	0.222 [0.063]	0.232 [0.065]
	Export orders	Retrospective	0.107 [0.072]		0.117 [0.057]	
		Prospective		0.093 [0.062]		0.094 [0.058]
	Output	Retrospective				
		Prospective	0.164 [0.079]			
Retail Trade	Sales	Retrospective	0.116 [0.088]	0.189 [0.074]	0.126 [0.059]	
		Prospective				0.078 [0.051]
Services	Domestic sales	Retrospective	0.238 [0.085]		0.232 [0.074]	0.260 [0.067]
		Prospective		0.170 [0.073]		
	Exports	Retrospective		0.214 [0.096]		0.247 [0.086]
		Prospective	0.283 [0.107]		0.128 [0.084]	
	Employment [b]	Retrospective	-0.289 [0.069]		-0.223 [0.072]	-0.217 [0.067]
Construction	Building starts	Retrospective	0.232 [0.095]	0.204 [0.083]		
Revenue index	Hard data [c]	Second lag		0.119 [0.078]	0.100 [0.079]	0.116 [0.070]
Revenue index	Hard data [c]	Third lag		-0.036 [0.075]	0.057 [0.073]	-0.015 [0.074]
Number of accepted simulations (out of 350)			**332**	**293**	**270**	**126**
Sentiment Mean and Standard deviation [d]			**3.60%** [0.82%]	**3.59%** [0.81%]	**3.59%** [0.73%]	**3.59%** [0.72%]
Average Correlation with interpolated GDP growth			**0.656** (<0.0001)	**0.683** (<0.0001)	**0.617** (<0.0001)	**0.625** (<0.0001)
Panel C. With past values of industrial production index						
Manufacturing	Domestic sales	Retrospective		0.215 [0.084]	0.218 [0.078]	0.226 [0.074]
	Export orders	Retrospective			0.135 [0.058]	
		Prospective		0.170 [0.084]		0.038 [0.072]
	Output	Retrospective				
		Prospective				
Retail Trade	Sales	Retrospective		0.165 [0.082]	0.129 [0.062]	
		Prospective				0.085 [0.056]
Services	Domestic sales	Retrospective			0.217 [0.088]	0.229 [0.085]
		Prospective		0.168 [0.082]		
	Exports	Retrospective		0.236 [0.092]		0.272 [0.094]
		Prospective			0.178 [0.103]	
	Employment [b]	Retrospective			-0.235 [0.107]	-0.205 [0.114]
Construction	Building starts	Retrospective		0.256 [0.150]		
Industrial production	Hard data [c]	Second lag		-0.114 [0.073]	-0.122 [0.081]	-0.113 [0.104]
Industrial production	Hard data [c]	Third lag		-0.041 [0.061]	-0.005 [0.084]	-0.011 [0.091]
Number of accepted simulations (out of 350)				**218**	**200**	**87**
Sentiment Mean and Standard deviation [d]				**3.62%** [0.64%]	**3.59%** [0.73%]	**3.60%** [0.82%]
Average Correlation with interpolated GDP growth				**0.533** (<0.0001)	**0.596** (<0.0001)	**0.684** (<0.0001)

[a] The parameters are given for standardized variables. The number in brackets is standard deviation of the parameter over simulations accepted by cross-validation. Estimates over the sample 2011:01-2019:12 are quite similar.

[b] Compiled as mean balance of employment in Manufacturing and Services sectors.

[c] Seasonally adjusted and log-differenced CBS monthly index.

[d] Actual average of monthly interpolated series is 3.81% (in annual growth terms), standard deviation is 2.30%.