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Nowcasting the Global Economy

by James Rossiter

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James Rossiter

International Economic Analysis Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
jrossiter@bankofcanada.ca

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Abstract

Forecasts of global economic activity and inflation are important inputs when conducting monetary policy in small open economies such as Canada. As part of the Bank of Canada's broad agenda to augment its short-term forecasting tools, the author constructs simple mixed-frequency forecasting equations for quarterly global output, imports, and inflation using the monthly global Purchasing Managers Index (PMI). When compared against two benchmark models, the results show that the PMIs are useful for forecasting developments in the global economy. As the forecasts are updated throughout the quarter with the monthly release of the PMI, forecasting performance generally improves. An analysis of the forecasts over the period of the Great Recession (in particular, 2008Q4 to 2009Q2) shows that, while models that include the "soft" PMI indicators did not fully capture the sharp deterioration in the global economy, they nevertheless improved the forecasts relative to the benchmark models. This finding highlights the usefulness of such indicators for short-term forecasting.

JEL classification: E37, F47
Bank classification: Economic models; International topics

Résumé

Les prévisions de l'activité économique et de l'inflation à l'échelle mondiale sont des intrants importants dans la conduite de la politique monétaire au sein des petites économies ouvertes comme celle du Canada. Dans le cadre du vaste programme que s'est donné la Banque du Canada pour étoffer ses outils de prévision à court terme, l'auteur construit des équations de prévision simples à fréquence mixte pour la production, les importations et l'inflation mondiales trimestrielles en utilisant les indices des directeurs d'achats (indices PMI) mondiaux mensuels. La comparaison des résultats à ceux de deux modèles de référence montre que les indices PMI sont utiles pour prévoir l'évolution de l'économie mondiale. À mesure que les prévisions sont mises à jour tout au long du trimestre en fonction des indices PMI diffusés mensuellement, leur qualité s'améliore de façon générale. L'analyse des prévisions durant la période de la Grande Récession (en particulier du quatrième trimestre de 2008 au deuxième trimestre de 2009) révèle que, même si les modèles intégrant les indicateurs qualitatifs des indices PMI n'ont pas rendu pleinement compte de la brusque détérioration de l'économie mondiale, ils ont néanmoins permis d'améliorer la qualité des prévisions par rapport aux modèles de référence. Cette conclusion fait ressortir l'utilité de tels indicateurs dans l'établissement des prévisions à court terme.

Classification JEL : E37, F47
Classification de la Banque : Modèles économiques; Questions internationales

1. Introduction and Motivation

Small open economies are, by definition, highly exposed to foreign economic developments. Global activity and inflation, in particular, play important roles: they transmit foreign shocks to the domestic economy through trade and financial linkages. For Canada, global output growth is a key variable used in policy-making, since it is a useful gauge of demand for the country's exports (in the order of 40 per cent of GDP between 2000 and 2009) and a strong driver of commodity prices. Global imports add another layer of detail—they provide a more fine-tuned view of foreign demand.[1] Global inflation is important when assessing foreign price pressures on domestic inflation. For these reasons, it is important to have an accurate gauge of foreign economic developments when conducting domestic monetary policy.

As part of the Bank of Canada's broad agenda to augment its short-term forecasting tools, this paper develops simple mixed-frequency forecasting equations for quarterly global output, imports, and inflation using the monthly global Purchasing Managers Index (PMI). This paper complements Godbout and Jacob (2010) by demonstrating that the PMIs can be useful in forecasting global aggregate macroeconomic aggregates.[2] Since the forecast horizon under consideration is the current quarter, this type of forecasting is often referred to as "nowcasting."[3]

Few forecasting models of the global economy exist, and most are not geared towards short-term forecasting. Furthermore, to the author's knowledge, only three papers exist that focus on direct (near-) global *aggregates*: Jakaitiene and Dées (2009) for global growth, the OECD for its composite leading indicators (CLIs) (Nilsson and Guidetti 2008), and the aforementioned Godbout and Jacob (2010).[4] There are two possible reasons why forecasting short-term developments of key *global* macroeconomic variables has not been explored much in the literature. On an applied level, data quality and timeliness

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[1] Global imports are used to proxy global trade, since global exports *should* equal global imports, and import data are generally of higher quality, due to customs tracking.

[2] Godbout and Jacob (2010) focus primarily on country-specific PMI forecasts, and do not examine the forecasting ability of the PMIs on global inflation or imports.

[3] See Perevalov and Maier (2010) for an example of the Bank of Canada's work on nowcasting the U.S. economy, and Zheng and Rossiter (2006) and Gosselin and Tkacz (2010) for Canada.

[4] For real variables, Jakaitiene and Dées (2009) show that forecasting the global aggregate is improved by forecasting the aggregate directly.

concerns make short-term forecasting of the global economy particularly difficult. There is also an acute lack of truly "global" indicators, especially for real activity.

It is with these challenges in mind that this paper proposes a straightforward mixed-frequency model to forecast global economic variables in the short term. While the most simple nowcasting models are autoregressive (AR) or random-walk (RW) models, this paper investigates other timely and accurate high-frequency global economic indicators to determine whether the AR or RW models can be augmented to produce more accurate forecasts. The model is driven in large part by the monthly global PMI, which, as described in the following section, has a number of advantages over other global macroeconomic indicators.

The model works by forecasting missing monthly values for the PMI, and uses a quarterly "bridge" equation to provide forecasts for the first quarter of the forecast horizon. The focus of this exercise is narrow—in essence, it aims to extract information from the PMI data and lags of the dependent variable. As a result, the models can be used as a tool to assess the information content of the monthly PMI releases, providing a timely alternative forecast of global macroeconomic aggregates.[5]

Overall, the paper finds that the PMIs are a helpful addition to the global economic forecasting toolkit, with the nowcasts outperforming the benchmark models and generally improving within the quarter with each successive release of the monthly PMI data. The PMI-augmented forecasting equations, while superior to the benchmark AR and RW models, nevertheless underestimate the severity of the Great Recession.

The paper is organized as follows. Section 2 presents a discussion of the data. It is followed by a discussion of the methodology used and the presentation of the results. Next, the model's performance and predictions through late 2008 and early 2009 are examined. Finally, the conclusion summarizes the main findings.

[5] Similar research has been conducted at the European Central Bank (e.g., *Monthly Bulletin*, November 2007, Box 1), but it does not consider global imports or inflation, nor does it address the mixed-frequency nature of the PMI and global growth data.

2. Data

There are a number of issues that need to be considered when dealing with global aggregates, particularly in the short term. The dependent variables in this paper—global output, imports, and inflation—suffer from problems such as timeliness and quality. The model in this paper addresses the issue of timeliness by predicting global macroeconomic variables for the current quarter prior to their release.

A key goal of this paper is to augment the AR and RW models of global output, imports, and inflation with other timely indicators. Few such indicators exist on a global basis, though one could consider using data such as the OECD CLIs, industrial production, merchandise trade, and so on.[6] While these indicators may help explain historical movements in the global economy, they have two distinct shortcomings: they are released with a significant lag and they can be revised. The PMIs, however, are an ideal indicator for nowcasting the global economy, since they are released at a global level, on a monthly basis, within days following the reference month. As such, they should give a good idea of current global economic conditions.[7] In addition, they are one of the few direct measures of *real* global economic activity. Chronologically speaking, the next global indicator of real activity to be released for a given month is the OECD CLIs, which are published with about a 6-week lag and summarize growth only in the OECD (and some additional) countries.

The monthly PMI data are published by Markit Economics. The data cover various indicators in several sectors, including manufacturing and services (see Figure 1). They are published monthly, within days of the reference month, and the raw data are never revised.[8] The PMI data are created by surveying purchasing managers around the world and asking them a number of questions about their production and prices.[9] Answers are typically "yes," "no," or "no change," and the resulting index is a diffusion index

[6] The OECD CLIs are diffusion indexes designed to give early indications of which way an economy is heading. The CLIs include information from many sectoral monthly indicators across OECD (and some non-member) countries, such as retail sales, manufacturing orders, etc. The series is revised as indicator data are released and revised.

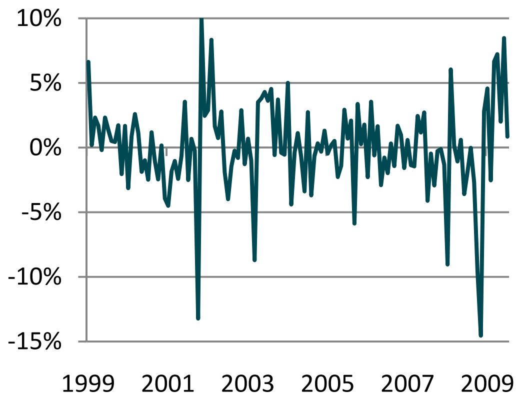
[7] For example, the global PMI data for September give us a good idea of real economic activity that month within the first few working days of October.

[8] The seasonal adjustment factors may be revised from time to time. More broadly speaking, real-time analysis of the models in this paper would be desirable to assess their forecasting performance. However, the global macroeconomic series is not available on a real-time basis.

[9] Markit Economics does not publish a detailed methodology for the PMIs. As such, it is impossible to know how the weighting scheme differs from that of the global macroeconomic aggregates.

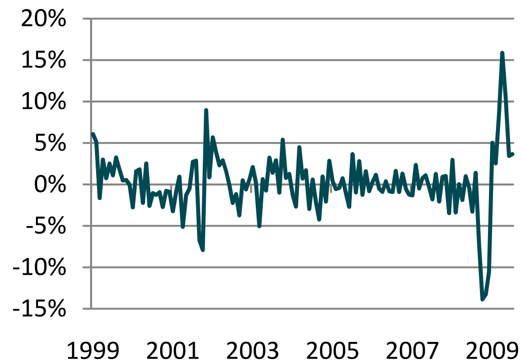
calculated as a sum of the “yes” plus one-half of the “no change” answers. As a result, 50 becomes a midpoint, with values below (above) 50 representing a deceleration (acceleration). One drawback of the survey is its simplistic response options: it lacks quantitative measures. For example, while all firms may report an expansion in production in a given month, there is no indication as to whether this expansion is by 2 per cent or 20 per cent. Another limitation of the PMI data for this paper is that they date back only to 1998. Finally, the PMI provides no information on the *levels* of economic activity. However, since forecasters are generally concerned with growth rates, this does not prove to be a significant problem.

Figure 1a: Global PMI Total Output



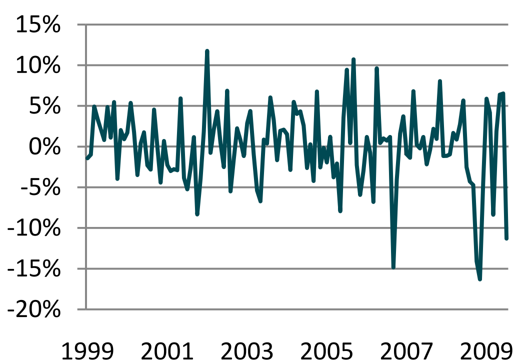
Sources: JPMorgan and Markit Economics

Figure 1b: Global PMI Manufacturing New Export Orders



Sources: JPMorgan and Markit Economics

Figure 1c: Global PMI Services Input Prices



Sources: JPMorgan and Markit Economics

The global aggregate data for output, imports, and CPI inflation cover close to 100 per cent of the world; Figure 2 plots the data and Table 1 provides summary statistics. The GDP and CPI data are calculated using purchasing-power parity weights (from the International Monetary Fund [IMF]), which vary over time. The imports data are calculated using nominal trade weights (again, consistent with IMF methodology). Most data are sourced from national statistical agencies, though some smaller countries’ data come from IMF databases. For global output growth and inflation, the unit root null hypothesis is not rejected, and so the forecasting equations are estimated using as dependent variables the *changes* in global output growth and inflation.[10] Global imports, however, are reported as quarter-on-quarter seasonally adjusted annualized per cent changes, for which the null hypothesis of a unit root is rejected.

Figure 2a: Global Output Growth

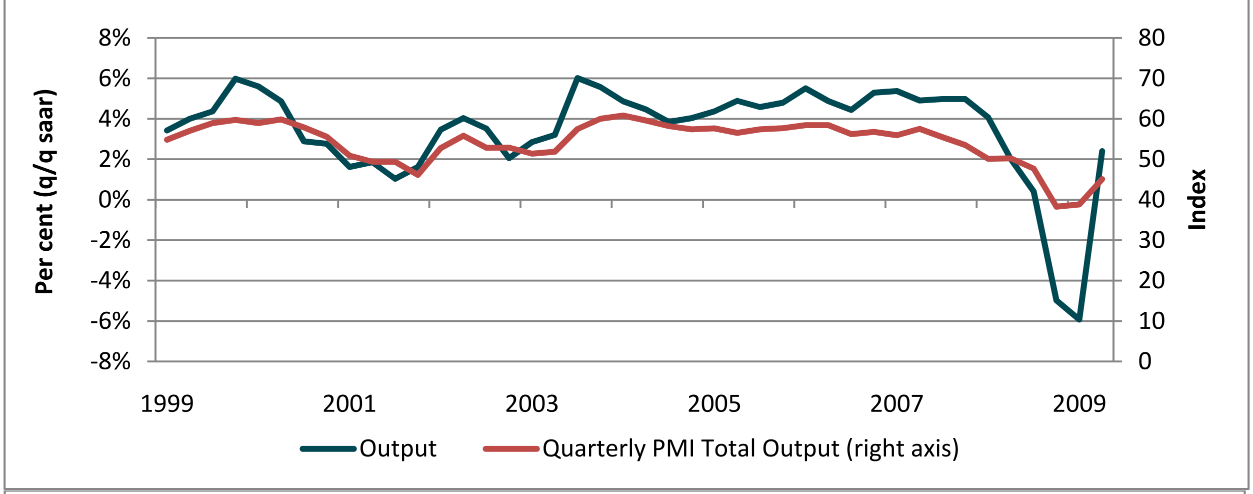
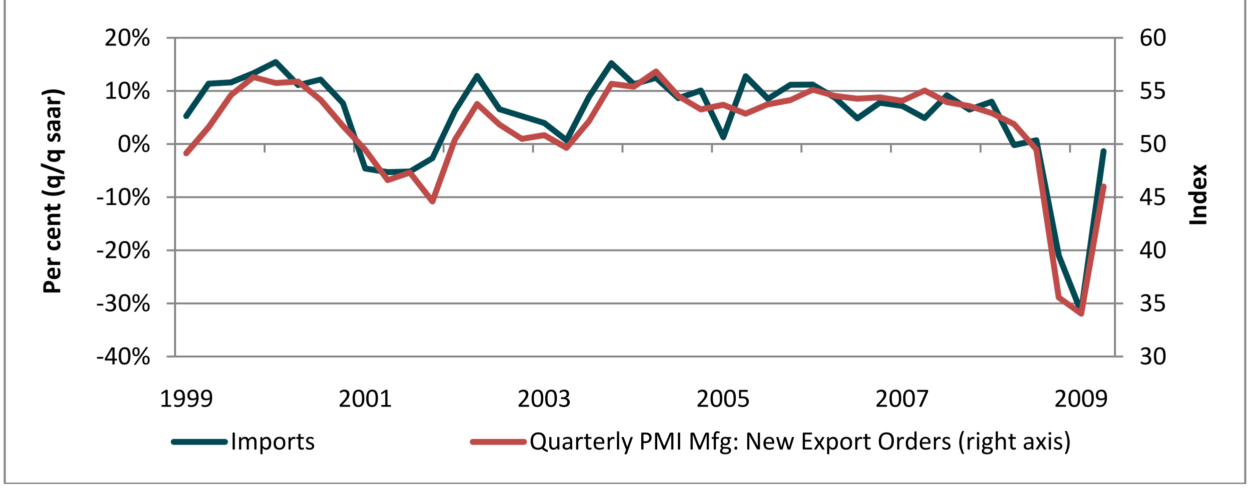


Figure 2b: Global Imports Growth



[10] The forecasted differences in the growth rates are then added to the previous period's growth rate, so that the results reported in tables and graphs in this paper are in the more familiar formats of output growth and inflation, and not of their differences.

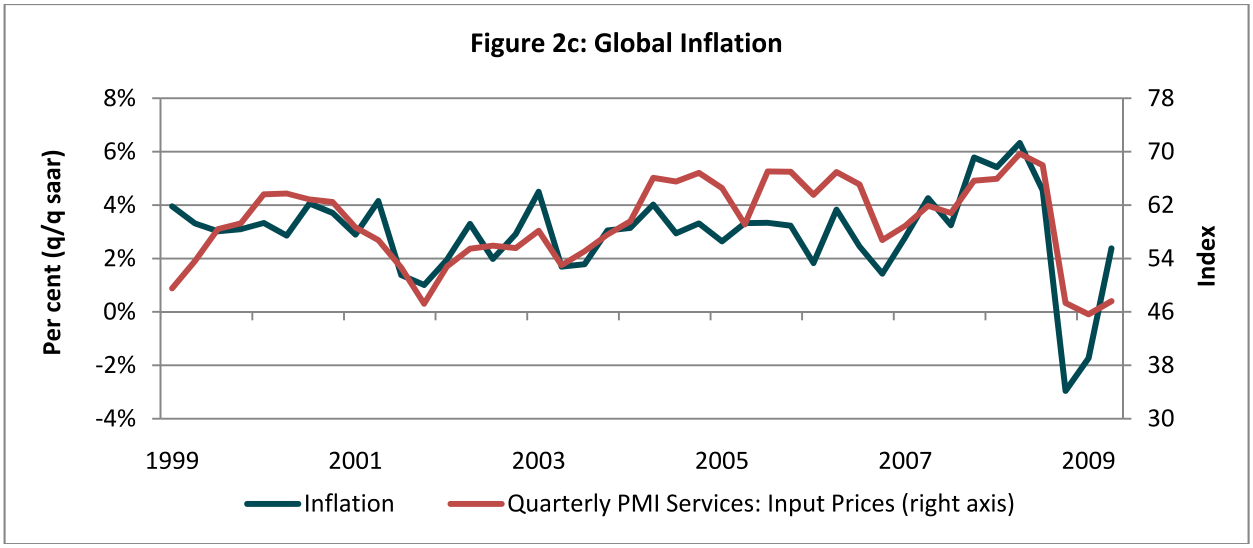


Table 1: Summary Statistics (%)

	Mean	Std Dev
Output Growth	3.5	2.5
Import Growth	5.3	9.1
Inflation	2.9	1.7

The PMI data are included in the models in two ways. First, like the macroeconomic aggregates, the PMI series enter as (stationary) quarter-on-quarter seasonally adjusted annualized growth rates. Second, they enter as a signed squared deviation from 50.[11] This is intended to capture possible non-linearities in the data. For example, it is possible that, during a time when many firms are increasing production, they are doing so by a faster rate than when only some firms are increasing production.[12]

3. Methodology

This paper first establishes two naïve benchmark models against which to compare the results of the PMI-augmented model. The first benchmark is a random-walk model, where the first-period forecasts for the global output growth, import growth, and inflation are equal to the last observed value. The second benchmark model is an autoregressive model, in which each global variable is regressed on lags itself. For macro data, these types of models traditionally perform reasonably well (Wallis 1989; Edge, Kiley, and Laforte 2009). The key challenge, then, is to determine whether the addition of global indicator variables—in this case, the PMI—can improve the forecasting performance of the benchmark models.

[11] More explicitly, as [(|PMI-50|) x (PMI-50)].

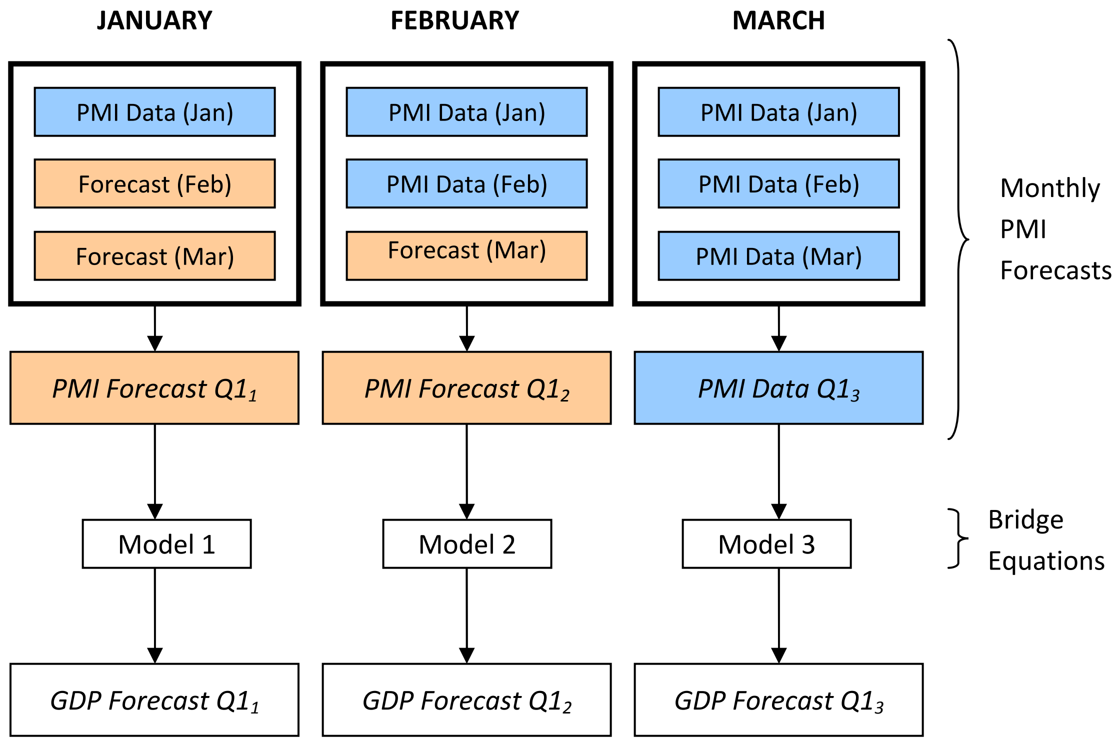
[12] Other variations were also tried, but not found to be significant.

The methodology used to incorporate the monthly PMI data into the quarterly model broadly follows that used in Ingenito and Trehan (1996) for the United States; Rünstler and Sédillot (2003) for the euro area; and Zheng and Rossiter (2006) for Canada. Like Jakaitiene and Dées (2009), this paper takes a global perspective, but merges the multi-frequency techniques of the former papers with the global focus of the latter (which uses only monthly data).

There are three steps to building the models. Figure 3 shows a schematic of the forecasting equations, using as an example the forecast of global output in the first quarter of the year. First, a quarterly *bridge* equation is specified, which maps growth rates in the known *quarterly averages* of the PMI data (*PMI Data* $Q1_3$) to the growth of the *quarterly* global macroeconomic variable in question. This equation contains only lagged growth of the dependent variable and the quarterly PMI data, and corresponds to "*GDP Forecast* $Q1_3$." Second, once it has been determined which PMI series best forecasts the global aggregate, monthly PMI forecasting equations are constructed. These serve to forecast the PMI data over months in the most recent quarter for which the PMI data have not yet been released. These monthly models thus provide a mix of historical (blue) and forecasted (orange) monthly PMI data over the entire quarter, which can then be converted into a quarterly value (*PMI Forecast* $Q1_1$ and $Q1_2$). Finally, once the growth rates of the quarterly aggregates of the PMI forecasts have been constructed, the bridge equations are then re-estimated two more times (*GDP Forecast* $Q1_1$ and $Q1_2$), so that there are three bridge equations for the first quarter: one for each month's PMI release.

The presumption is that the PMI variables will improve the forecasts relative to the benchmark models. Furthermore, the performance is expected to improve as the quarter progresses and more monthly PMI data are added to the model. In terms of model structure, a reasonable hypothesis is that the PMI series most important for each global variable is the one with which it most closely accords. For example, the PMIs for global output (total output, manufacturing output, or services activity) should be most significant in the global GDP equation. Likewise, the PMIs for new orders or, more narrowly, new export orders, should play an important role in the equation for global trade (proxied by global imports). Finally, one would expect the PMIs for input prices to play an important role in determining global inflation. The methodology, however, does not restrict itself to these priors, and tests many different PMI series in the equations, in order to construct the best nowcast of the global economy.

Figure 3: Schematic of the Forecasting Models



3.1. Quarterly bridge equations

The first step is to build a bridge equation, which is a statistical mapping of the various manipulations of the quarterly averaged PMI data (PMI^q), a constant (c_1), and lags of quarterly global differenced output growth, import growth, or differenced inflation (X) on itself:

$$\hat{X}_t = c_1 + \sum_{i=1}^{N} \hat{\beta}_i X_{t-i} + \sum_{j=1}^{M} \hat{\beta}_j PMI_{t-j}^{q} \tag{1}$$

The bridge equations are derived using a general-to-specific methodology.[13] The purpose of the bridge equation is straightforward: it links the quarterly averaged PMI data to the quarterly global economic variables.

[13] The most general specification includes up to four lags of the dependent variable, and up to four lags each of up to six relevant PMI variables. This implies as many as 30 independent variables, most of which are eliminated from the specification, since they are found to be statistically insignificant.

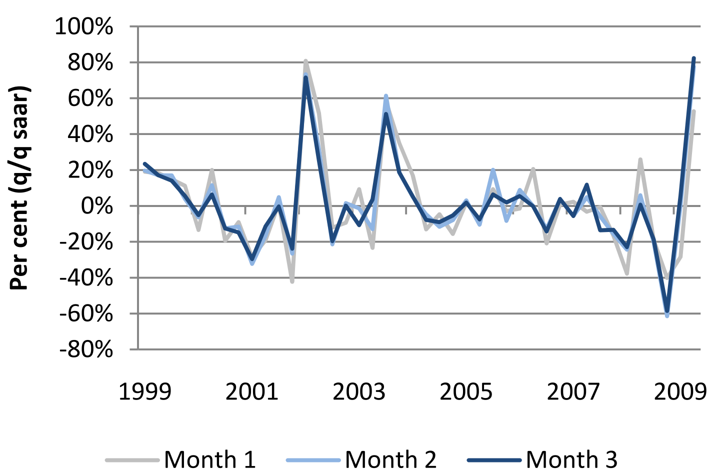
Since the initial bridge equations are estimated using three complete months of PMI data, they can be used only in one out of every three months of the quarter, when the PMI has been released for all three months (for example, this corresponds to the "March" column in Figure 3). In order to address the times when only one or two months of the PMI data are available (e.g., January or February in Figure 3), the monthly PMI data are forecasted over the remainder of the quarter, and the bridge equations are re-estimated using the *forecasted* quarterly averages of the PMI. Section 3.2 discusses how the monthly PMI forecasts are constructed.

3.2. Monthly PMI forecasts

The monthly forecasts of the missing current-quarter PMI data help bridge the frequency gap between the *monthly* PMI observations and the *quarterly* bridge equations. Growth rates of the unreleased monthly PMI data (PMI^m) are forecasted to the end of the current quarter as autoregressive processes with a constant c_2:[14]

$$\widehat{PMI}_t^m = c_2 + \sum_{i=1}^{N} \hat{\beta}_i PMI_{t-i}^m \quad (2)$$

Figure 4: Quarterly Forecasts for PMI: Total Output



In other words, for each month of the quarter for which the monthly PMI data have not yet been released, the dynamic forecasts are constructed. The monthly mix of historical and forecasted PMI data for the most recent quarter can then be averaged into a quarterly value that enters the quarterly bridge Equation (1) (see Figure 3).

[14] Technically speaking, the PMIs should not contain unit roots, since they are bounded by 0 and 100. However, statistical tests of the unit root null hypothesis are not rejected. For this reason, the monthly growth rates are used as regressors.

As each month of PMI data is released over the course of a quarter, the quarterly average PMI forecast is updated (as shown by the three lines in Figure 4). For this reason, when constructing the model, the bridge Equation (1) is re-estimated for each of the three sets of monthly information.

3.3. Quarterly bridge equations with monthly PMI forecasts

The quarterly bridge equations are re-estimated to include the Month 1 and Month 2 PMI forecasts, again using the general-to-specific methodology (this corresponds to Models 1 and 2 in Figure 3). The choice of PMI data is not limited to those used in the initial full-information quarterly bridge equations—the full general-to-specific exercise is repeated for each monthly information set. The adapted quarterly bridge equation is:

$$\hat{X}_t = c_3^q + \sum_{i=1}^{N} \hat{\beta}_i^q X_{t-i} + \sum_{j=0}^{M} \hat{\beta}_j^q \widehat{PMI}_{t-j}^q \tag{3}$$

Note the one important distinction from Equation (1): the quarterly PMI variable on the right side of Equation (3) may be a *forecast* of the growth rate or squared deviation from 50, depending on the number of months of PMI data available (only when all three of the quarter's months of PMI data are released is this variable purely historical data, as in Equation (1)).

4. Results

This section discusses the models used to construct nowcasts of the global economy. All equations are estimated over the sample period 1999Q1 to 2008Q3.[15]

4.1. Benchmark models

The quarterly benchmark models perform largely as expected. The root mean squared errors (RMSE) for the random-walk models are provided in Table 2.[16]

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[15] Estimates that include the most recent historical data are problematic, since the variance during that period dominates the rest of the sample, and severely affects the estimates. Thus a variable that closely follows the large downswings in growth and imports over just two recent quarters may be highly statistically significant in the regression, even if it has little explanatory power earlier in the sample.

[16] Since the nowcasts produced by the model concern only the first quarter for which data are unavailable, the RMSEs are equal to the in-sample root mean squared forecast errors.

Table 2: RMSEs for Random-Walk Models (q/q saar)

	Output Growth	Import Growth	Inflation
RMSE	1.0%	4.9%	1.2%

The RMSEs are 1 per cent for output growth, 5 per cent for import growth, and just over 1 per cent for inflation. The higher RMSE for global import growth is due to the series being more volatile (see Table 1). Results for the autoregressive benchmark models are shown in Table 3.

Table 3: Results for Autoregressive Models

		Output Growth*	Import Growth	Inflation*
Constant			0.0275 (2.23)	
Lags	T-1		0.603 (4.42)	-0.519 (-3.12)
	T-2			-0.314 (-1.88)
	T-3	-0.388 (-2.25)		
R^2 Adjusted		0.10	0.33	0.19
RMSE		0.9%	4.6%	1.1%

* Output and inflation estimated as the difference of the growth rate.

Predictably, the RMSEs for these forecasting equations are lower than for their RW counterparts. While the forecasting performance of the RW and AR models may appear poor, these types of naïve time-series models often outperform more complex econometric macroeconomic models, especially in the near term, and therefore form suitable benchmarks for the analysis.

4.2. Quarterly bridge equations

Table 4 reports the results for the quarterly bridge equations for differenced global GDP growth, import growth, and differenced inflation. The change in global output growth is well described by the PMI data; the RMSE of the global growth forecast is considerably below those of the benchmark models, at 0.7 per cent (q/q saar).[17] The model is parsimonious—only the third lagged value of global output and the contemporaneous change in the PMI series for *Total Output* are significant (and of the expected sign). The regressions pass statistical tests (Breusch-Godfrey, Ljung-Box, and Durbin-h), as shown in the table.

[17] Note that the RMSEs shown in the tables are calculated as the RMSEs of the growth rate, and not the change in the growth rate (the dependent variable for the global output equations).

Table 4: Quarterly Bridge Equations with Full-Quarter PMI Data

		Output Growth*	Import Growth	Inflation*
Constant			0.0281 (3.81)	
Lagged Dependent	T-1			-0.407 (-3.22)
	T-3	-0.355 (-2.52)		
PMI Total: % (Output)	T	0.0279 (4.25)		
PMI Manufacturing: % (New Export Orders)	T		0.178 (5.52)	
	T-1		0.257 (7.81)	
Squared Dev from 50	T-2		0.00275 (6.97)	
PMI Services: % (Input Prices)	T			0.0269 (4.57)
R^2 Adjusted		0.40	0.72	0.44
RMSE		0.73%	3.0%	0.90%
Breusch-Godfrey X^2 (p-val)		0.89	0.73	0.16
Ljung-Box Q-Stat (p-val)		0.63	0.68	0.41
Durbin-h Statistic (p-val)		0.89	0.75	0.17

* Output and inflation estimated as the difference of the growth rate.

The quarterly bridge equation for global import growth also performs quite well. As expected, the role for the *PMI Manufacturing: New Export Orders* series is important for explaining global import growth, and its growth rate appears in the equation both contemporaneously and with a lag. The squared deviation is also significant at two lags. The RMSE, at 3.0 per cent (q/q saar), is unsurprisingly higher for trade than for output, since the series is much more volatile. However, relative to the series' standard deviation, it is comparable to that of the global output equation (see Table 1), and again, the addition of the PMI variables makes the model superior to the benchmark models. The equation passes all statistical tests presented in the table.

Finally, differenced global inflation is well described by its lags and the PMI for *Services: Input Price*, which enters contemporaneously into the quarterly bridge equation. The R^2-adjusted of the equation is 0.44, and the RMSE is lower than those of the benchmark models.

4.3. Monthly PMI forecast equations

The growth rates of the monthly PMIs are forecast as autoregressive functions. However, the best forecast for all three series is no change, implying a random walk in levels for the PMI series.[18] Quarterly averages of the PMI series are thus constructed using the monthly forecasts of no change, and the new quarterly series are used as dependent variables to estimate the bridge equations for each of 1- and 2-month's availability of PMI data (as in Equation (3)). Figure 4 shows an example of such quarterly PMI forecasts for the series *PMI: Total Output*.

4.4. Quarterly bridge equations with monthly PMI forecasts

Table 5 reports the results of the quarterly bridge equations for each monthly PMI release, estimated from 1999Q1 to 2008Q3.[19] To facilitate comparison across monthly information sets, the quarterly bridge equations from Table 4 that contain all three months of PMI data are reproduced in Table 5. Some broad trends are evident in the results. Generally speaking, for each indicator, each of the three equations is relatively similar, both in structure and in coefficients. Diebold-Mariano tests using a squared loss function show that the forecasting performance (as measured by the RMSEs) is relatively unchanged between the first and second month's release of the PMI, but improves between the second and third month's release (see Figure 5). The statistical significance of the PMI series in each global equation matches our priors; for example, the PMI series for *Total Output* matters most for global GDP. The results suggest that the PMI-augmented models are superior to the benchmarks, regardless of the months of PMI data available, confirming our priors.

[18] This is purely coincidental. Because the third step in constructing the quarterly forecasting equations requires a respecification of the bridge equation, monthly forecasts were constructed for more PMI series than just those presented in the previous section. Other monthly PMI series were forecastable using autoregressive specifications, though the explanatory power remained weak due to the volatility of the series.

[19] The equations are estimated using Newey-West corrected errors.

Table 5: Forecast Equations for Each Month's Information Set

		Output Growth*			Import Growth			Inflation*		
		Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3
Constant					0.0249 (2.27)	0.0230 (2.05)	0.0281 (3.81)			
Lagged Dependent	T-1							-0.613 (-4.02)	-0.468 (-3.66)	-0.407 (-3.22)
	T-2				0.538 (4.48)	0.563 (4.54)				
	T-3	-0.380 (-2.43)	-0.390 (-2.75)	-0.355 (-2.52)						
PMI Total: % (Output)	T	0.0158 (2.87)	0.0248 (4.15)	0.0279 (4.25)						
PMI Manufacturing: % (New Export Orders)	T				0.130 (4.03)	0.146 (3.91)	0.178 (5.52)			
	T-1				0.159 (4.26)	0.171 (4.61)	0.257 (7.81)			
Squared Dev from 50	T-2						0.00275 (6.97)			
PMI Services: % (Input Prices)	T							0.0260 (3.39)	0.0264 (4.51)	0.0269 (4.57)
R^2 Adjusted		0.26	0.39	0.40	0.57	0.57	0.72	0.32	0.43	0.44
RMSE		0.81%	0.74%	0.73%	3.7%	3.7%	3.0%	0.99%	0.91%	0.90%
Breusch-Godfrey X^2 (p-val)		0.36	0.69	0.89	0.48	0.63	0.73	0.45	0.41	0.16
Ljung-Box Q-Stat (p-val)		0.94	0.73	0.63	0.93	0.93	0.68	0.87	0.22	0.41
Durbin-h Statistic (p-val)		0.38	0.70	0.89	0.51	0.65	0.75	0.46	0.42	0.17
Diebold-Mariano (p-val) (relative to previous month)			0.63	0.13		0.40	0.13		0.27	0.10

* Output and inflation estimated as the difference in the growth rate.

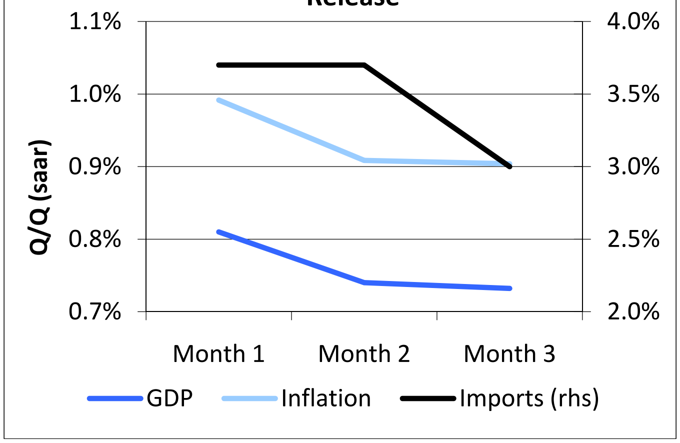


Figure 5: RMSEs for Each Month's PMI Release

Figure 6 shows the evolution of the forecast errors over each quarter. The grey bar shows the forecast error with only one month of PMI data; the light blue bar shows the forecast error when two months of PMI data are available; the dark blue bar shows the error for when all three months are available. Table 6 reports the momentum ratio results.[20] The models all forecast the correct momentum of the dependent variable at least 50 per cent of the time. As expected, the ratio improves (or, at minimum, remains unchanged) as the monthly PMI data are added to the information set.

Table 6: Momentum Ratio (%)

	Month 1	Month 2	Month 3
Output Growth	50	55	60
Import Growth	78	78	80
Inflation	73	83	88

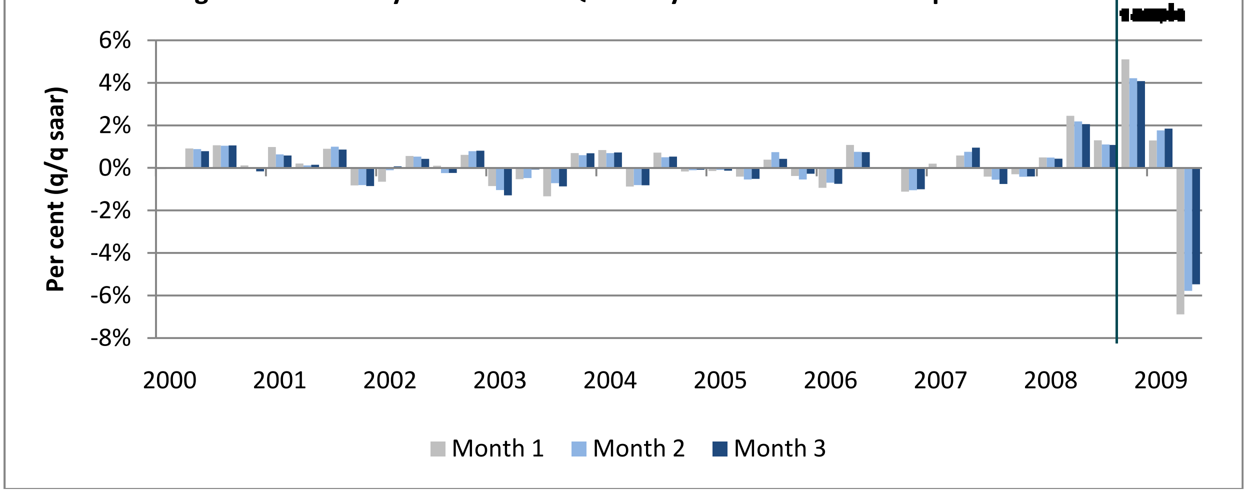


Figure 6a: Monthly Evolution of Quarterly Forecast Errors: Output Growth

[20] The statistics show the frequency with which the models predicted the correct direction of change in the *growth rate*.

Figure 6b: Monthly Evolution of Quarterly Forecast Errors: Import Growth

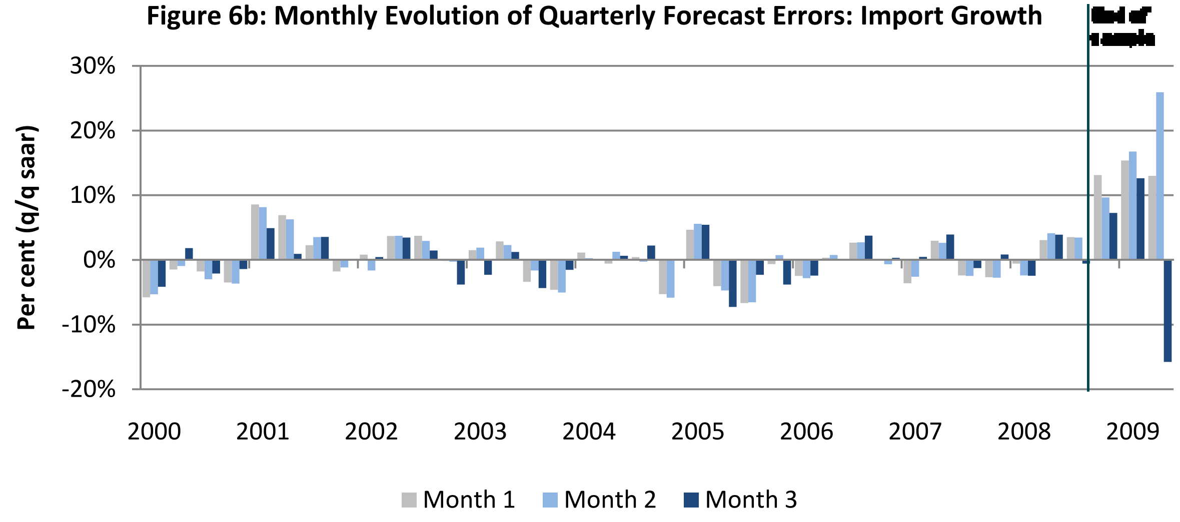
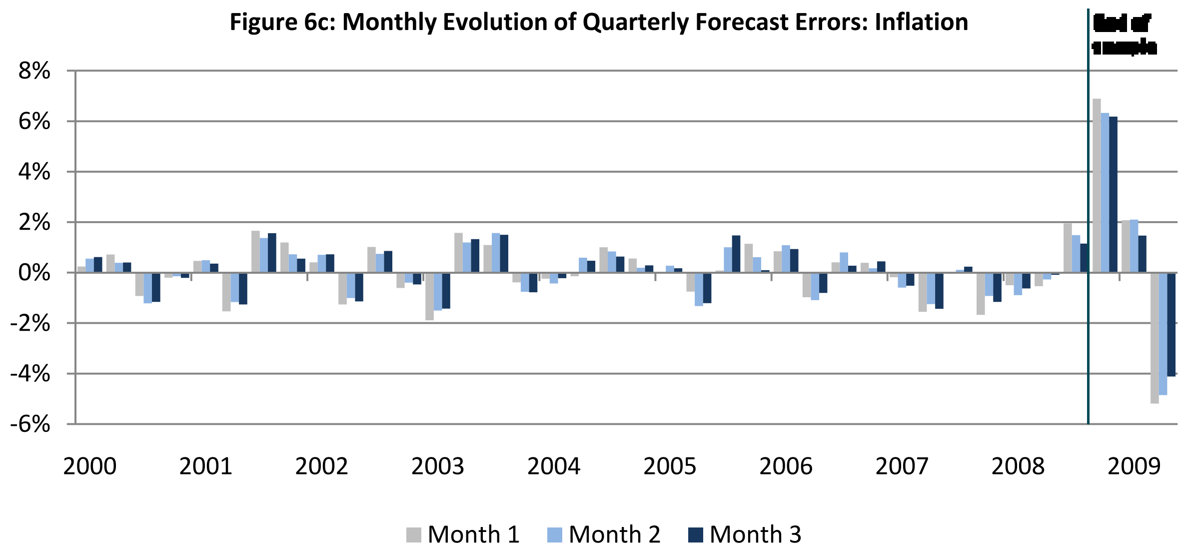


Figure 6c: Monthly Evolution of Quarterly Forecast Errors: Inflation



5. The Great Recession

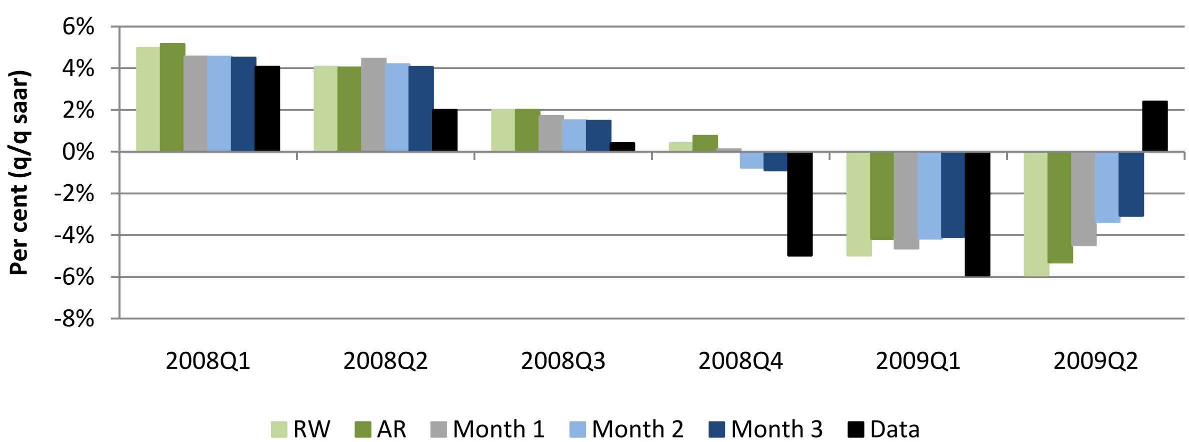
The speed of the sharp deterioration in the global economy at the end of 2008 (as shown in Figure 2) came as a surprise to most forecasters. The synchronous declines in output and imports among industrial countries, in particular, were unprecedented since the Great Depression, and the downward pressure on inflation from the sharp drop in economic activity and lower commodity prices was considerable. Since the benchmark models rely only on lags, they did not predict the sudden deterioration. The PMI data, however, with its global scope and rapid publication, may have provided an early indication of the degree and pace of deterioration in the global economy (as shown in Figure 2).

This section investigates the performance of the models containing the PMIs versus the benchmarks over the “Great Recession” period, focusing on 2008Q1 to 2009Q2.

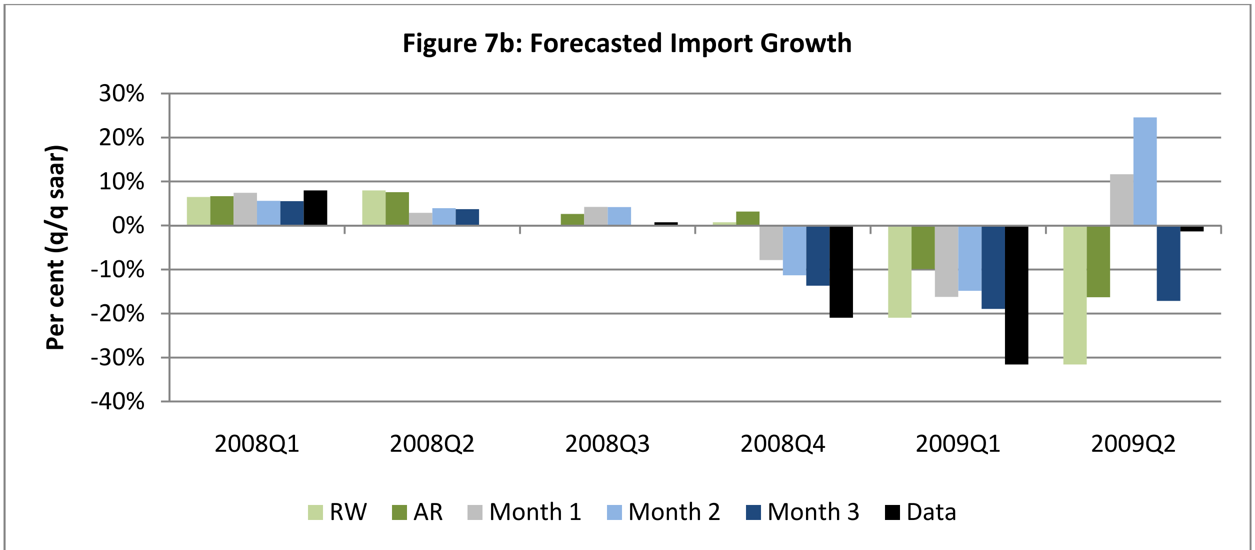
5.1. Benchmark models

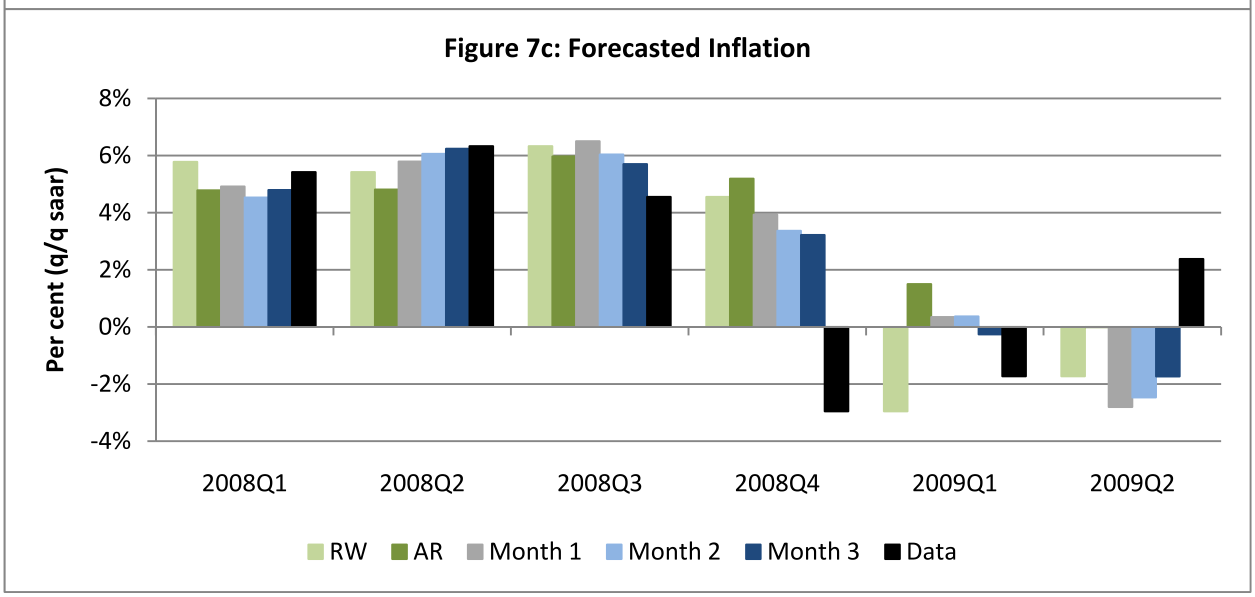
The AR and RW models are again used as benchmark models for the analysis of the Great Recession. Figure 7 plots the forecasts of global output growth, import growth, and inflation over the period 2008Q1 to 2009Q2 for the benchmark models, the quarterly bridge equations, and the historical data.[21] Table 7 summarizes the root mean squared forecast errors (RMSFE) of the models over this period. The graphs and table show that the naïve benchmark models generally did not foresee the sharp declines in output, imports, and inflation at the end of 2008.

Figure 7a: Forecasted Output



[21] The estimation sample includes data to 2008Q3, just before the Great Recession started. The period 2008Q1 to 2008Q3 is shown in the graphs for illustrative purposes.





5.2. Did the PMIs help forecast the Great Recession?

This section focuses first on how large the forecast errors are during the period, and then on how much the forecasts improve as more information is added to the model. Since the estimation sample does not include the Great Recession, this gives a good idea of what the PMIs would have forecasted at the time. Figure 6 shows the forecast errors over this period, and Figure 7 the monthly evolution of quarterly forecasts, along with the benchmarks. Table 7 reports the root mean squared forecast errors over this period, as progressively more data are added to the models.

Table 7: RMSFEs: 2008Q1 to 2009Q2 (%)

	Model	RMSFE (q/q saar)
GDP Growth	RW	3.2
	AR	3.3
	Month 1	2.9
	Month 2	2.6
	Month 3	2.5
Import Growth	RW	12.2
	AR	12.0
	Month 1	8.1
	Month 2	10.4
	Month 3	7.1
Inflation	RW	2.7
	AR	2.9
	Month 1	2.9
	Month 2	2.7
	Month 3	2.3

For global output growth, the bridge equations generally predict the correct sign over the first two quarters examined. The model underpredicts the magnitude of the decline in 2008Q4 quite significantly, but does an adequate job in 2009Q1. In 2009Q2, the indicator model underpredicts all three variables, even with all three months of data. Compared with the benchmark models, however, the PMIs reduce the RMSFE fairly significantly—especially once the second month's PMI has been released.

The bridge equations for global import growth tend to perform somewhat better. The sign of the deterioration is correctly predicted in both 2008Q4 and 2009Q1. For 2009Q2, however, the PMI data provide a mixed picture. The equation forecasts increasing imports for that quarter during the first two months, but then forecasts a decline in imports with all three months of PMI data. In the end, imports fell only slightly. Again, the inclusion of the PMI in the models improves the RMSFEs relative to the benchmark models.

Finally, the quarterly bridge equations for global inflation tend to converge towards the final data release as more PMI data are released, but they generally do not predict the correct sign of global inflation. The discrepancy between the forecasts and released data is at its greatest in 2008Q4 and 2009Q2: in both these periods, neither the bridge equations nor the benchmarks correctly predicted the sign of inflation, with the exception of the RW model in 2009Q1.

As Table 7 shows, the addition of the PMI data to the models generally improves the forecasts, in some cases considerably. For global output, each additional month of data reduces the RMSFE (relative to the benchmarks), with the largest improvements coming from the first month's PMI release. For global imports, the first month's PMI release also reduces the RMSFE considerably, though, curiously, the addition of the second month of PMI data unwinds about half the improvement. For global inflation, the biggest gains come from the third month's release of the PMI data.

Overall, the models that include the PMI data outperform the benchmarks during this period of high economic volatility, suggesting that the "soft" PMI indicators contain useful information for forecasting.

6. Conclusion

Global economic developments are important to small open economies such as Canada. Therefore, policy-makers need tools to gauge accurately the state of the global economy. This paper contributes to the Bank of Canada's agenda to augment its short-term forecasting tools by constructing a model that uses mixed-frequency forecasting equations to forecast quarterly global output growth, import growth, and inflation with the monthly global Purchasing Managers Index. When compared against two benchmark models, the results suggest that the PMIs are useful for forecasting developments in the global economy. As the forecasts are updated throughout the quarter with the monthly release of the PMI data, forecasting performance generally improves. However, an analysis of the performance of the models over the period of the Great Recession (in particular, 2008Q4 to 2009Q2) shows that the performance of the models containing these soft indicators did not forecast the full extent of the strong deterioration in the global economy. Still, compared to the benchmark models during this period, the PMI indicator models provided more accurate forecasts. This suggests that soft indicators, while not perfect forecasters, do add important additional information to short-term nowcasting models.

One key extension to this model would be to assess its forecasting performance in real time. However, as mentioned, real-time data for global output, imports, and inflation are not available. One could perhaps use the OECD's real-time database to proxy revisions to the global aggregates, but this method would be imperfect, since data on non-OECD countries tend to be more heavily revised. Another extension would be to extend the forecasting horizon to two or three quarters. However, the results of the nowcasting exercise indicate that the PMIs have the strongest predictive power for the contemporaneous quarter, so it is not clear how accurate longer-horizon forecasts would be. For the longer-horizon forecasts, structural models of the global economy, such as the Bank of Canada's version of the Global Projection Model, would likely be superior.

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