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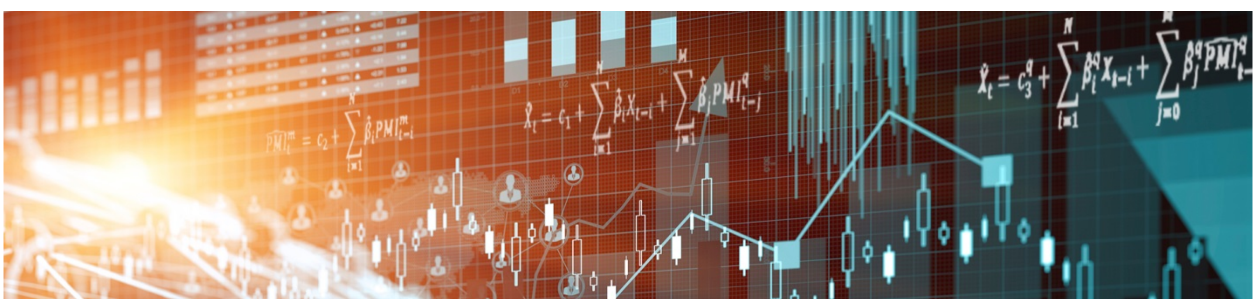
Global Real Activity for Canadian Exports: GRACE



by André Binette, Tony Chernis and Daniel de Munnik

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Abstract

Canadian exports have often disappointed since the Great Recession. The apparent disconnect between exports and the Bank of Canada's current measure of foreign demand has created an impetus to search for an alternative. Based on a dynamic factor model (DFM) methodology, we use a broad range of international economic indicators (close to 300) to estimate external demand for Canadian exports. The new measure, Global Real Activity for Canadian Exports (GRACE), follows Binette et al. (2014) who suggest that a mix of global final expenditure and production variables could help better identify activity relevant to Canadian exports. They also suggest that non-US variables might be relevant. GRACE uses final expenditure and production variables not only from the United States but also for all of Canada's major trading partners. We apply this approach to total exports and 14 subaggregates of Canadian exports. Overall, we find that this new measure has good theoretical and empirical properties, especially for higher-level aggregates.

Bank topics: Econometric and statistical methods; Balance of payments and components; Exchange rates

JEL codes: F10; F14; F43

Résumé

Les chiffres des exportations canadiennes tendent à décevoir depuis la Grande Récession. L'apparent décalage entre les exportations observées et la mesure de la demande étrangère utilisée par la Banque du Canada a constitué une incitation à rechercher une autre mesure. En nous appuyant sur un modèle factoriel dynamique et un grand nombre d'indicateurs économiques internationaux (près de 300), nous estimons la demande extérieure de biens et de services canadiens. La nouvelle mesure — GRACE (pour *Global Real Activity for Canadian Exports*) — s'inspire de Binette et autres (2014), dont l'étude semble indiquer qu'un groupe de variables internationales concernant la dépense finale et la production pourrait permettre de mieux discerner les secteurs où l'activité influe sur les exportations canadiennes. Il ressort aussi de cette étude que des variables relatives à d'autres pays que les États-Unis pourraient avoir de l'importance. GRACE exploite des variables liées à la dépense finale et à la production, aussi bien pour les États-Unis que pour tous les principaux partenaires commerciaux du Canada. Nous appliquons notre méthode à l'ensemble des exportations ainsi qu'à quatorze sous-catégories de biens et de services exportés par le Canada. De façon générale, la nouvelle mesure a de bonnes propriétés théoriques et empiriques, tout particulièrement en ce qui a trait aux grandes catégories de biens et services.

Sujets : Méthodes économétriques et statistiques; Balance des paiements et composantes; Taux de change
Codes JEL : F10; F14; F43

I. Introduction

Given Canada is a small open economy, exports are a fundamental component of the country's economic fortunes. Canadian exports account for over one-third of gross domestic product (GDP) and the data are highly volatile on a quarterly basis, with a standard deviation of more than 10 per cent since 1981 (quarter-over-quarter at annual rate). This means that exports can routinely drag or add about 3 percentage points to GDP growth.[1] Altogether, this makes understanding the drivers of exports critical for monetary policy in Canada.

Unsurprisingly, a significant amount of work at the Bank of Canada has focused on creating a measure of foreign activity that is useful for explaining Canadian exports. Recently, Morel (2012) constructs a measure of foreign activity that takes into account the composition of US demand for Canadian exports.[2] While this framework has some desirable properties (i.e., estimate weights and identify key components of US demand), it is limited to non-commodity exports (NCX). Furthermore, Canadian exports have often disappointed since the Great Recession. In particular, they stumbled in 2012 and in the past year. While the weakness is more obvious in NCX, non-energy commodity exports (NECX) have also been weak. The apparent disconnect between exports and the Bank's current measure of foreign demand created an impetus to search for an alternative.

In this context, we propose a more comprehensive approach to measuring foreign demand for Canadian exports. Our approach builds on work by Binette et al. (2014), which suggests that a mix of global final expenditure and production variables could help better identify activity relevant to Canadian exports. They also suggest that non-US variables might be important. To incorporate these findings, we use a factor model, which is a standard methodology used to summarize co-movement across many variables (e.g., Binette and Chang 2013; Khan, Morel and Sabourin 2015). In brief, our method focuses on a subset of about 300 international variables, from which we select those most strongly related to Canadian exports. Using this preselected set of variables, we generate a measure of global real activity for Canadian exports (GRACE) with a dynamic factor model (DFM). We then use the DFM results in a traditional error-correction model (ECM) framework, controlling for structural factors such as competitiveness and loss of capacity. We find that GRACE is a good measure of foreign demand—it has a clear long-run relationship with exports and the other variables used in the equation (cointegration), it explains a large proportion of its movements (in-sample fit) and it is useful for forecasting. Our approach focuses on total exports but given the flexibility of this method, we also applied it to 14 different subaggregates of exports.

[1] The mean absolute contribution to GDP growth is 2.7 percentage points, while the 75th percentile is 3.7.
[2] The first measure of foreign demand used by the Bank of Canada was the US Activity Index (Bank of Canada 2009). A precursor to all of this work on foreign demand is Dion, Laurence and Zheng (2005).

The paper is structured as follows. We first review the Canadian exports and international data utilized in this paper. Second, we discuss the methodology used to select the data and extract the measure of global real activity. This is followed by an overview of the ECM framework, after which we examine in-sample and pseudo-out-of-sample results. Finally, we conclude with a brief summary.

II. Data

Canadian exports data

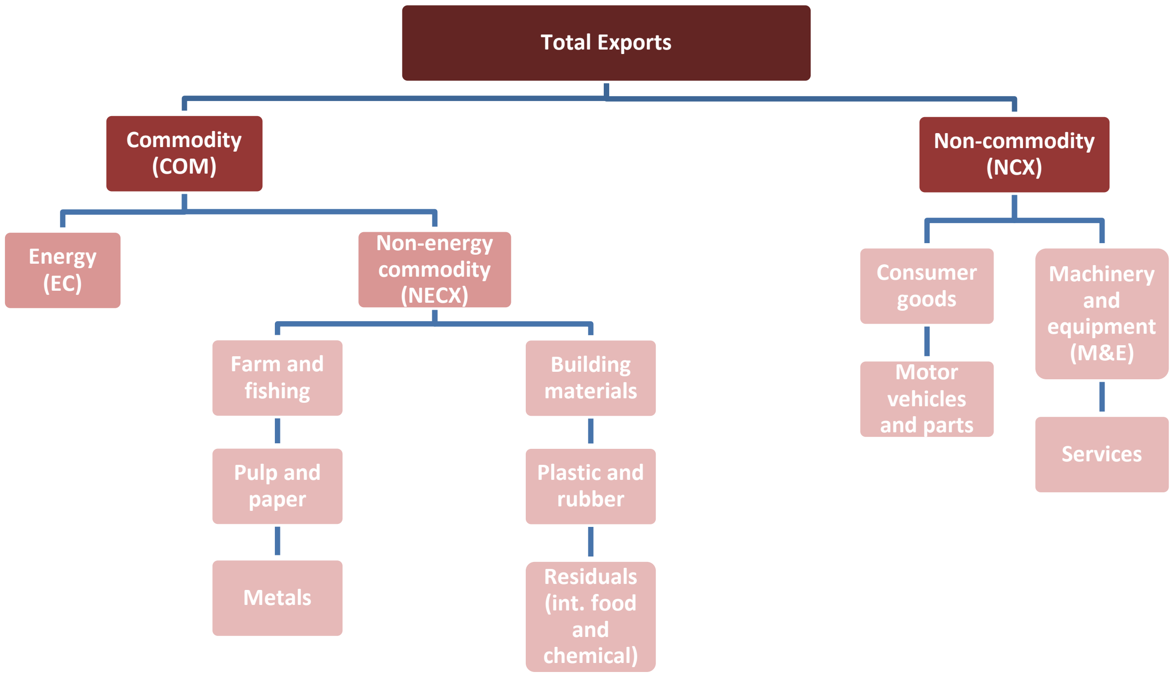
Quarterly Canadian export data are extremely volatile and are subject to revisions, rendering forecasting very challenging.[3] That said, many product categories are available—36 are released with the quarterly Canadian System of National Accounts—which allows for detailed analysis.

The initial objective of this work is to build a measure of foreign demand that can explain and forecast total exports (as opposed to the previous work by Morel (2012), which focused mostly on NCX). That said, our framework allows us to explore exports at a more disaggregated level. Figure 1 shows the different categories we examine. We look at 14 aggregates of exports based on our ability to model it successfully.[4] At the lowest level of aggregation, we choose 10 categories to balance the need for a richer analysis against the difficulty in modelling lower aggregates. Even for large aggregates such as NCX and commodities (COM), the standard deviation of their annualized quarterly growth rates are 11.9 per cent and 9.3 per cent, respectively. For more specific product categories, the volatility can increase to astounding sizes, such as for motor vehicles and parts (32 per cent) and farm and fishing (33 per cent). There are many reasons for the substantial variation, such as lumpy shipments, weather conditions, etc. This makes it challenging to examine much lower export aggregates as it becomes more difficult to tune the variable selection, extract a meaningful measure of global demand, and thus specify the ECM while maintaining parsimony.

[3] Monthly export data are also published by Statistics Canada but exclude services.

[4] GRACE is estimated for NCX and commodity exports, as well as for the following subaggregates: consumer goods, machinery and equipment, motor vehicles and parts, services, energy products and non-energy commodity exports, which can be further decomposed into farm and fishing, building materials, pulp and paper, plastic and rubber, metals, and a residual that includes intermediate foods and chemical products.

Figure 1: Export subaggregates



International data

The international data set used to estimate foreign demand covers Canada's top trading partners (the United States, euro area, China, the United Kingdom, Japan and Mexico), which represented about 90 per cent of our exports in 2015. The data set was built to be as comprehensive as possible, covering many indicators of economic activity. It includes hard indicators such as US industrial production and the National Accounts of Japan, and soft indicators such as China's Purchasing Manager Index (PMI) and euro area consumer confidence.

Overall, we have 298 global activity indicators. These series are seasonally adjusted and appropriately differenced to obtain stationarity. Table 1 and Figure 2 summarize the panel of international variables (a detailed list of variables is available upon request). Overall, roughly 30 per cent of the data set is represented by US variables (88), followed by the euro area, United Kingdom and Japan with about 15 per cent each. The remainder is split between Mexico, China and some global activity measures such as the Baltic Dry Index and the global PMI.

Regarding the categories of data, roughly one-third is production data, and the rest can be associated with various final expenditures categories. The 103 production variables encompass GDP variables, different aggregations of industrial production, and PMI. There are 61 consumption-related variables (household spending, consumer confidence and retail sales), and numerous investment indicators, including various aggregates of business investment measured in the National Accounts and surveys on investment intentions, such as the Bank of England Agents' Business Conditions Survey. Residential investment covers indicators such as housing starts and building permits, while international trade includes exports and imports data.

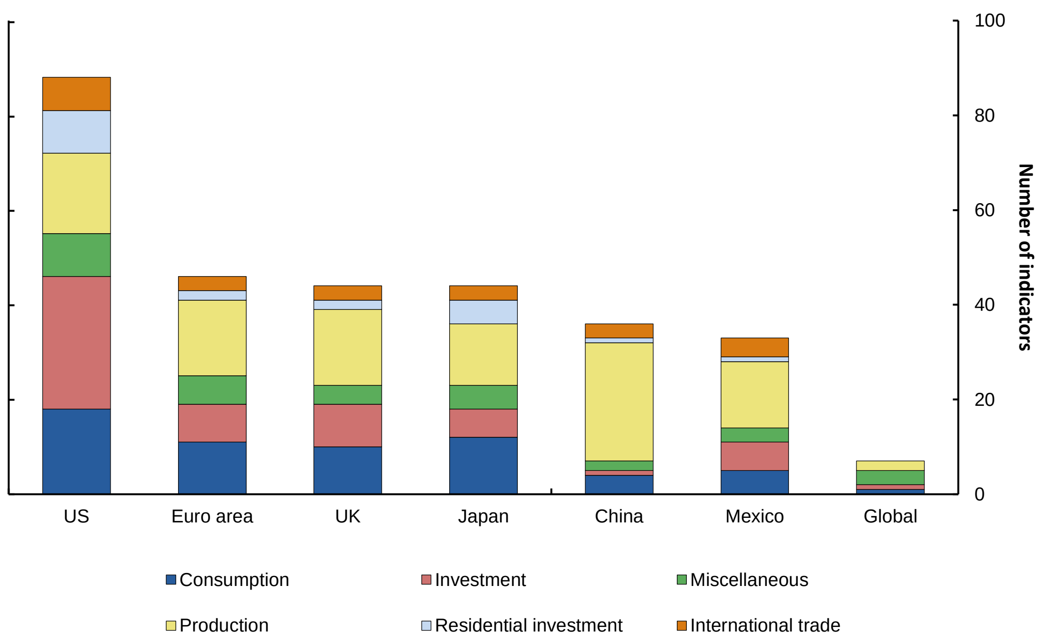
Table 1: Summary of the data by region and category

Region	Consumption	Investment	Miscellaneous*	Production	Residential investment	International trade	Total
US	18	28	9	17	9	7	88
Euro area	11	8	6	16	2	3	46
UK	10	9	4	16	2	3	44
Japan	12	6	5	13	5	3	44
China	4	1	2	25	1	3	36
Mexico	5	6	3	14	1	4	33
Global	1	1	3	2	0	0	7
Total	61	59	32	103	20	23	298

* This category includes variables that do not clearly fit into the other categories, such as the Baltic Dry Index, the Chicago Fed National Activity Index, the Eurocoin, and aggregate employment indicators.

Figure 2: Summary of the data by region and category

Count of global activity indicators



III. Methodology

Pre-selection

While DFM can handle a large number of indicators, the literature suggests that there are significant gains to narrowing down the number of variables through pre-selection (Boivin and Ng 2006; Bai and Ng 2008; Alvarez, Camacho and Perez-Quiros 2016). Limiting the number of variables often prevents the addition of unnecessary noise—simply, fewer appear to be better. Overall, the literature suggests that using a medium-sized data set performs at least as well as a large data set that includes over 100 variables. Therefore, we build a data set of 40 variables by pre-selecting the top 36 indicators and include four key global macro variables projected by the International Economic Analysis department at the Bank of Canada (the United States, Japan, China and euro area GDP).[5] To select the top 36 variables, we run a linear regression for a given export component on its lag, the international economic indicators, and a dummy for the 2008–09 recession.[6] The ranking is based on the *t*-statistic. Because of data limitations, the pre-selection process makes use of the 2005–16 periods.[7] Overall, we find that restricting the number of variables to 36 yields similar results to using a hard threshold of 1.65 for many export aggregates. Although it results in more trimming for some aggregates, it gives a better outcome. In some cases (NECX residuals and farm and fishing), hard thresholding at 1.65 is a more stringent criterion, but it also improves results. Again, fewer appear to be better.

Figure 3 and Figure 4 show the distribution of variables selected for each model by region and category. For total exports, just over 40 per cent of the variables selected are from the United States, compared with 29 per cent in our overall data set. Production variables are very important, followed by investment and international trade indicators. This is similar to Binette et al. (2014), who emphasize the importance of production variables, and Morel (2012), who finds US investment to be a key predictor of Canadian NCX. On average, for all other models, more global than US variables are selected. Regarding categories of variables, on average, 45 per cent of those selected are production indicators. The next-most important indicators are investment and consumption variables.

We find that there are significant gains to be made by making a few exceptions to this general process. Some exceptions are energy and motor vehicles and parts exports, which are restricted to use only US variables since almost all of these products are shipped to the United States. Also, for

[5] These four variables are not included in the data set for the pre-selection step. Since they are key projection variables for the International Economic Analysis department, we decided to include them to influence GRACE forecasts regardless of whether or not they are selected. Furthermore, in the case of consumer goods, US consumption is added as a conditioning variable despite not being preselected.

[6] Several categories of exports were not significantly affected by the Great Recession and in these cases, the dummy was excluded.

[7] Going forward, as more data become available, this approach will have the additional benefit of allowing the selected variables to change over time.

motor vehicles and parts exports, we use staff expertise to manually select variables from those chosen by our algorithm. We obtain large gains by including only data related to motor vehicle activity (e.g., US motor vehicle sales, production and consumption).

Figure 3: **Variables selected for each model by region**

Share (%)

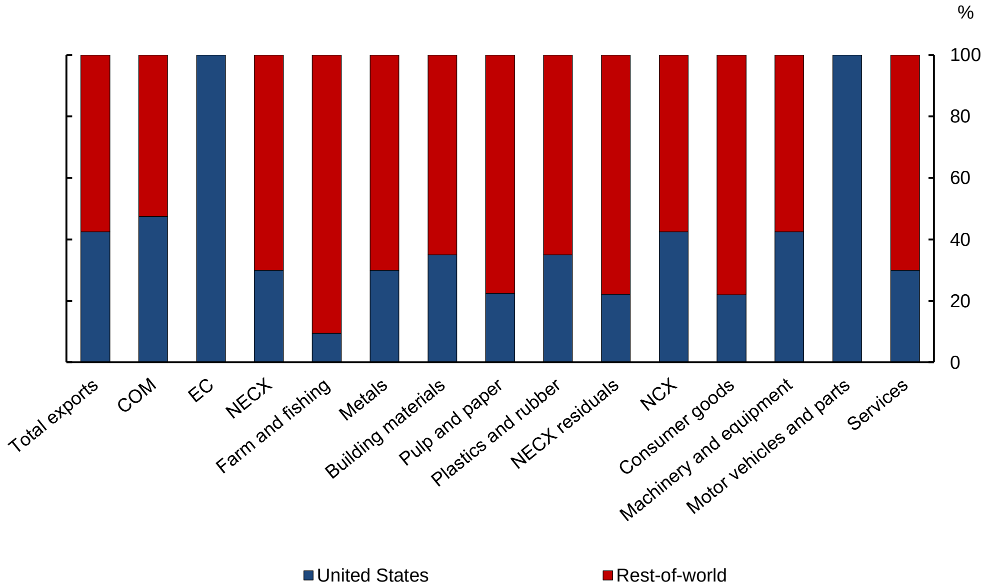
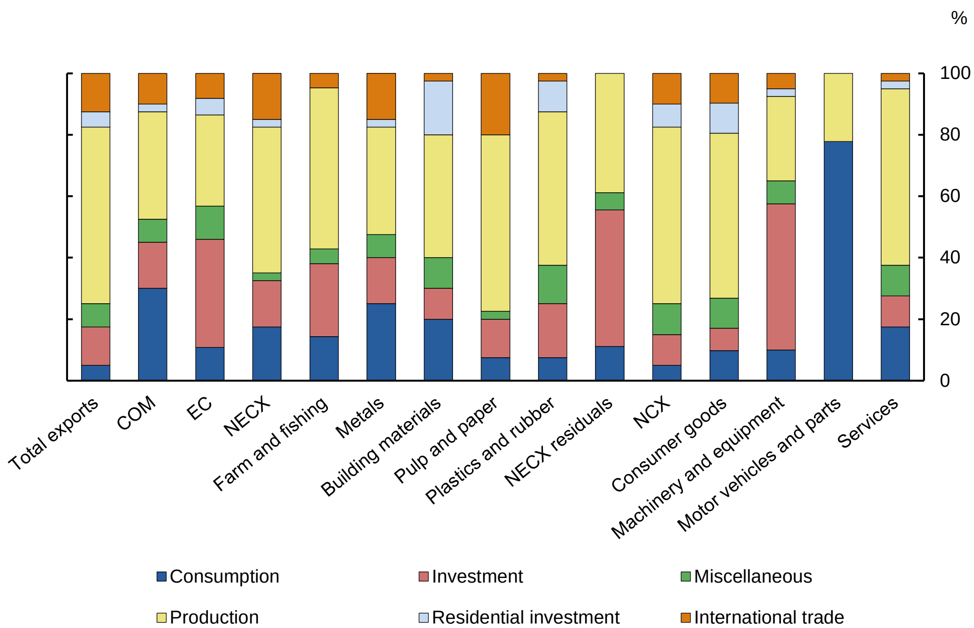


Figure 4: **Variables selected for each model by category**

Share (%)



Dynamic factor model

Factor models summarize the information contained in large data sets by constructing a handful of variables (factors) to capture the co-movement of the underlying data. This approach has proven successful in nowcasting,[8] the construction of coincident indicators,[9] and more recently the identification of macroeconomic shocks.[10] We adopt the DFM methodology because of its ability to create a coincident indicator.

Furthermore, in a data-rich environment, the DFM approach is appealing for several reasons. First, the DFM methodology is robust to data irregularities (mixed frequencies and ragged edges). In practice, this means there is no need for a balanced panel. This is essential for our application since many of the data used have different start dates (e.g., a large portion of Chinese data begins in 2005). Second, the DFM approach allows for the use of the large data set discussed in the previous section. Finally, we can condition forecasts on a set of variables provided by the Bank of Canada's International Economic Analysis department. There are two sets of forecasts provided: those from the projection models and nowcasts. This ensures that the future path of our global real activity measure reflects the Bank's view about international developments.

The proposed factor model detailed below is estimated using the algorithm of Bańbura and Modugno (2014) and uses a block structure similar to D'Agostino, Modugno and Osbat (2015).

The model is of the following form:

$$Y_t = \Lambda \mathrm{F}_t + \varepsilon_t \, ,$$
$$F_t = A_1 F_{t-1} + v_t \, ,$$
$$\varepsilon_{i,t} = \rho_i \varepsilon_{i,t-1} + u_{i,t} \, ,$$

where Y_t is a vector of observables, F_t is a vector of underlying factors driving the dynamics in the data, and ε_t is the vector idiosyncratic components. The errors, ε_{it}, follow an auto-regressive process. Furthermore, u_t and v_t are white noise errors. Λ is the loadings matrix, and A is the matrix of coefficients governing the vector autoregressive process of the factors.

In our application, GRACE is the common component of the above dynamic factor model. The common component is simply the fitted values of the factors and the respective series loadings, and thus represents the part of the series that is explained by the co-movement in the underlying data. Since we use only activity data and target the variables in the model, these summary

[8] See, among others, Giannone, Reichlin and Small (2008) and Chernis and Sekkel (2017).
[9] See, among others, Stock and Watson (2002) and Aruoba et al. (2009).
[10] See, among others, Bernanke, Boivin and Eliasz (2004), Bork (2009), Luciani (2015) and Stock and Watson (2015).

measures reflect international demand for the targeted subaggregates of exports. To further improve our interpretation of these common components, we identify factors by estimating the model in blocks. Thus we can then create a common component to see the contribution of each block of activity indicators. For example, one could write the common component for variable i from a two-block model as:

$$\hat{Y}_t^i = \Lambda_A^i F_{At} + \Lambda_B^i F_{Bt} ,$$

where $\hat{Y}_t^i$ is the common component for variable i, Λ_A^i is the loading for variable i from block A, and F_{At} is the factor associated with block A. So by looking at $\Lambda_A^i F_{At}$, we could see the contribution to the common component of variable i from block A, where block A would be a subset of the data we are interested in. This decomposition gives an interpretation to the common components produced by the model. In this way, we can better understand what is driving the model.

To simplify the choice of block structure and to maintain parsimony, we choose two blocks: US and rest-of-world (ROW) variables. This is a reasonable choice considering that the United States is Canada's largest trading partner. This specification works well for most export categories,[11] but in cases where the interpretation of the common component is challenging, we use a one-factor model.

ECM forecasting framework

Once our measure of GRACE has been estimated, we incorporate it into a traditional ECM framework. There are two reasons for this. First, the Bank's projection process uses a similar approach to an error-correction model and is, therefore, a natural starting point. Second, and most importantly, it is intuitive to think that a measure of foreign demand must have a long-run relationship with exports along with other variables such as relative prices. We start with the formulation used by Morel (2012),[12] in which the log level of exports (x) is a function of a constant, relative price (the foreign denominated relative price of exports, *rp*), a measure of global activity (GRACE) and a measure of trade openness (Trade):

$$\ln x_{it} = \beta_{i0} + \beta_{i1} rp_t + \mathrm{GRACE}_{it} + \beta_{i3} \mathrm{Trade}_t + \epsilon_{it}.$$

The coefficient on GRACE is imposed to be 1 in the long run because the Bank's projection models require a balanced growth path assumption to hold (i.e., it requires a stable ratio of Canadian exports to foreign demand in steady state). The cost of this restriction is minimal since, when

[11] Exceptions are machinery and equipment, building materials, farm and fishing, consumer goods, COM, and EC.
[12] This formulation is similar to the theoretical framework in the Bank's large-scale DSGE model, ToTEM (Dorich et. al 2013; Murchison and Rennison 2006).

estimated free of restrictions, the coefficient for total exports is very close to 1 (0.97). However, this does not hold for all subaggregates.

We make two modifications to this framework. First, we make use of the new Canadian effective exchange rate (CEER, export-weighted) calculated by Barnett et al. (2016) when computing relative prices, to better capture third-party competitiveness in foreign markets.[13] This new measure is the most advanced real effective exchange rate series yet developed for Canada and should help reconcile the findings of Barnett and Charbonneau (2015) regarding the loss of market share in the United States. We also add a new control variable to further account for competitiveness challenges or structural factors. We proxy for these structural factors using the trend component of the share of manufacturing output in Canada (SMY) in the ECM long-term equation. While this proxy is imperfect and may capture other phenomena in addition to Canada's international competitiveness (including supply-side factors such as loss of capacity during and after the Great Recession, as well as technological change adversely affecting the sector), it stresses the need for an additional control variable in the ECM framework. We find that including the SMY helps significantly in explaining Canada's export dynamics (which becomes more apparent below).

IV. Results

In this section, we assess the measure in three ways. First, we inspect the measure for total exports and the aforementioned disaggregates. Second, we examine the in-sample properties. Third, we present a pseudo-out-of-sample exercise. Overall, a measure of global real activity should have good theoretical (i.e., cointegration) and empirical (i.e., degree of fit in- and out-of-sample) properties.

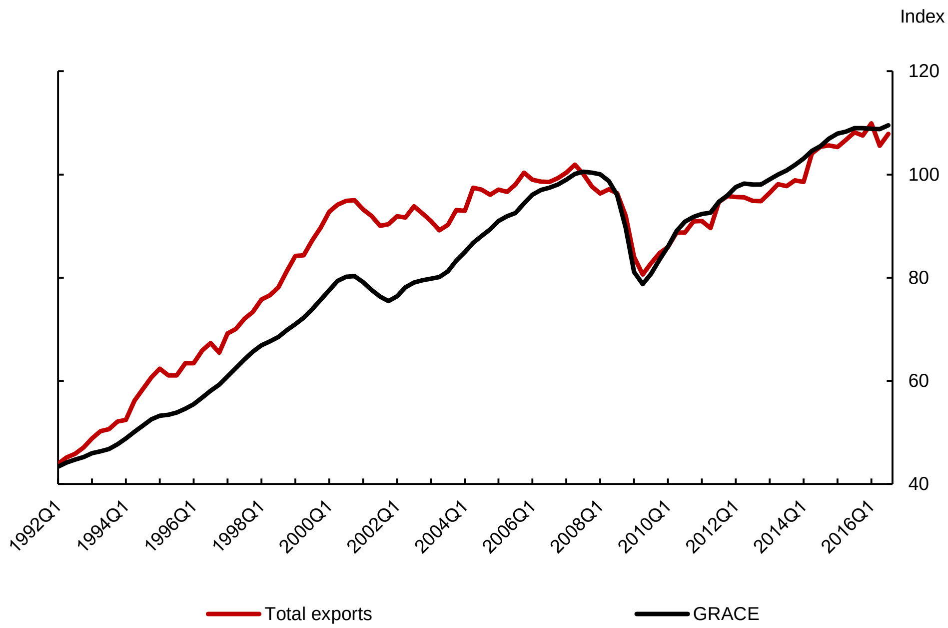
First, we examine the measures. Figure 5 shows GRACE for total exports indexed to 2007. In general, GRACE tracks exports relatively well in the most recent period but less so in the 1990s and before the mid-2000s. These periods, however, were times of significant structural adjustments not captured by our measure of global real activity. As reported by de Munnik, Jacob and Sze (2012), the gradual tariff reductions that occurred after the 1988 signing of the *Canada–United States Free Trade Agreement* gave Canada special access to the US market during a period of robust US growth.[14] The signing of the *North American Free Trade Agreement* in 1994 (an extension to include Mexico) eroded some of these gains beginning in the mid-1990s. Canada's

[13] This includes a broad set of countries and uses competition-based weights. These weights account for both Canada's bilateral trade with another country and the competition Canada faces from that country on a product-by-product basis in third markets.
[14] They report that Canada's exports going to the United States increased from 75 per cent in 1990 to 87 per cent in 2000.

special market access was further eroded through the mid-2000s as the US market opened to China and other emerging-market economies. Also, this period saw the development of global value chains and a sharp appreciation of the Canadian dollar. These important structural factors underscore the need for additional variables (such as SMY) beyond those utilized in previous works.

Figure 5: Total exports and GRACE

Index level 2007 = 100, quarterly data



Measures of GRACE for export subcomponents are quite different through time. Figure 6 and Figure 7 present GRACE for each of the export subaggregates presented in Figure 1. The underlying trends show significant divergence. For example, energy exports (EC) and NECX have diverged significantly since the Great Recession. Interestingly, we also observe a weakening of demand over the last two years for both NCX and NECX. The most disaggregated GRACE measures are shown in Figure 7. There is a large amount of heterogeneity between categories. Some categories have much weaker foreign demand after the recession, such as pulp and paper, NECX residuals, and metals. On the other hand, demand for services has been barely affected. Demand measures for some other product categories resemble that of a linear trend, such as agriculture and consumer goods. Furthermore, there is a handful of categories that were hurt by the Great Recession and until recently were showing signs of growth (machinery and equipment (M&E), plastics and rubber, and motor vehicles and parts).

Figure 6: GRACE—Major export categories

Index level 2007 = 100, quarterly data

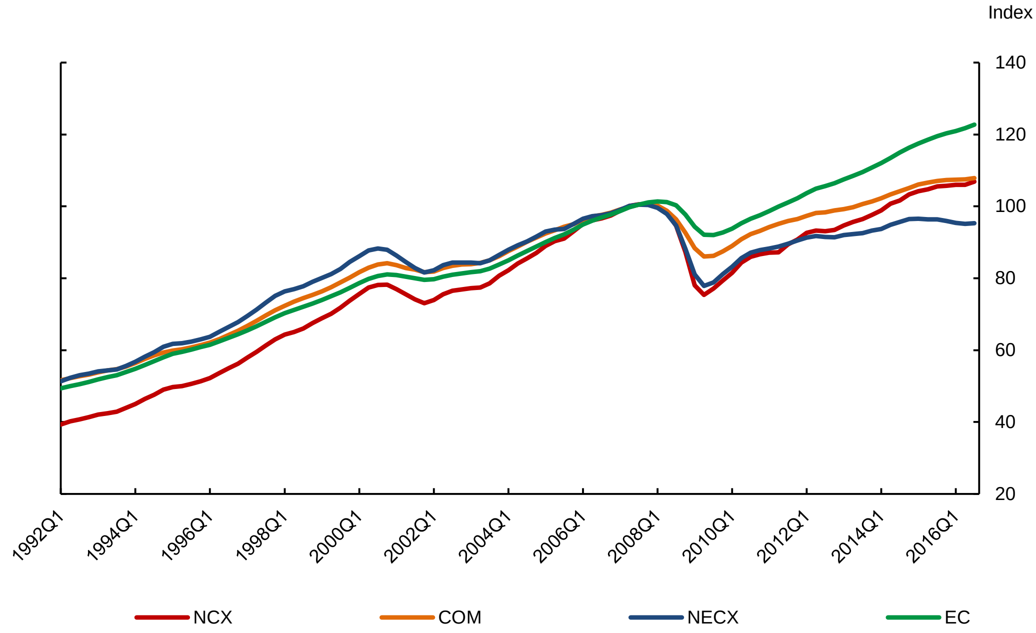
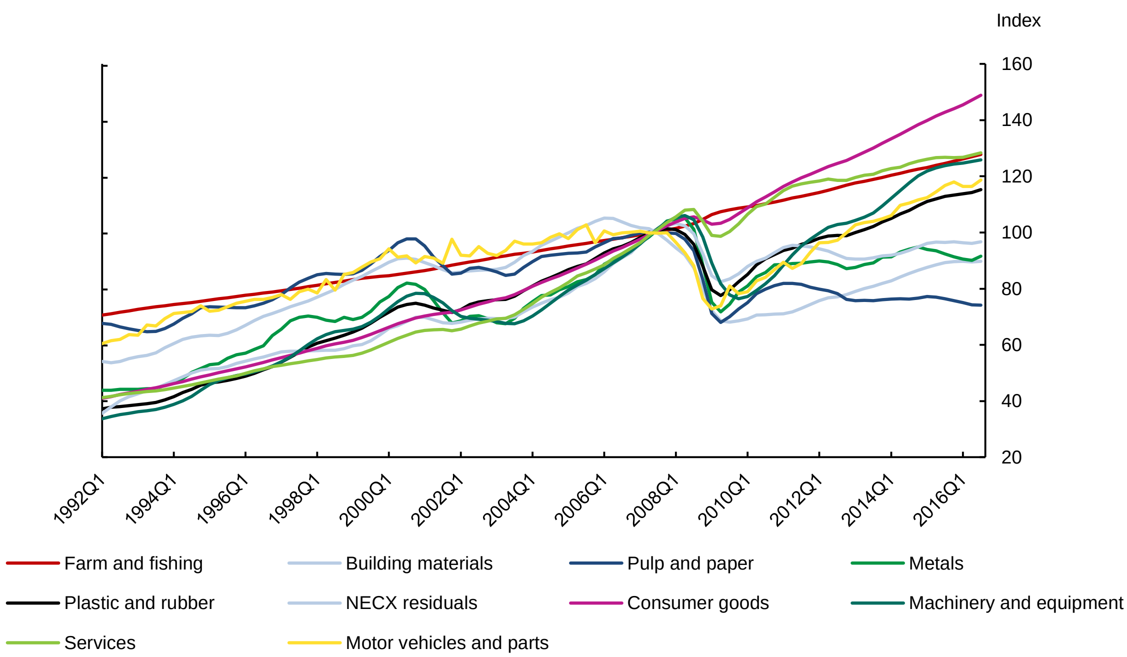


Figure 7: GRACE—Disaggregated export categories

Index level 2007 = 100, quarterly data

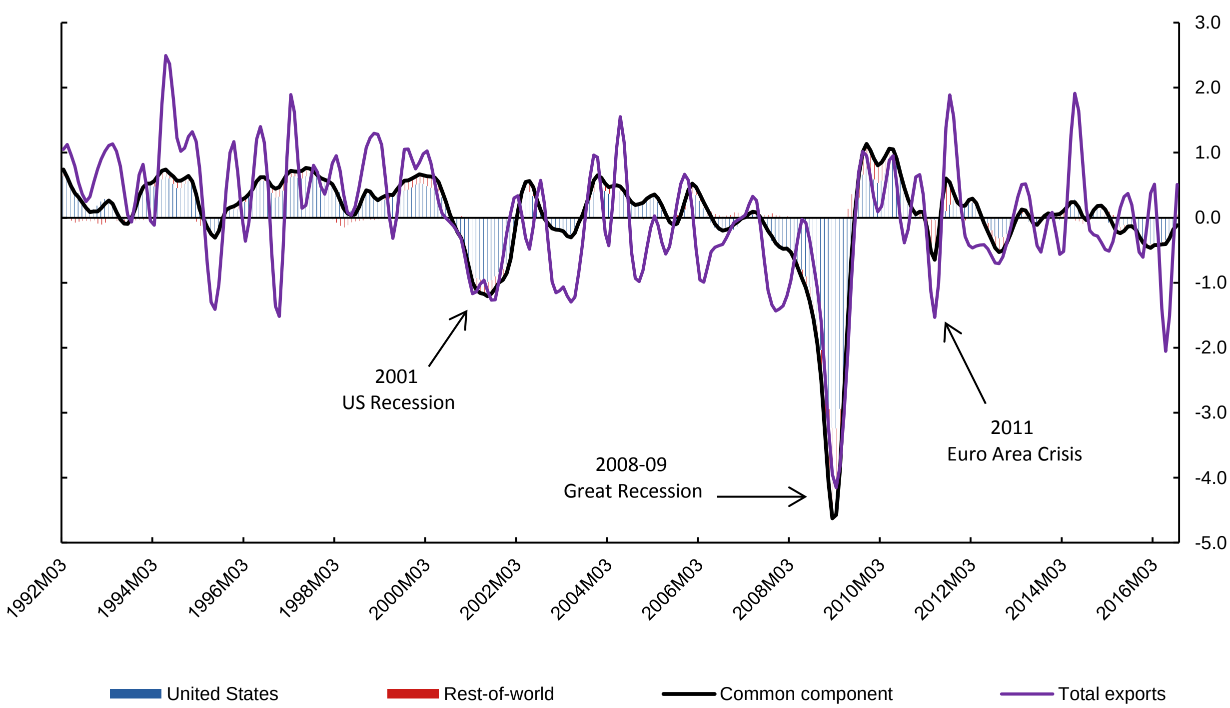


One interesting aspect of our dynamic factor model is the ability to decompose the common component into contributions from the two blocks of variables. Figure 8 shows this decomposition for total exports. It shows the standardized contributions to GRACE from the US and ROW blocks.

Since the model is estimated on a monthly basis, it produces an underlying monthly series of exports. Exports broadly follow the common component but not perfectly, as the common component is significantly smoother than the very volatile exports series. Intuitively, most of the movement in GRACE is due to the US block—Canada's biggest trading partner. The major events of the period—the US 2000–01 recession and the Great Recession—are easily visible in the data. While the two common components are heavily synchronized, this is not always the case. During the euro area crisis in 2011, for example, the ROW block drags on Canadian exports while the US block does not significantly contribute in either direction.

Figure 8: **Contributions to the common component (GRACE) of total exports**

Month-over-month standardized data



Model performance: In-sample and pseudo-out-of-sample

Long-run relationship and in-sample performance

With GRACE in hand, we use this measure of global real activity in a reduced-form ECM. After controlling for a measure of relative prices and structural factors, we test for cointegration in the long-term equation and record the in-sample fit of the short-run equation.

We assess cointegration using two criteria. First, we look for stationarity of the residuals from the model estimated by Dynamic OLS (Saikkonen 1992; Stock and Watson 1993). Second, we look at the size and significance of the error-correction term in the dynamic equation. These will show that a long-run relationship exists between export, global real activity and the other variables used in the equation (e.g., structural factors). This is true for most exports subaggregates.

Table 2 below shows the specifications of our ECMs for each aggregate. We use the general framework in Morel (2012) as a starting point with the addition of the CEER and SMY (as described above). However, we find that this framework is not always sufficient to find cointegration in the long-term equation. When needed, we substitute the traditional relative prices measure for the CEER and include additional trend variables, such as a linear trend or a measure of trade openness.[15] We also consider the Bank of Canada's Commodity Price Index of non-energy commodities (BCNE) (Kolet and Macdonald 2010) when optimal. When needed, we augment our specification with sectoral specific dummies to capture large transitory exogenous shocks—e.g., drought (DR), bovine spongiform encephalopathy (BSE), and Y2K. Finally, the relative price measure enters with a lag in the short-run equation, and if the *t*-statistic is below 1 or the sign is counterintuitive, we exclude it from the equation.

Table 2: ECM specifications for each aggregate

Aggregates	Relative price measures	Other variables
Total Exports (XQ)*	CEER	SMY, BCNE, Y2K
COM	CEER	Linear trend, BCNE
EC	CEER	Linear trend, BCNE
NECX	CEER	Linear trend, BCNE
Farm and Fishing**	–	Linear trend, DR, BSE
Metals**	CEER	Linear trend
Building Materials	CEER	SMY
Pulp and Paper	CEER	SMY, Linear trend, BCNE
Plastic and Rubber	rp	SMY, Trade openness
NECX Residuals**	rp	SMY, BCNE
NCX	rp	SMY, Y2K
Consumer Goods	rp	SMY, Trade openness
M&E	rp	SMY, Y2K
MV and Parts	rp	SMY
Services**	CEER	SMY

*BCNE in both short- and long-run equations. ** No relative prices in the short-run equation.

[15] Trade openness is the ratio of International Monetary Fund (IMF) world trade to IMF world GDP, which is similar to that used by Morel (2012). We use the measure based on market exchange rates.

First focusing on total exports, Table 3 shows the coefficient estimates and diagnostics results. The statistics of the Augmented Dickey-Fuller (ADF) test signal with a high probability that the equation is cointegrated. Figure 9 shows the fitted values of the long-run equation for total exports. Furthermore, the value of the adjustment parameter in the dynamic equation is -0.37, which further signals cointegration given its magnitude and significance. This suggests that our measure fulfills the requirement of having a long-run relationship with exports and the other variables used in the equation. Additionally, the in-sample fit of the model is reasonably high—adjusted R-squared of the short-run equation is 0.62. Further examining Table 3, we see that the signs and coefficient estimates are as expected.

Table 3: Coefficient estimates and diagnostics for total exports

	Long-run equation	Dynamic equation
GRACE	1	1.09***
Manufacturing Share of Output	0.29***	-
Relative Prices—CEER	-0.38***	-0.17***
BCNE	0.01	0.028
Adjustment Parameter	-	-0.37***
Adjusted R-squared	-	0.62
ADF test statistic	-5.19***	-

Significance: *10 per cent, **5 per cent, ***1 per cent, calculated using Newey-West errors for coefficients, and the critical values for the ADF test are from MacKinnon (1996).

Figure 9: Total exports and fitted values

Index level 2007 = 100, quarterly data

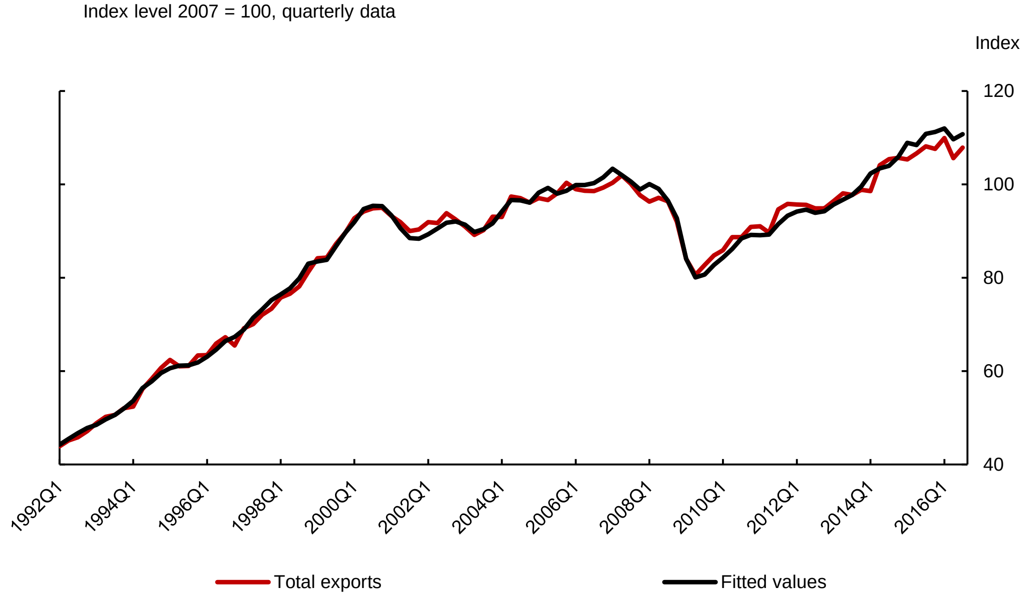


Table 4 and Table 5 show more key sample statistics for NCX and COM. For brevity, we have restricted the table to the statistics concerning cointegration, in-sample fit, and the coefficient on the relative price from the dynamic equation. Figure 10 and Figure 11 display the fitted values of the long-run equation for NCX and COM.

First, NCX shows signs of cointegration. The ADF test statistic is significant, rejecting the null of a unit root and the adjustment parameter is significant. Also, the dynamic equation has relatively high in-sample fit. The same can be said for most of the disaggregate categories of NCX. The only case where the ADF test statistic is not significant is for M&E, but the adjustment coefficient is highly significant. Furthermore, half the models have in-sample fits above 0.4, and only service exports have a low R-squared (0.17). Overall, the higher-level aggregates perform well, and as we apply the methodology to lower-level aggregates, it remains feasible but is more challenging. As a reminder, not all of the dynamic equations have a measure of relative price. If the price measure had a *t*-statistic lower than 1, or if it had the wrong sign (as in the case of services), it was dropped from the equation.

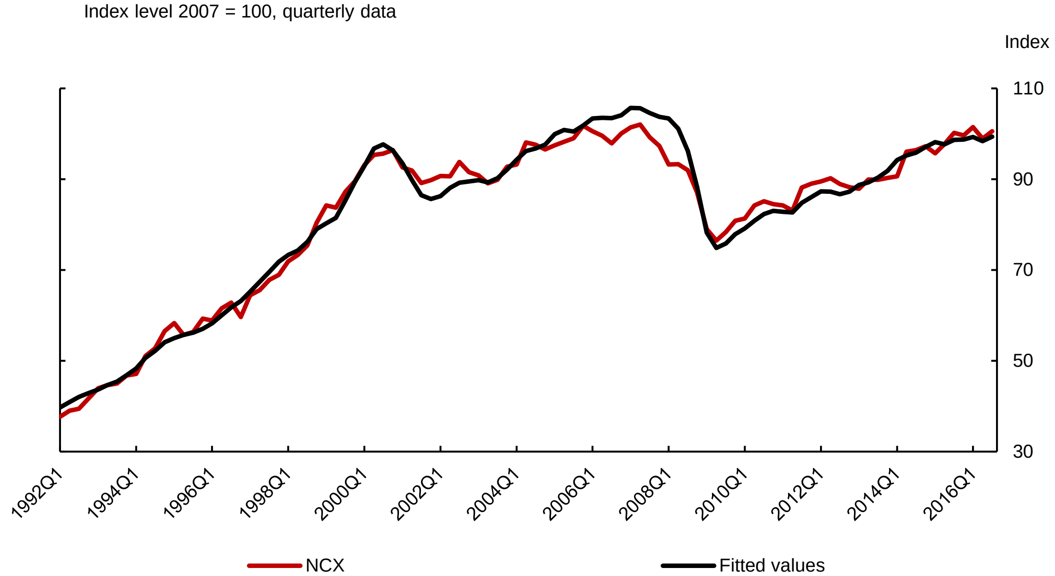
Table 4: In-sample statistics of NCX categories

	ADF test statistic	Adjustment parameters	Relative prices—CEER (short-run)	Adjusted R-squared
NCX	-4.07**	-0.21**	-0.23*	0.52
Consumer Goods	-4.35**	-0.60***	-0.12	0.31
Motor Vehicles and Parts	-4.78***	-0.56***	-0.84*	0.47
M&E	-2.61	-0.22***	-0.15	0.43
Services	-3.57*	-0.29***	n/a	0.17

Significance: *10 per cent, **5 per cent, ***1 per cent, calculated using Newey-West errors for coefficients, and the critical values for the ADF test are from MacKinnon (1996).

Figure 10: **NCX and fitted values**

Index level 2007 = 100, quarterly data



The same theme applies to COM categories (Table 5 below). However, COM perform slightly worse than NCX. While the long-term equations are cointegrated, the in-sample fits are comparatively lower. Examining the next level of disaggregation suggests that the relatively lower fit is due in part to EC. This is not surprising given the unique nature of the EC market. Specifically, oil sands production is slow to react to changes in economic conditions because they cannot be expanded or shut down easily in response to changes in demand, but, perhaps more importantly, Canada is not the marginal supplier of crude oil to the US market and therefore is less responsive to demand changes.[16] As a result, prices respond to demand shocks rather than volumes. On the other hand, NECX shows all the signs of cointegration coupled with a relatively high in-sample fit. Similar to the NCX categories, the lower-level aggregates are more challenging to fit into this framework. Although most categories show some sign of cointegration, all pass the ADF test except metals. Furthermore, half the categories have adjusted R-squared greater than 0.4, while the remainder are all at or above 0.25.

Table 5: In-sample statistics of COM categories

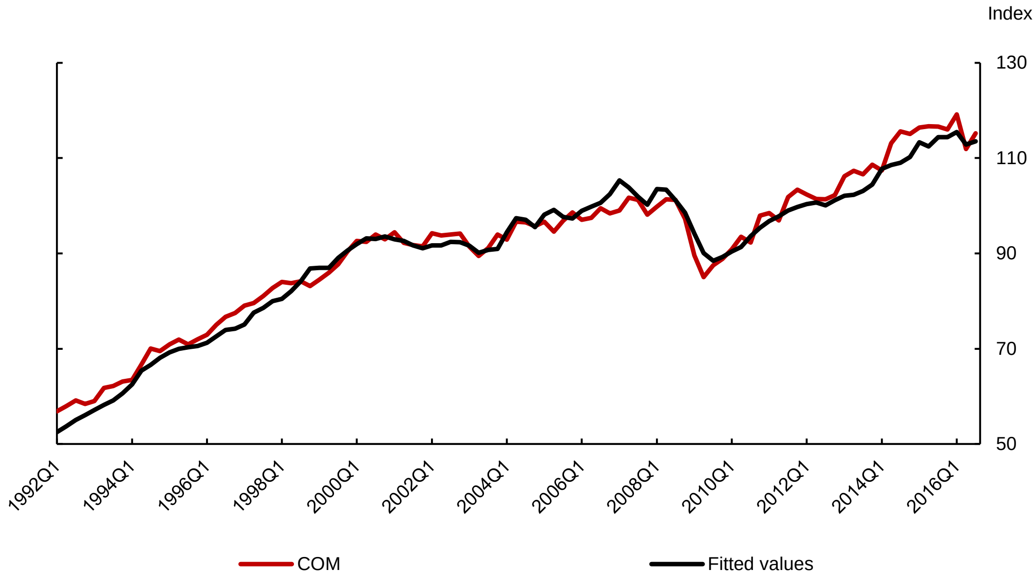
	ADF test statistic	Adjustment parameters	Relative prices—CEER (short-run)	Adjusted R-squared
COM	-4.43**	-0.19**	-0.12	0.33
EC	-4.96***	-0.22**	-0.12	0.24
NECX	-3.93*	-0.21***	-0.18**	0.43
Farm and Fishing	-6.54***	-0.71***	n/a	0.27
Pulp and Paper	-4.24*	-0.39***	-0.09	0.50
Metals	-3.10	-0.13**	n/a	0.26
Building Materials	-3.53*	-0.26***	-0.31**	0.50
Plastics and Rubber	-4.37**	-0.33***	-0.18*	0.45
Residuals	-5.36***	-0.38***	n/a	0.25

Significance: *10 per cent, **5 per cent, ***1 per cent, calculated using Newey-West errors for coefficients, and the critical values for the ADF test are from MacKinnon (1996).

[16] Canada crude oil exports have gained significant US market share over the last decade by squeezing out higher-cost and more volatile producers. The integrated pipeline and rail infrastructure gives Canada a significant advantage over its competitors.

Figure 11: COM and fitted values

Index level 2007 = 100, quarterly data



One general theme emerges from the in-sample results: the methodology works for larger export categories but is more challenging for lower-level aggregates. During the pseudo-out-of-sample, we see a similar conclusion.

Pseudo-out-of-sample performance

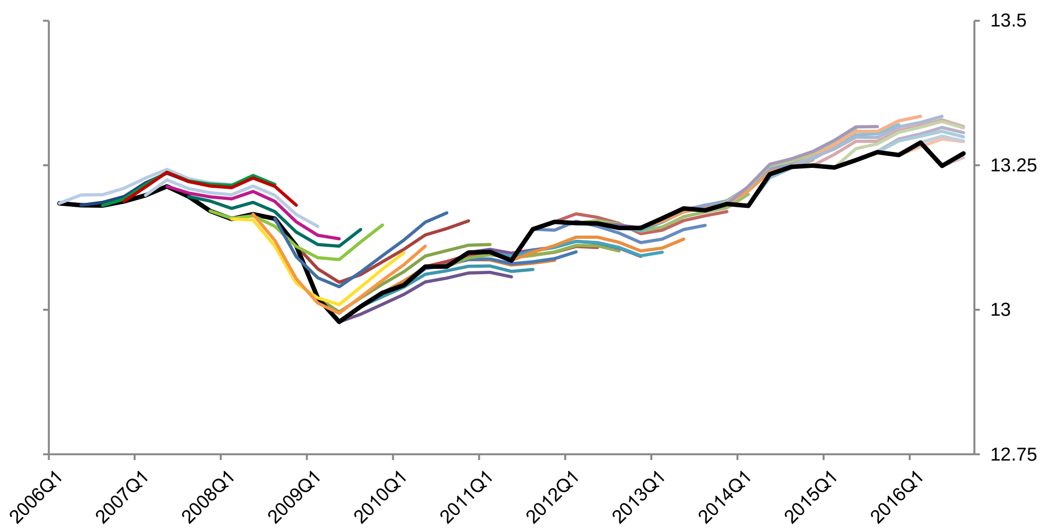
To find out how successful GRACE is at forecasting, we perform a pseudo-out-of-sample conditional forecasting exercise within the ECM framework discussed above. It is a pseudo-out-of-sample exercise because we use final data and perform conditional forecasts. The model is evaluated over the period 2006Q2 to 2016Q3 using an eight-quarter forecast horizon. The models are estimated recursively starting in 1992Q2 to 2006Q1. This means the first forecast is made with the model estimated on the sample 1992Q2 to 2006Q1 with forecasts made for eight quarters, after which the next forecast is made by rolling forward one quarter and repeating the exercise. This is repeated until 2014Q2, so the out-of-sample period covers close to 10 years of data (2008Q1 and 2016Q3—totalling 35 predictions). We calculate the root-mean-squared forecast error (RMSFE) for the annualized average growth forecast for eight quarters. Focusing on the average growth over a fixed horizon serves two reasons. First, pinning down the quarter-to-quarter volatility over a projection horizon of two years is likely impossible due to the extreme volatility in the quarterly exports data. Second, and most importantly, from an economic policy perspective, it is the average pace of growth over the policy horizon that matters (not the quarterly movements).

During this exercise, we make several assumptions on the available information set. First, we do not take ragged edges into account, such that our data set in 2016Q1 will contain all available information up until 2016Q1. Second, we condition our forecasts on a set of variables provided by the Bank of Canada's International Economic Analysis department. There are two sets of forecasts provided: those from the projection models and nowcasts. We assume the true path of projected variables over eight quarters and the true path of nowcasted variables for two quarters. In the ECM, we also assume the model contains the true values of the deterministic trend variables and the relative price.[17] Overall, these assumptions let us evaluate how the model will perform if the Bank's view on international developments, along with the CEER assumption and trend assumptions, are correct.

Figure 12 shows a tentacle plot of the pseudo-out-of-sample conditional forecasts. The black line is the actual data, while the "tentacles" are the level forecasts generated by the ECM. We can see the forecasts broadly track total exports. In this conditional out-of-sample exercise the model captures the significant downturn and slower rebound after the Great Recession. However, perhaps not surprisingly, forecasts made in the pre-recession period miss the full depth of the downturn. After the recovery period, the model captures relatively well the last several years of modest growth (2012 to 2016).

Figure 12: Tentacle chart of total exports forecast

8-quarter log level forecast



[17] As a robustness check, we estimate the ECM with naïve deterministic trends (holding them constant at t-1). Knowing the true level of the deterministic trend improves the accuracy of the forecasts, but the difference is marginal, suggesting the results are not entirely driven by the deterministic trend.

Figure 13 shows the RMSFE for total exports and for simple benchmarks. Also, forecasts are made for many disaggregates of exports, which allows a bottom-up forecasting approach. GRACE A is the aggregate forecast, GRACE B is the second level of aggregation (COM and NCX), GRACE C is the next level lower (EC, NCX and NECX), while GRACE D is the lowest level of aggregation (10 subaggregates). We can see that all aggregations beat the simple benchmarks; however, the bottom-up approach performs slightly worse than directly forecasting total exports.

Figure 13: Pseudo-real-time RMSFE for total exports

Forecast horizon = 8, average Q/Q growth rates at AR, %, 2006Q2–2016Q3

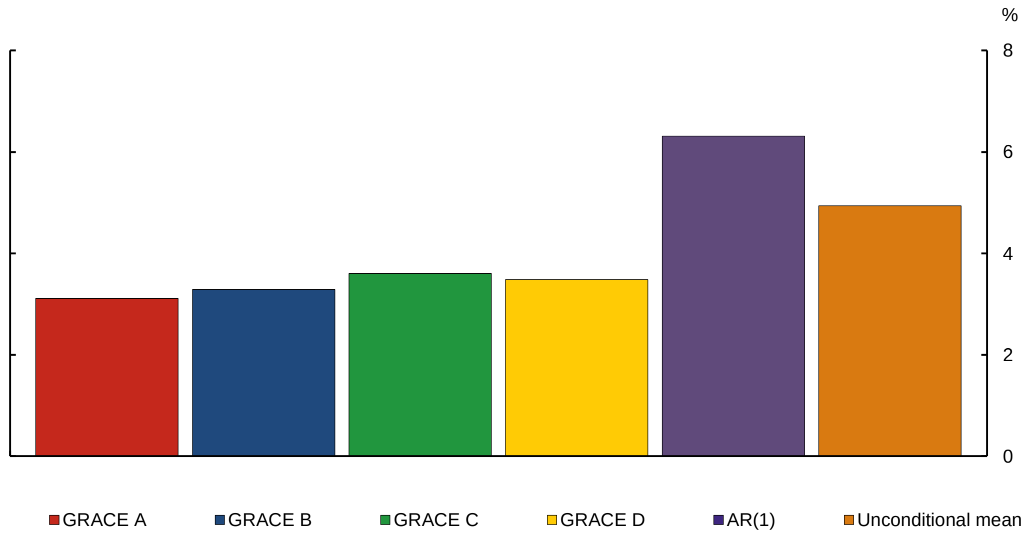


Figure 14 and Figure 15 show results for several subaggregates. It is clear that the performance of the model for NCX is quite good, beating the standard deviation by 34 per cent at the eight-quarter horizon. The model for COM also outperforms the benchmarks, albeit less so. Digging deeper into COM, we find that EC appears to be more difficult to forecast than NECX. This corroborates what was found in the in-sample analysis, which suggests that the difficulty in forecasting COM originates in part from the energy sector. This is, as previously mentioned, unsurprising given the unique energy market in North America.

Figure 14: Pseudo-out-of-sample results for main aggregates

Forecast horizon = 8, average Q/Q growth rates at AR, %, 2006Q2–2016Q3

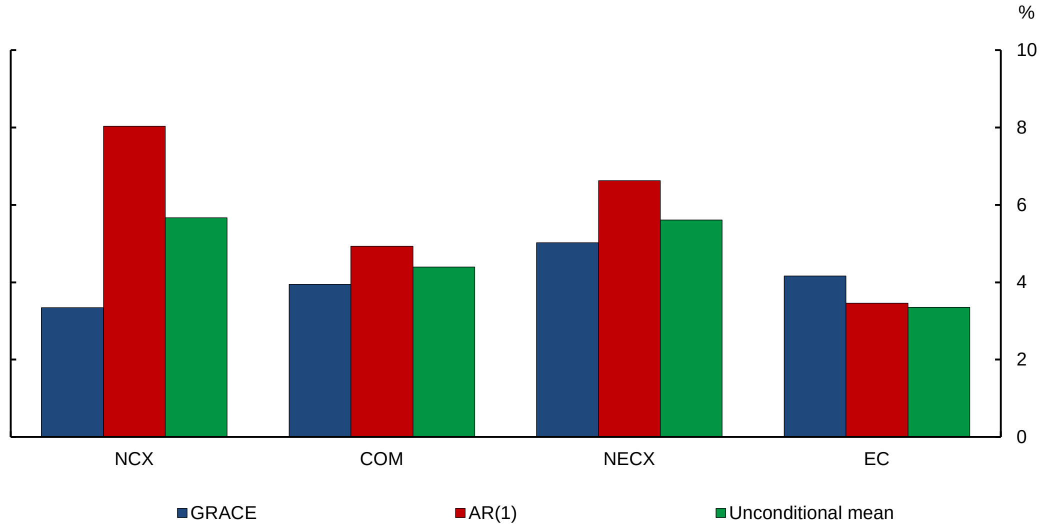
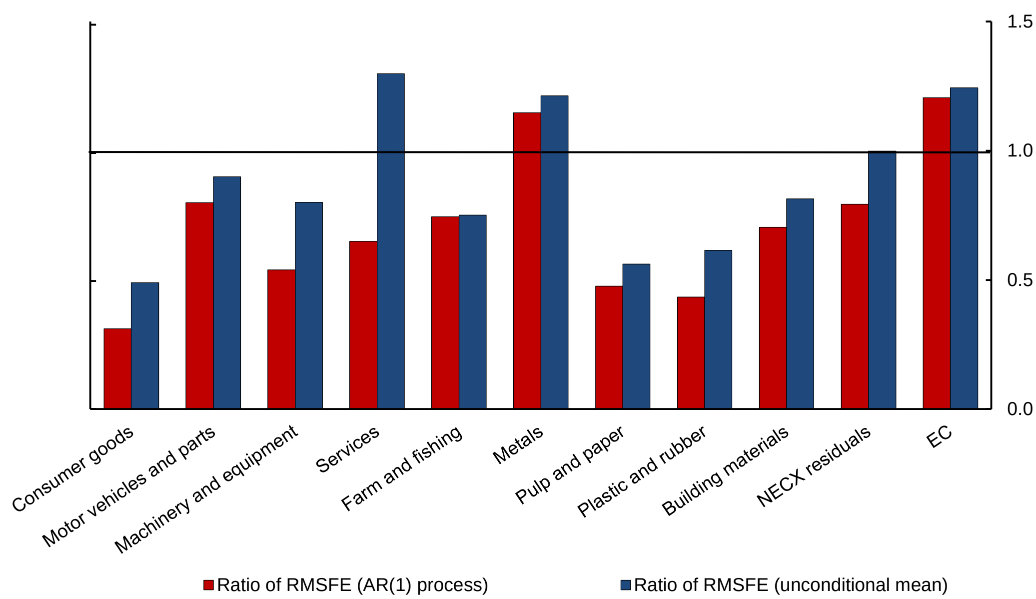


Figure 15 shows the performance for the lowest levels of aggregation. The results are decidedly more mixed, consistent with the in-sample results. Many categories perform very well, such as consumer goods, plastic and rubber and M&E. On the other hand, some categories remain very challenging to forecast, such as services, metals and energy goods. To a lesser extent, this is also true of the NECX residuals and motor vehicles and parts.

Figure 15: Pseudo-real-time RMSFE ratio for export subaggregates

Forecast horizon = 8, average Q/Q growth rates at AR, %, 2006Q2–2016Q3



V. Conclusion

We have constructed new measures of foreign demand for Canadian exports—GRACE. The process starts with a large data set of international activity variables, from which we select the most relevant predictors for each subaggregate. With these targeted predictors we use a dynamic factor model to construct common components representing global real activity for Canadian exports. This approach is flexible and has been applied to 15 different aggregates.

The common component is then assessed as a measure of foreign demand. This is done by testing for cointegration, examining the in-sample fit, and comparing performance against simple benchmarks in a stylized forecasting exercise. We find the model performs well both in- and out-of-sample for total exports. All the requirements above are passed. The cointegration tests reveal an important result: the need to take into account structural change in the global economy. This is not surprising given previous works describing the significant structural adjustments in the global export market over the last three decades.

When the methodology is applied to other categories of exports the results are more mixed, but on average GRACE proves to be a good measure of demand and could be used to increase the richness of analysis. This is further emphasized by the fact that the bottom-up forecasts perform only slightly worse than the direct forecasts. Of special importance are the promising results for NCX.

This paper takes an important step forward in how the prospects for Canadian exports are forecast. It uses a data-driven approach that considers a large number of predictors and thoroughly examines many categories of Canadian exports while highlighting the importance of structural factors.

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