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Dissecting the Purchasing Managers' Index: Are all relevant components included? Are all included components relevant?*

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Abstract

We apply the novel approach of Siliverstovs (2015) to modelling data sampled at different frequencies in order to scrutinise the composition of one of the most influential economic indicators in Switzerland. The Purchasing Managers' Index consists of eight sub-indices out of which only five enter the total index with differentiated weights, which were specified for its American counterpart about thirty years ago. In this paper, we address the question whether the current fixed weighting scheme of the PMI components is supported by the data. 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.

Keywords: GDP growth, MIDAS, LASSO, MIDASSO, PMI, real-time data, Switzerland
JEL code: C22, C53

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1 Introduction

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.

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 Levanon et al. (2011). The call to modify the traditional NBER index based on the four economic indicators was made in Lahiri and 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 Abberger et al. (2014). The fourth generation of the KOF Economic Barometer was launched on 31st of March 2014.

In this paper, we turn our attention to the Purchasing Managers' Index (PMI) which is one of the most important early economic indicators in Switzerland as well. The closely followed monthly releases of the PMI are the result of cooperation between the Credit Suisse and the Swiss Association of Purchasing and Supply Management[1]. The Swiss PMI continues the long tradition dating back to 1931, when the National Association of Purchasing Management (NAPM) started to collect business tendency surveys from purchasing and supply executives in manufacturing companies in the US. 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: output, backlog of orders, employment, suppliers' delivery times, and stocks of purchases. Using historical data, the PMI was calculated backwards and is available since 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

[1] In German, Fachverband für Einkauf und Supply Management, www.procure.ch.

weights were as follows: output(0.25), backlog of orders(0.30), 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.[2]

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 relative importance of 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 PMI.

The Swiss version of the PMI is based on eight components listed in Table 1. 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 a monthly indicator. 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 this paper we adopt a novel approach suggested in Siliverstovs (2015) for modelling data observed at different sampling frequencies. Siliverstovs (2015) suggests to use a combination of a version of the MIxed DAta Sampling (MIDAS) approach of Ghysels, Santa-Clara, and Valkanov (2004) and Ghysels, Sinko, and Valkanov (2007) and targeted-regressor approach of Bai and Ng (2008) based on a

[2]The press release is available at `http://www.ism.ws/about/MediaRoom/newsreleasedetail.cfm?ItemNumber=17500`.

version of the penalised regression called *elastic net* (Zou and Hastie, 2005). As mentioned in Bai and Ng (2008) the elastic net is special case of the Least Absolute Shrinkage and Selection Operator (LASSO) suggested in Tibshirani (1996). We refer to the approach of Siliverstovs (2015) as the MIDASSO approach deriving its name from the two mentioned abbreviations.

The MIDASSO approach consists of two steps. In the first step, we adopt a so-called skip-sampling procedure in order to convert the monthly time series of the PMI 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. 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.

The rest of the paper is organised as follows. The next section contains a description of data and our modelling approach. In Section 3 results are presented. The final section concludes.

2 Econometric methodology

Let $t = 1, 2, ..., T-1, T$ denote a time scale at the quarterly frequency at which we observe a target variable y_t. 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 $t_m = 1/3, 2/3, 1, 1+1/3, 1+2/3, 2, ..., T-1, T-2/3, T-1/3, T$. Let $X_{t_m} = (X_{1,t_m}, X_{2,t_m}, ..., X_{N,t_m})'$ denote a $N \times 1$ vector of potential predictors observed at monthly frequency.

In the first step we 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. If we correspondingly denote by $X_t^{(1)}$ values of the monthly variables observed in the first month of each quarter $t^{(1)} = 1/3, 1+1/3, ..., T-2/3$, by $X_t^{(2)}$ — in the second month of each quarter $t^{(2)} = 2/3, 1+2/3, ..., T-1/3$, and by $X_t^{(3)}$ — in the third month of each quarter $t^{(3)} = 1, 2, ..., T$, 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. Note that in this case the lag operator, e.g.

$L(X_t^{(1)}) = X_{t-1}^{(1)}$, operates at the quarterly frequency. As a result of the skip-sampling procedure, we have both dependent and explanatory variables at the common frequency, implying that the targeted regressors approach of Bai and Ng (2008) is straightforward to apply.

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

$$y_{t+h}^h = \alpha' W_t + \gamma' X_t + \epsilon_{t+h}, \tag{1}$$

where W_t is a vector of predetermined regressors like a constant and lagged values of the dependent variable. Equation (1) is specified according to the direct forecasting approach (see discussion in Marcellino et al., 2006) directly relating the dependent variable of interest to observed values of W_t and X_t. Note that the model specification is specific for every forecasting horizon, h. The penalized regression—a so-called elastic net Zou and Hastie (2005)—is capable not only to estimate slope parameter but also remove irrelevant regressors, i.e. perform a variable selection. The corresponding optimization problem is

$$\widehat{\beta}(\lambda_1, \lambda_2) = \arg\min_{\beta} \left\{ RSS + \lambda_2 \left\|\beta\right\|^2 + \lambda_1 \left\|\beta\right\|_1 \right\}, \tag{2}$$

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 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 λ_1, governing the strength of penalising term and, as a result, the severance of the regressor selection procedure, is then chosen by cross-validation.

Let X_t^* be a subset of predictors for which $\gamma \neq 0$, i.e. $X_t^* \subset X_t$. 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.

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 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.

In this sub-section we report the selection frequency of each out of the eight PMI components based on estimation of Equation (2). We used the L_2-norm penalty $\lambda_2 = 0.75$, the value of the L_1-norm penalty was chosen by cross-validation.[3]The selection frequency is summarised over all 23 recursive estimation samples as described above. 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 initial number of eight monthly explanatory variables we have in total 72 quarterly potential predictors 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 $8 \times 3 = 24$ quarterly predictors. By taking first and second lags of each of the newly created quarterly variables we arrive at 72 quarterly explanatory variables in total. 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.

[3]Alternatively, we tried values $\lambda_2 = 0.25$ and $\lambda = 0.50$. The results turned out to be rather insensitive to the choice of the λ_2 parameter in the optimisation problem given in Equation (2).

An additional detail of our variable selection procedure is that the vector of pre-determined variables W_t in Equation (1) contains only one element—a constant. 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.[4]

The selection frequency of each of 72 predictors is shown in Figures 1, 2, and 3 for $h = 0, 1, 2$, respectively.[5] Obviously, 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 selection frequency is presented in Table 2. 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.

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 are 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

[4] We also conducted the same exercise 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.

[5] 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 $X_{t-2}^{(1)}$.

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 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 two most heavily weighted components (output and backlog of orders).

4 Conclusion

We apply the MIDASSO approach for modelling mixed-frequency data suggested in Siliverstovs (2015) in order to dissect the composition of the Purchasing Managers' Index that is computed for Switzerland. To this end, we use the real-time vintages of both the quarterly year-on-year real GDP growth as well as the Purchasing Managers' Index, closely simulating information flow in the past. We utilise the variable selection feature of the MIDASSO approach in order to verify whether relative weights attached to the PMI components are empirically supported by the data. We find that they indeed are generally supported, despite the fact that these weights were determined using US data about thirty years ago. The only exception is that one component, that according to our analysis has a rather high explanatory power of GDP growth (quantity of purchases), is not currently included in the composite PMI indicator.

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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

Table 2: Selection incidence over 23 samples, 2008q1—2013q3, $\lambda_2 = 0.75$

Components	Selection frequency						Weight in PMI
	Absolute			Relative			
Forecast horizon, h	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

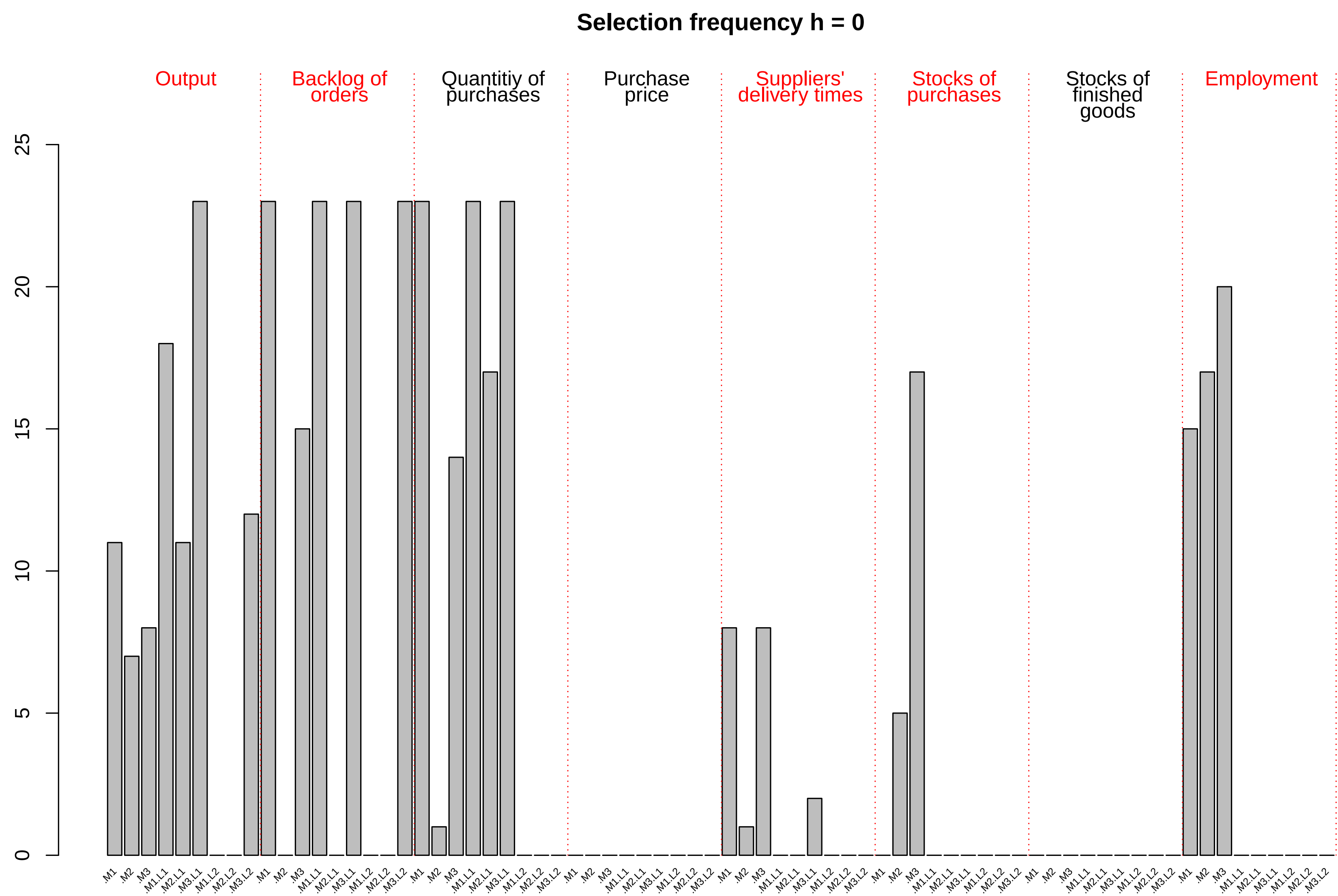

Figure 1: Selection frequency of each PMI component, $h = 0$

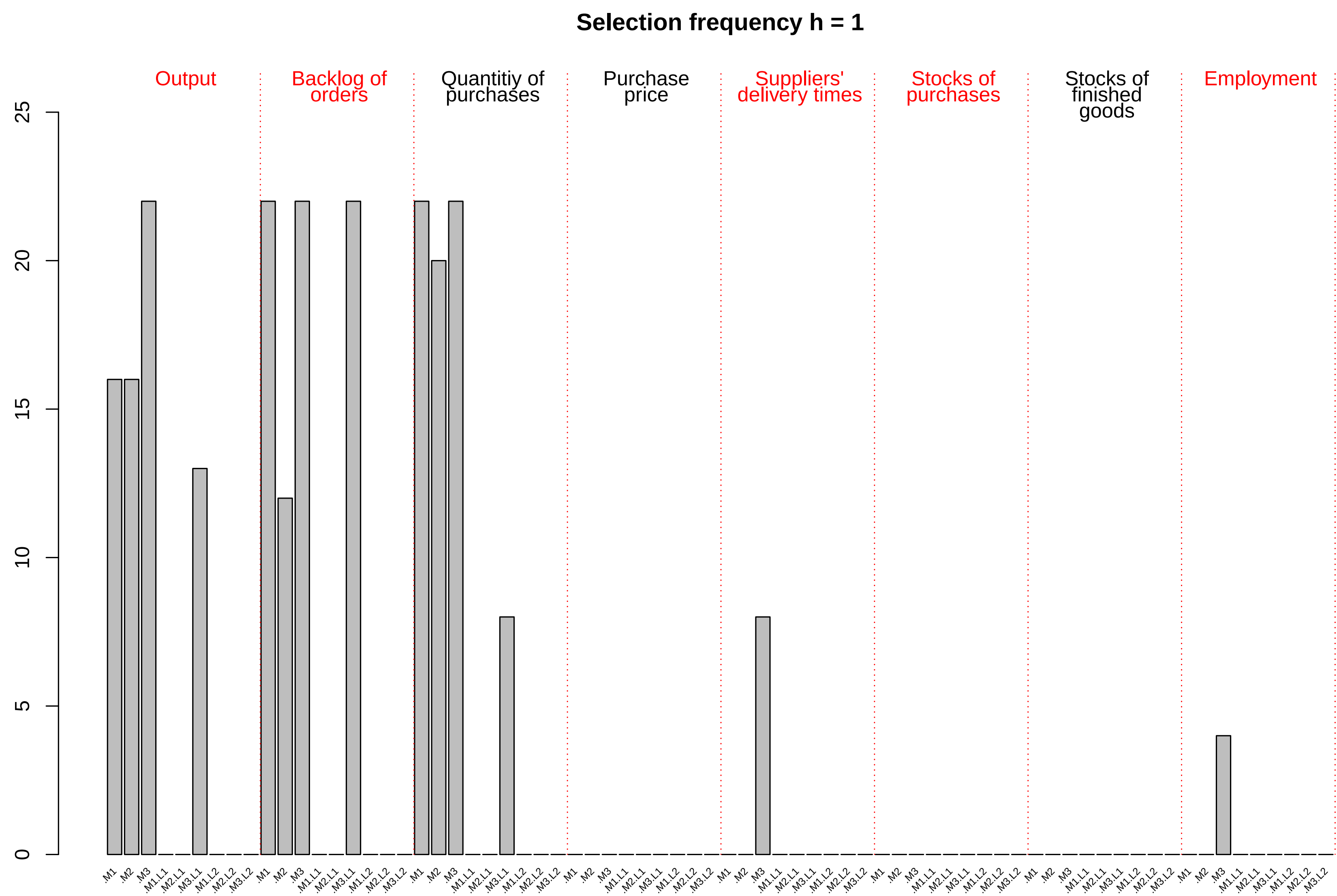

Figure 2: Selection frequency of each PMI component, $h = 1$

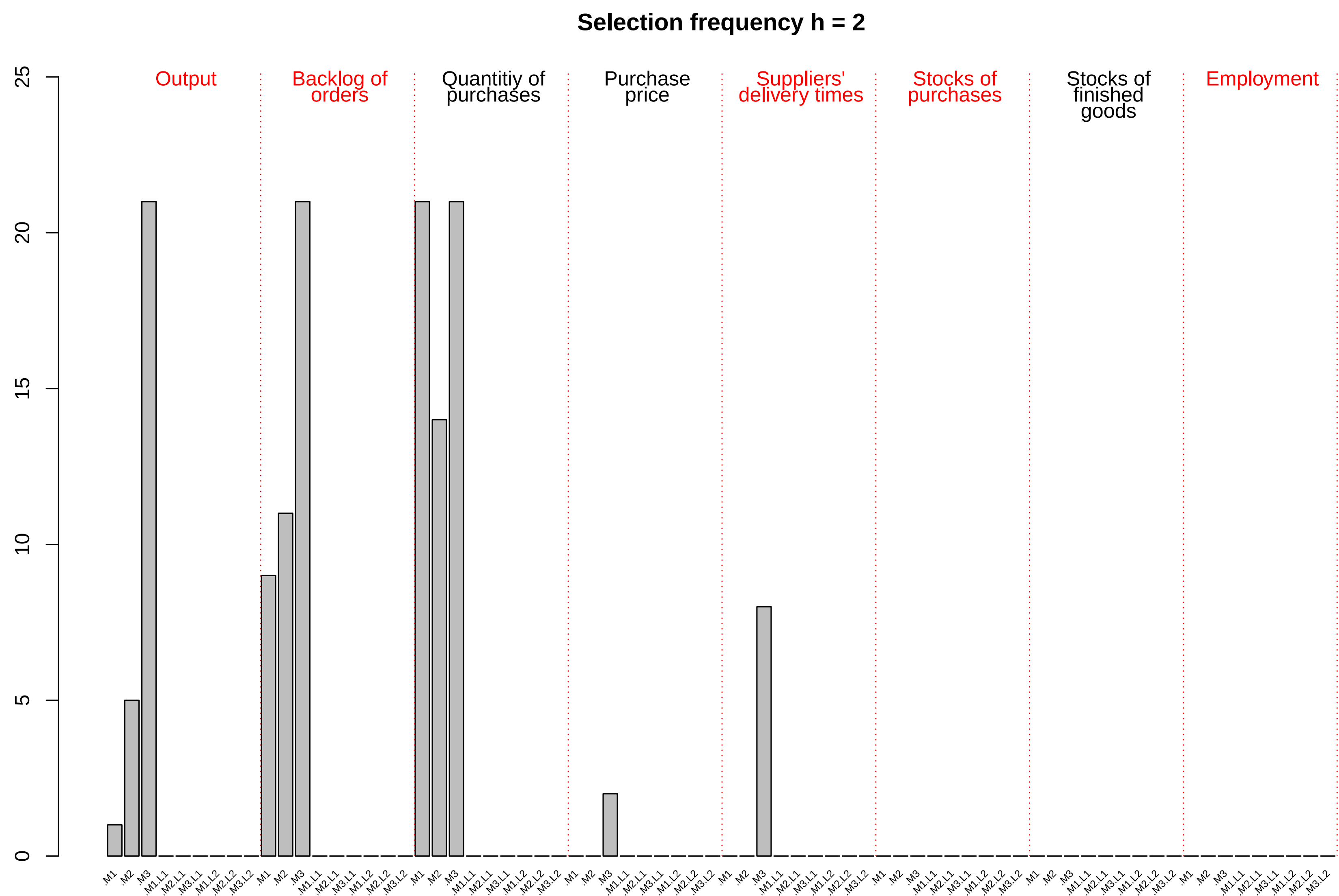

Figure 3: Selection frequency of each PMI component, $h = 2$