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Dissecting the Purchasing Managers' Index: Are All Relevant Components Included? Are All Included Components Relevant?

Summary: In this paper we scrutinise the composition of one of the most renowned economic indicators that is regularly released for more than 30 countries and regions. The composite Purchasing Managers' Index (PMI) is constructed by pooling several survey based sub-components with certain fixed weights. Its characteristic feature is that its computation is based on the standardised methodology by that was developed for the PMI in the US more than thirty years ago. Though the uniform methodology makes the international comparison of national PMIs an easy and transparent task, it is not immediately clear whether the current fixed weighting scheme of the PMI components is supported by the data for other countries than US. We address this question using Switzerland as an example and our approach, based on Boriss Siliverstovs (2017), can be easily extended to other national PMIs. We find that the relative weights of the PMI components are generally supported by the data, except the fact that one component, found very informative for explaining GDP growth, is currently omitted from the PMI composition.

Key words: PMI, MIDAS, LASSO, Real-time data, Switzerland.

JEL: C22, C53.

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The Purchasing Managers' Index (henceforth, PMI) is a renowned economic indicator regularly released at the monthly frequency for more than 30 countries and regions that is widely used for assessing current economic conditions well ahead of the official publications of GDP (Evan F. Koenig 2002; Claudia Godbout and Jocelyn Jacob 2010; James Rossiter 2010; Marco J. Lombardi and Philipp Maier 2011; Kajal Lahiri and George Monokroussos 2013; YiLi Chien and Paul Morris 2016; David Iselin and Siliverstovs 2016; Zubeyir Kilinc and Eray Yucel 2016, *inter alia*).

A characteristic feature of the PMIs produced for most of the countries in question is that these are constructed as a composite index based on the unified methodology of aggregating five survey questions regarding backlog of orders (0.30), output (0.25), employment (0.20), suppliers' delivery times (0.15), and stocks of purchases (0.10), with the corresponding weights shown in parentheses. These weights attached were determined in 1982 by the US Department of Commerce so as to maximise the correlation between the national PMI and GDP growth.

Given the diversity of the 30+ countries/regions for which the composite PMIs are released and their different characteristics from those of the US economy, a question arises whether the use of this one-for-all weighting scheme derived in 1982 for the US economy is still warranted in these countries. Or, more precisely, it is natural to ask the following two questions: "*Are all relevant components included?*" and "*Are all included components relevant?*" in the way the national PMIs are constructed.

The question on whether the above mentioned weighting scheme is optimal was critically examined for the US economy in several studies (Rolando F. Pelaez 2003a, b; Danny I. Cho and Tomson Ogwang 2006). In this paper we address this question for the first time for a different country than US, namely, Switzerland, as follows. An overview of the relevant literature is provided in the next section. The econometric methodology is described in Section 2. Section 3 describes the data and the empirical results and the final section concludes.

1. Literature Review

Because of substantial publication lags of official economic statistics, most often in the form of a quarterly System of National Accounts, policy-makers and other interested parties traditionally rely on sentiment and business tendency surveys as well as composite economic indicators made thereof in order to monitor the current pulse of the economy. Compared with official data these indicators are typically available with a much shorter publication delay and at a higher frequency.

Regular monthly releases of the PMI for more than 30 countries and regions inevitably attract a lot of attention. Moreover, the fact that the PMI is constructed using the standardised methodology ensures that outcomes are comparable across different countries. However, the fact that this selection of the core components and the specified weights was calibrated using US data more than 30 years ago raises a question whether the automatic extension of this construction framework to other countries is supported by the relevant national data.

Indeed, even in the US the adoption of the component-specific weights was somewhat controversial. In 1980, the first version of the PMI was introduced by Thedore Torda, a senior economist of the US Department of Commerce. Initially it was calculated as the average of the following five components: backlog of orders, output, employment, suppliers' delivery times, and stocks of purchases. Using historical data, the PMI was calculated backwards up to 1948. In 1982, the US Department of Commerce abolished equal weighting and introduced differential weights so as to maximise correlation between the PMI and GDP growth in the US. The assigned weights were as follows: backlog of orders (0.30), output (0.25), employment (0.20), suppliers' delivery times (0.15), and stocks of purchases (0.10). However, in 2008 the equal weighting scheme was again re-introduced in computation of the PMI for the US, according to the Institute for Supply Management (2014)[1]. It is worthwhile pointing out that despite the re-introduction of the equal weights in

[1] **Institute for Supply Management.** 2014. http://www.ism.ws/about/MediaRoom/newsreleasedetail.cfm?ItemNumber=17500 (accessed March 17, 2014).

computation of the composite PMI in the US, the scheme with the differentiated weights is still applicable for the PMIs released by the Markit Group for other economies than US. Similarly, the PMI for Switzerland, released by the Credit Suisse and the Swiss Association of Purchasing and Supply Management, also follows this tradition.

The transition from the initial equal-weighting scheme to differentiated weights and then back to the equal weights seems to suggest that the question of a relative importance of the PMI components was and, probably, still is at the centre of the debate within those organisations directly involved in the production process of the PMI in the US. The same question also did not slip the attention of academic circles. In the US, this question has been a subject of investigation in several studies. For example, Pelaez (2003a) suggests to use time-varying rather than fixed weights. Pelaez (2003b) proposes to compute a version of the PMI based only on the following three components: backlog of orders, employment, and suppliers' delivery times, effectively attaching a zero weight to output and stock of purchases. Cho and Ogwang (2006) are even more restrictive in suggesting to use only the employment component of the composite PMI.

More generally, the largely unexpected outbreak of the Great Recession has questioned the validity of existing economic indicators and significantly spurred the quest for improvement of their reliability. In principle, there is no limit for continuous improvement of economic indicators as these are often needed to be adjusted in order to accommodate undergoing changes in the economic environments accompanied by changes in relationships between economic variables, changes in definitions in the reference time series that these indicators attempt to track, modification of data collection procedures as well as the growth in scope and depth of available data sources. For example, a recent benchmark revision of one of the most prominent economic indicators for the US economy (the Leading Economic Index released by the Conference Board) is described in Gad Levanon et al. (2011). The call to modify the traditional NBER index based on the four economic indicators was made in Lahiri and Wenxiong Yao (2012), suggesting to include the transportation services output index. In Switzerland, a complete overhaul of the KOF Economic Barometer released at the monthly frequency since 1976 is documented in Klaus Abberger et al. (2014). The fourth generation of the KOF Economic Barometer was launched on 31st of March 2014 (Abberger et al. 2018).

In the present paper, we intend to scrutinise the composition of the PMI computed for Switzerland. The Swiss version of the PMI is based on eight components listed in Table 1 (see the Appendix). Observe that only five out of eight components receive non-zero weights in the composition of the total PMI. For those five selected components the weights mirror exactly the weights suggested in 1982 for the American version of the PMI. Given the fact that these weights were chosen so as to maximise correlation between the US GDP growth rate and PMI calculated for the US economy more than thirty years ago, it is of a great interest to investigate to what extent this weighting scheme is empirically supported for the PMI calculated using Swiss data. In Switzerland, to the best of our knowledge, this question has not been formally addressed so far.

Thence this defines the contribution of the present paper which addresses the extent to which the chosen relative importance of components is reflected in actual data. In other words, we would like to investigate the following two related questions: "*Are all relevant components included?*" and "*Are all included components relevant?*".

Observe that GDP data are reported at the quarterly frequency, whereas the PMI is published monthly. Hence a direct computation of correlation or any other measure of association between these two time series is not possible without undertaking further intermediate steps in order to match these variables sampled at the heterogeneous frequencies.

In this paper we adopt an approach that was recently proposed in Siliverstovs (2017) for modelling data observed at different sampling frequencies. Siliverstovs (2017) suggests to use a combination of a version of the Mixed Data Sampling (MIDAS) approach of Eric Ghysels, Pedro Santa-Clara, and Rossen Valkanov (2004) and Ghysels, Arthur Sinko, and Valkanov (2007) and a targeted-regressor approach of Jushan Bai and Serena Ng (2008) based on a version of the penalised regression called elastic net (Hui Zou and Trevor Hastie 2005). As mentioned in Bai and Ng (2008) the elastic net is special case of the Least Absolute Shrinkage and Selection Operator (LASSO) earlier suggested in Robert Tibshirani (1996). We refer to the approach of Siliverstovs (2017) as the MIDASSO approach deriving its name from the two mentioned abbreviations.

In the nutshell, the proposed MIDASSO approach consists of two steps. In the first step, we adopt a so-called skip-sampling procedure in order to convert each monthly PMI component time series into three quarterly time series, such that each of the newly created time series retains all observations in the first, second and third months of each quarter, respectively. In the second step, we apply the targeted-regressor approach, where by means of the elastic net the most informative components concerning the target time series (GDP growth) are retained. Here we rely on the property of the elastic net to set some coefficients to zero in a linear regression, i.e. its ability to select most relevant variables for the variable of interest and, correspondingly, discard irrelevant ones. Consequently, the selection incidence of a particular PMI component will reflect its relative importance. PMI components that have the most explanatory power for GDP growth will be selected more frequently than those components with less explanatory power. We expect that PMI components that are irrelevant for predicting GDP growth will not be selected at all. In the next section, we provide a more formal description of the econometric approach adopted here.

2. Econometric Methodology

Let $t = 1,2,\dots,T-1,T$ denote a time scale at the quarterly frequency at which we observe a target variable y_t, e.g. the GDP growth rate. Then, by assigning integer values of the time scale to the last month of each quarter, the corresponding time scale at the monthly frequency can be represented as $t_m = 1/3, 2/3, 1, 1+1/3, 1+2/3, 2, \dots, T-1, T-2/3, T-1/3, T$. Let $X_{t_m} = \left(X_{1,t_m}, X_{2,t_m}, \dots, X_{N,t_m}\right)$ denote a $N \times 1$ vector of potential predictors observed at the monthly frequency.

In the first step of the MIDASSO approach we apply the skip-sampling procedure in order to block monthly variables into three quarterly time series, each of them retaining values of the original monthly variables in the first, second and third months, respectively. If we correspondingly denote by $X_t^{(1)}$ values of the monthly variables observed in the first month of each quarter $t^{(1)} = 1/3, 1 + 1/3, \ldots, T - 2/3$, by $X_t^{(2)}$ - in the second month of each quarter $t^{(2)} = 2/3, 1 + 2/3, \ldots, T - 1/3$, and by $X_t^{(3)}$ - in the third month of each quarter $t^{(3)} = 1, 2, \ldots, T$, then instead of the $N \times 1$ vector of monthly predictors X_{t_m} we have a $(3 \times N) \times 1$ vector of original predictors converted to the quarterly frequency $X_t = \left(X_t^{(1)}, X_t^{(2)}, X_t^{(3)}\right)$. The dimension of X_t can be further increased by including their lagged values, i.e. by allowing for up to p lags of X_t we end up with the vector of explanatory variables $\mathbf{X}_t = (X_{t'}, X_{t-1}', \ldots, X_{t-p}')'$ of dimension $(3 \times N \times (p + 1)) \times 1$. Note that in this case the lag operator, e.g. $L(X_t^{(1)}) = X_{t-1}^{(1)}$, operates at the quarterly frequency. Thus, as a main result of the skip-sampling procedure, we observe both dependent and explanatory variables at the common sampling frequency, implying that the targeted regressors approach of Bai and Ng (2008) is straightforward to apply in the second step of the MIDASSO procedure.

Bai and Ng (2008) proposed to apply a penalized regression to the following forecasting model:

$$y_{t+h}^{h} = \alpha' W_t + \gamma' \mathbf{X}_t + \varepsilon_{t+h}, \tag{1}$$

where W_t is a vector of predetermined regressors like a constant. Lagged values of the dependent variable may also be included in W_t. Observe that Equation (1) is specified according to the direct forecasting approach (see discussion in Massimiliano Marcellino, James H. Stock, and Mark W. Watson 2006) directly relating the dependent variable of interest to observed values of W_t and X_t. This means that the model specification is specific for every forecasting horizon, h.

Recall that as the result of the skip-sampling procedure we significantly blew up the dimension of the vector of predictors $\mathbf{X}_t$. Hence running a regression, specified in Equation (1), is not optimal as we may end up with the problem of over-fitting. Fortunately, the problem of over-fitting can be solved by resorting to the kind of penalized regression - a so-called elastic net of Zou and Hastie (2005) - which is capable not only to estimate model parameters but also to force some of the coefficients to take zero values, i.e. perform a model selection exercise. As a result, the most relevant explanatory variables for the dependent variable in question are retained and those irrelevant and least important ones are effectively removed. The corresponding optimization problem is:

$$\hat{\beta}(\lambda_1, \lambda_2) = \underset{\beta}{\operatorname{argmin}} \{RSS + \lambda_2 \|\beta\|^2 + \lambda_1 \|\beta\|_1\}, \tag{2}$$

where RSS is the h-specific residual sum of squares of Equation (1) and β represents coefficient vector $(\alpha', \gamma')'$. For a fixed value of the L_2-norm penalty term λ_2, this minimisation problem can be reformulated in terms of the LASSO estimator of

Tibshirani (1996) and the efficient algorithm based on the least angle regression can be used in order to estimate model parameters. The optimal value of the L_1-norm penalty term λ_1, governing the severance of the regressor selection procedure, is then chosen by cross-validation.

Let $\mathbf{X}_t^*$ be a subset of predictors for which $\gamma \neq 0$, i.e. $\mathbf{X}_t^* \subset \mathbf{X}_t$. For each forecast horizon we record which variables were retained by the elastic net. Repeating this estimation and variable selection procedures over several data vintages will allow us to collect evidence on a relative importance of each indicator for explaining current as well as future GDP growth, which we can compare with the actual weights used in the construction of the composite PMI.

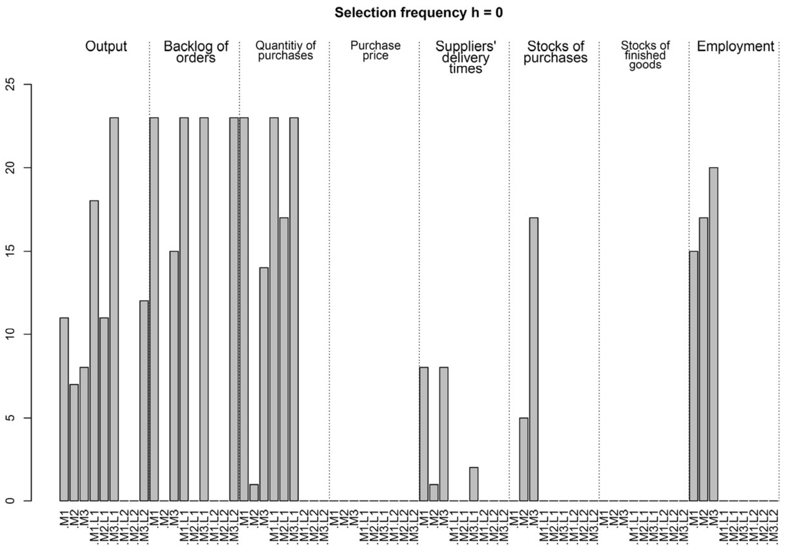
3. Results

This section contains description of empirical estimation results. The dependent variable is the year-on-year quarterly GDP growth rate in Switzerland, for which we have real-time historical vintages. The original explanatory variables, observed at the monthly frequency, are the eight seasonally adjusted components of the Purchasing Managers' Index, for which we also have real-time vintages. The PMI data extends back to January 1995, which also constrains the beginning of the estimation sample. The end of the estimation sample reflects the information set available on the first business day of the first month of each quarter, when the values of the PMI and its components are released for the third month of the previous quarter. This means that for each quarter we have a complete set of monthly values of the PMI and its components.

The whole available sample for our analysis is from 1995Q1 until 2013Q3. We start our analysis using the initial sample 1995Q1-2008Q1, which we expand recursively until the last quarter 2013Q3. The initial sample reflects an information set available to a forecaster at the first business day after the end of the quarter 2008Q1, when the PMI and its components are released for the third last month of 2008Q1. Given the publication lag of about two months of GDP data, official estimate of GDP growth in 2008Q1 is not yet known to the forecaster and therefore it is absent in this information set. We are interested in using the most recent values of PMI for forecasting GDP growth in the current quarter 2008Q1, the next quarter 2008Q2, and two quarters ahead in 2008Q3. Let h be a forecast horizon, then we have $h = 0$ for 2008Q1, $h = 1$ for 2008Q2, and $h = 2$ for 2008Q3. For each forecast horizon h we record which PMI subcomponents were selected by the elastic net using Equation (2). Next, we enlarge the information set by one quarter (2008Q2), re-estimate Equation (2) and record selected variables by the elastic net for each forecast horizon h, etc. Below we summarise the empirical results.

The importance of each component for explaining GDP growth is assessed by evaluating the selection frequency of each out of the eight PMI components based on the recursive estimation of Equation (2). We fixed the L_2-norm penalty term at $\lambda_2 = 0.75$ and let the value of the L_1-norm penalty to be chosen by cross-validation. As an alternative, we also re-estimated Equation (2) using the following values of $\lambda_2 = 0.25$ and $\lambda_2 = 0.50$. The results turned out to be robust with respect to the choice of the alternative values of the λ_2 parameter.

Observe that for this exercise we consider not only the contemporaneous values of the PMI components but also their first and second lags. This means that out of the initial number of eight monthly explanatory variables we have in total 72 quarterly potential predictors collected in $\mathbf{X}_t$ that appear on the right-hand side of Equation (2). This number is achieved as follows. First, the blocking procedure makes three quarterly time series out of each monthly variable by retaining values observed in the first month of each quarter to the first quarterly variable, values observed in the second month - to the second quarterly variable, and values observed in the third month - to the third quarterly variables. This gives us first $3 \times 8 = 24$ quarterly predictors. By taking first and second lags of each of the newly created quarterly variables, i.e. setting $p = 2$, we arrive at $3 \times 8 \times (2 + 1) = 72$ quarterly explanatory variables. By allowing for the lagged values of the PMI components we acknowledge that some of them may have more pronounced leading-indicator properties than others.

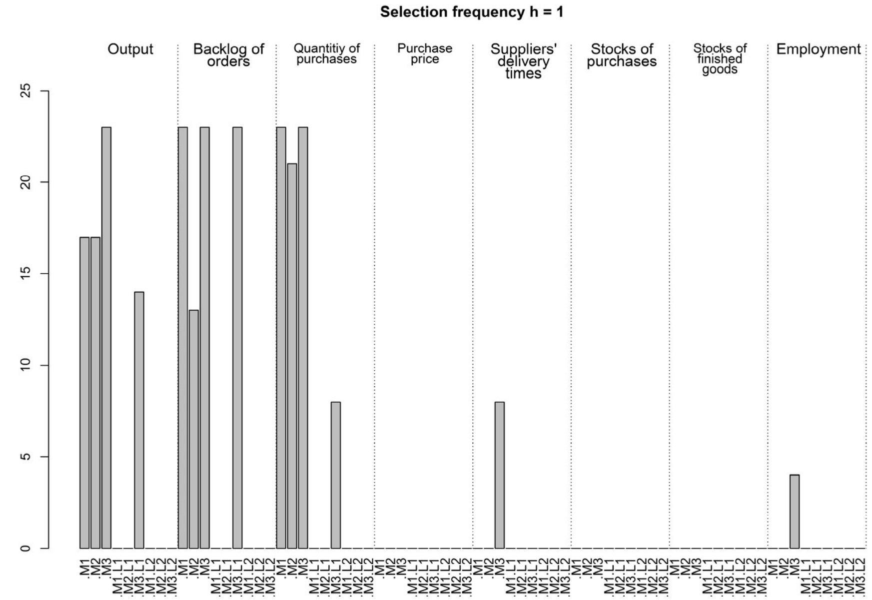


Source: Author's calculation.

Figure 1 Selection Frequency of Each PMI Component, *h* = 0

An additional detail of our variable selection procedure is that the vector of predetermined variables W_t in Equation (1) contains only one element - a constant, which we always kept in the regression while finding solution paths of the elastic net optimisation problem. This means that we pre-select variables according to their explanatory power of GDP growth without taking into account the effect of the past values of GDP growth. We also verified the robustness of our results after controlling for the effect of the past values of the dependent variable, by regressing both dependent and explanatory variables on the predetermined variables W_t and then using the saved OLS residuals instead of actual data in Equation (1). The relative selection frequency of various PMI components remained very similar, although the absolute selection frequency was somewhat lower.

The selection frequency of each of 72 predictors is shown in Figures 1, 2, and 3 for $h = 0,1,2$, respectively, where by the labels on the X-axis in each plot we denote a variable containing all the values pertaining to the first month of each quarter as $.M1$, i.e. $X_t^{(1)}$, to the second month as $.M2$, i.e. $X_t^{(2)}$, and correspondingly to the third month as $.M3$, i.e. $X_t^{(3)}$. The abbreviations like $.M1.L1$ and $.M1.L2$ indicate the first and second lags of the respective variable, i.e. $X_{t-1}^{(1)}$ and $X_{t-2}^{(1)}$.

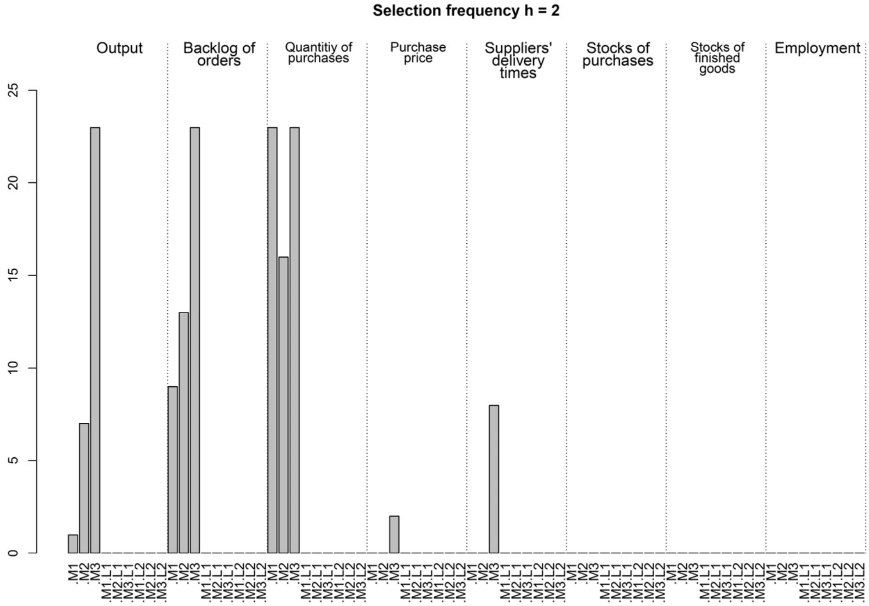


Source: Author's calculation.

Figure 2 Selection Frequency of Each PMI Component, *h* = 1

As seen, the selection frequency varies from predictor to predictor, but there are some predictors that were selected in each of 23 estimation samples for every forecast horizon. The summary of the horizon-specific selection frequency is presented in Table 2 (see the Appendix). Based on the evidence in the table we can draw the following conclusions. First, as the forecast horizon increases less indicators were retained by the elastic net. The three PMI components (output, backlog of orders, and quantity of purchases) have the highest selection frequency for all h. This implies that these group of components can be safely labelled as forward-looking indicators. Two PMI components (stocks of purchases and employment) that were selected at $h = 0$ were not selected at $h = 2$, implying that these can be best described as coincident rather than leading economic indicators.

Addressing the question "*Are all included variables relevant?*", we can state that the two components (purchase prices and stocks of finished goods) that according to our results have no explanatory power for GDP growth are rightfully not included in the PMI. However, addressing the related question "*Are all relevant variables* *included?*" we notice that one component (quantity of purchases) that has a comparable selection frequency to the two most heavily weighted components (output (0.25) and backlog of orders (0.30)) in the PMI is not included. It is also remarkable that the selection frequency of quantity of purchases is the highest among the rest of components for $h = 2$, characterising it as the most forward-looking component.



Source: Author's calculation.

Figure 3 Selection Frequency of Each PMI Component, *h* = 2

It is also interesting to observe that the relative selection frequency of five components that enter the PMI is very close to the actual weighting scheme for $h = 0$. For example, the two components (output and backlog of orders) that have the highest weights in the PMI also have the highest selection frequency among these five components. The component (employment) with the third-largest attached weight is also ranked as the third most frequently selected component in our exercise. Finally, the remaining two components (suppliers' delivery times and stocks of purchases) with the lowest weights attached in the PMI construction are also ranked as the least frequently selected components. For longer forecast horizons this coincidence in relative selection frequency and the assigned weights is less evident. This can be tentatively interpreted that the weights for the PMI components were chosen so as to maximise its contemporaneous correlation with GDP growth in order to boost its properties as a reliable coincident economic indicator. It is rather remarkable that the relative importance assigned to the five chosen components back in 1982 and calibrated using the US data is also supported in the Swiss data, apart from the non-inclusion issue of the component reflecting quantity of purchases in the PMI.

Summarising, our results confirm that all five out of eight components selected into the PMI are important for explaining GDP growth in the current quarter. Their relative ranking that come out of our exercise is in line with the weighting scheme actually implemented in the PMI construction. Out of the three components, that are actually not included into the PMI, two components (purchase prices and stocks of finished goods) are deservedly excluded, whereas the third excluded component (quantity of purchases) appears to be as of much importance in explaining GDP growth in Switzerland as the two most heavily weighted components (output and backlog of orders).

Our results are in strong contrast to those reported for the US economy in Pelaez (2003b) and Cho and Ogwang (2006) where it was found out that an optimal composite PMI should be constructed using three and one rather than five original sub-indices, respectively. On the opposite, our results confirm the empirical validity of the prevailing weighting scheme and point out that an inclusion - not exclusion - of one additional sub-component to the existing PMI composition may further improve its leading properties.

4. Conclusion

In this paper we scrutinise the composition of one of the most renowned economic indicators that is regularly released for more than 30 countries and regions. The composite Purchasing Managers' Index (PMI) is constructed using the standardised methodology that was developed for the PMI in the US more than thirty years ago. According to this methodology the composite PMI is constructed by pooling five survey-based sub-indices using component-specific fixed weights.

Though the uniform methodology makes the international comparison of national PMIs an easy and transparent task, it is not immediately clear whether the currently prevailing weighting scheme of the PMI components is supported by the data for other countries than the US. It is of a great interest to investigate this question for these countries as even for the American version of the PMI there are several earlier studies that concluded that the current weighting scheme is not optimal and therefore can be improved either using a time-varying weights or severely restricting the number of sub-indices underlying the composite PMI (Pelaez 2003a, b; Cho and Ogwang 2006).

To the best of our knowledge, this is the first paper that scrutinises the optimality of the adopted weighting scheme in other countries than the US. To this end, we use Switzerland as an example and our approach, based on Siliverstovs (2017), can be easily extended to other national PMIs. We utilise the variable selection feature of the MIDASSO approach of Siliverstovs (2017) in order to verify whether a weighting scheme based on the relative selection frequency of the sub-indices in question matches the prevailing weighting scheme used in the construction of the composite PMI. We find that the relative weights of the PMI components are generally supported by the data, except for the fact that one forward-looking component (quantity of purchases), found very informative for explaining GDP growth, is currently omitted from the PMI composition.

Thus, our results are in a sharp contrast to those reported in the earlier literature on the optimality of the current composition for the US data. Our results indicate that expanding rather than shrinking the current choice of sub-indices used in constructing the PMI is the right way to proceed in order to improve its leading properties.

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Appendix

Table 1 PMI Components in Switzerland

Components	Weights
Output	0.25
Backlog of orders	0.30
Quantity of purchases Purchase prices Suppliers' delivery times	0.15
Stocks of purchases	0.10
Stocks of finished goods Employment	0.20

Source: Procedure.ch (2014)[2].

Table 2 Selection Incidence Over 23 Samples, 2008Q1-2013Q3, $\lambda_2 = 0.75$

Components	Selection frequency						Weight in PMI
Forecast horizon, *h*	Absolute			Relative			
	0	1	2	0	1	2	
Output	90	71	31	0.23	0.30	0.21	0.25
Backlog of orders	107	82	45	0.27	0.34	0.30	0.30
Quantity of purchases	101	75	62	0.26	0.31	0.42	
Purchase prices	0	0	2			0.01	
Suppliers' delivery times	19	8	8	0.05	0.03	0.05	0.15
Stocks of purchases	22	0	0	0.06			0.10
Stocks of finished goods	0	0	0				
Employment	52	4	0	0.13	0.02		0.20
Total	**391**	**240**	**148**	**1.00**	**1.00**	**1.00**	**1.00**

Source: Author's calculation based on data from Procedure.ch (2014).

[2] **Procedure.ch.** 2014. Purchasing Managers' Index (PMI). https://www.procure.ch/service/gewusst-wie/pmi-industriedienstleistung/ (accessed August 06, 2014).