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Forecasting Imports with Information from Abroad*

Abstract

Globalization has led to huge increases in import volumes, increasing the importance of imports for total output. Since imports are a volatile component, they are difficult to forecast and strongly influence the forecast accuracy of gross domestic product. We introduce the first leading indicator constructed to forecast import growth, the Import Climate. It builds on the idea that the import demand of the domestic country should be reflected in the expected export developments of its main trading partners. A foreign country's expected exports are, in turn, determined by its trading partners' business and consumer confidence and its own price competitiveness. In a real-time forecasting experiment, the Import Climate outperforms standard business cycle indicators at short horizons for France, Germany, Italy, and the United States for the first release of data. For Spain and the United Kingdom, our indicator works particularly well with the latest vintage of data.

JEL Code: F01, F10, F17

Keywords: Import climate, import forecasting, survey data, price competitiveness

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1. Introduction

There has been an exceptionally large increase in trade globalization over the last 25 years. This increase manifests in a higher interconnectedness of value-added chains between economies and, therefore, has led to an increased importance of imports for the growth of gross domestic product (GDP).[1] Since import growth rates are highly volatile, they heavily influence fluctuations in GDP and trade balances,[2] which is why accurately forecasting imports has become important in applied forecasting work.[3] In contrast to other economic aggregates such as exports and private consumption, there are no reliable leading indicators that increase the accuracy of import forecasting. In this paper, we close this gap and introduce the first leading indicator for imports, the Import Climate, whose performance is examined in a real-time forecasting experiment for six advanced economies.

Surveys are an often-used source for leading indicators. However, business and consumer surveys do not include information about future import demand.[4] Therefore, the import expectations of firms or households are not available as a first-best source of information. As a second-best source, our novel approach follows the idea that the import demand of the domestic country should be reflected in the expected export developments of its main trading partners. The expected export development of a foreign country is, in turn, determined by business and consumer confidence in its trading partners and its price competitiveness position. This is a country's Export Climate and reflects the factors behind changes in expected export development. We construct Export Climates for all major countries in the world. The Import Climate weights the Export Climates of the domestic country's main trading partners with their share in domestic imports.

We find that, compared to other relatively standard business cycle indicators, the Import Climate is the best predictor for the current quarter for France, Germany, Italy, and the United States. For one-quarter-ahead predictions, the Import Climate is again the best performing indicator for those countries and, in addition, for the United Kingdom. Over both forecast horizons, the dispersion of the forecast errors of our new leading indicator is smaller than the volatility in quarterly import growth rates for all the countries. Therefore, the Import Climate does not only perform well relative to other indicators, but truly provides

[1] The import shares have increased between 1996 and 2016 as follows: France: 21% to 31%, Germany: 22% to 38%, Italy: 19% to 26%, Spain: 23% to 30%, the United Kingdom: 26% to 30%, and the United States: 12% to 15%.

[2] From 1996 to 2016, the ratios in standard deviations between quarterly growth rates in real imports and GDP are 3.8 for France, 2.7 for Germany, 3.2 for Italy, 4.3 for Spain, 4.5 for the United Kingdom, and 3.5 for the United States. The ratios in standard deviations between the quarterly nominal trade balance as share of nominal GDP and the growth rates in nominal GDP are 3.1 for France, 3.1 for Germany, 2.2 for Italy, 2.8 for Spain, 1.1 for the United Kingdom, and 1.8 for the United States.

[3] Next to the forecast of exports and investments, import forecasts are one of the most biased demand-side components of GDP (see Döhrn and Schmidt, 2011; Sinclair *et al.*, 2016).

[4] The only exception is the questionnaire by the Institute for Supply Management from which the monthly Purchasing Manager Index is derived for the United States. Within this survey, firms are asked about the expected change in their material imports. Thus, the question is not concerned with total imports.

a value-added for applied forecasting.

For Spain and the United Kingdom, the Import Climate is not always ranked first among the set of indicators. However, for one-quarter-ahead forecasts our leading indicator is the best predictor for the two countries when we use the latest data vintage of imports; for the nowcast, the rank of the Import Climate improves. Since the first data release for imports for Spain and the United Kingdom is more heavily revised compared to that of the other four countries, our indicator is particularly well-suited for explaining the final import data vintage of these two economies.

In addition to these findings, we mainly run two robustness checks. First, by checking the forecast performance of the Import Climate over time, we show that its high average predictive power is not driven by single events. In fact, for both the nowcast and the one-quarter-ahead projections, the high accuracy of the Import Climate to forecast import growth is stable since the Financial Crisis. Second, we compare the Import Climate's overall accuracy to more sophisticated forecast methods, namely a factor model and forecast combinations. For one-quarter-ahead forecasts, the Import Climate is able to produce lower forecast errors than the more sophisticated methods. For the nowcast, our indicator remains either the best predictor or is among the best performing models. Therefore, both robustness checks underpin the high performance of our new indicator found in the baseline analysis.

Our paper differs from the rather scarce import forecasting literature as it is the first to construct a leading indicator from business and consumer surveys to forecast imports. All of the extant literature in the field either proposes a methodological innovation for import forecasts or compares the performance of existing models with each other. Cushman (1990) uses bilateral trade equations to forecast US trade flows. Strauß (2003) applies vector error correction (VEC) models to forecast German exports and imports. Hetemäki and Mikkola (2005) employ univariate time series models, vector autoregressive (VAR) models, and combinations of the models to forecast German imports of coated printing and writing paper. Pappalardo and Piras (2004) study the performance of univariate time series and VAR models in forecasting Italian imports. Yu *et al.* (2008) use a VEC model and augment it with an artificial neural network to forecast China's trade volume. Keck *et al.* (2009) employ univariate time series and VAR models to forecast import growth of the OECD countries. D'Agostino *et al.* (2017) forecast intra and extra Euro Area trade with a dynamic factor model.

One branch of the forecasting literature deals with the performance of disaggregated forecasts. This literature argues that forecasting each component of GDP separately and adding up these forecasts yields smaller forecast errors than forecasting GDP directly (see, e.g., Esteves, 2013; Golinelli and Parigi, 2007; Hahn and Skudelny, 2008; Heinisch and Scheufele, 2018a; Lehmann and Wohlrabe, 2014; Rünstler *et al.*, 2009). However, this requires reliable indicators for each of the GDP components. For private consumption and exports, different indicators are available and assessed with respect to their reliability (see, e.g., Vosen and

Schmidt, 2011; Lehmann, 2015; Hanslin and Scheufele, 2016). With respect to forecasting imports, we are the first to analyze the performance of different, rather general indicators and introduce a leading indicator that is specifically constructed to reflect import dynamics.

The remainder of the paper is organized as follows. Section 2 presents the theory behind the construction of our leading indicator. In Section 3 we describe our data set in detail and which variables are used to construct our indicator empirically. Section 4 outlines the pseudo out-of-sample, real-time forecasting experiment. We present the baseline results in Section 5 together with some robustness checks. Section 6 concludes.

2. Theoretical Construction of the Leading Indicator

In this section, we develop our new leading indicator for imports, which we call Import Climate henceforth. We start with the identity that domestic total imports M_t^d in quarter t can be expressed as the sum of imports from each trading partner k:

$$M_t^d = \sum_{k=1}^{K} M_{k,t}^d \, .$$

Applying a simple accounting framework, domestic import growth, ΔM_t^d, equals the sum of each trading partner's growth share

$$\Delta M_t^d = \sum_{k=1}^{K} \left(\underbrace{\frac{M_{k,\tau-1}^d}{M_{\tau-1}^d}}_{w_{k,\tau-1}^d} \times \Delta M_{k,t}^d \right) , \tag{1}$$

where $w_{k,\tau-1}^d$ is the import share of partner k in total domestic imports from the previous year $\tau - 1$, with $t \in \tau$. At this stage, we model imports from the domestic country's point of view. From the point of view of trading partner k, imports of country d from partner k equal the exports of k to d, $M_{k,t}^d = X_{d,t}^k$; in turn, these exports are a share of total exports of country k, $X_{d,t}^k = \gamma_{d,t}^k X_t^k$. Applying log differences and substituting into Equation (1) yields

$$\Delta M_t^d = \sum_{k=1}^{K} w_{k,\tau-1}^d \times \left(\Delta \gamma_{d,t}^k + \Delta X_t^k \right) , \tag{2}$$

where $\Delta \gamma_{d,t}^k$ is the change in the share of country d in total exports of k and ΔX_t^k denotes total export growth of trading partner k. From Equation (2) we derive the h-step ahead import growth expectation based on all available information in quarter t:

$$\mathrm{E}\left(\Delta M^{d}_{t+h|t}\right) = \sum_{k=1}^{K} \left\{ \mathrm{E}\left(w^{d}_{k,\tau+h-1|t}\right) \times \left[\mathrm{E}\left(\Delta\gamma^{k}_{d,t+h|t}\right) + \mathrm{E}\left(\Delta X^{k}_{t+h|t}\right)\right] \right.$$
$$\left. + \operatorname{Cov}\left(w^{d}_{k,\tau+h-1|t}, \left[\Delta\gamma^{k}_{d,t+h|t} + \Delta X^{k}_{t+h|t}\right]\right) \right\} . \quad (3)$$

Expectations for domestic import growth h-periods ahead are a function of the expected foreign export growth of country k, $\mathrm{E}\left(\Delta X^{k}_{t+h|t}\right)$, the expected change in the importance of the domestic economy for trading partner k's exports, $\mathrm{E}\left(\Delta\gamma^{k}_{d,t+h|t}\right)$, the expected share of country k in domestic imports, $\mathrm{E}\left(w^{d}_{k,\tau+h-1|t}\right)$, and the interaction between domestic import shares and the change in foreign exports to the domestic economy, represented by the covariance term. We therefore need reliable proxies for these terms.

In order to be able to empirically implement Equation (3) later, we require two assumptions. First, we proxy expectations about future import shares, $\mathrm{E}\left(w^{d}_{k,\tau+h-1|t}\right)$, by previous year values, $w^{d}_{k,\tau-1|t}$. This is a reasonable assumption since the import shares are relatively constant over time. Treating these shares as constant over the forecasting period, the covariance term is zero and, hence, drops out. Second, we assume that the expected change in the share of the domestic economy in trading partner k's total exports, $\mathrm{E}\left(\Delta\gamma^{k}_{d,t+h|t}\right)$, is zero. Thus, the shares remain constant, which is also broadly consistent with the data. With these two assumptions, Equation (3) simplifies to:

$$\mathrm{E}\left(\Delta M^{d}_{t+h|t}\right) = \sum_{k=1}^{K} w^{d}_{k,\tau-1|t} \times \mathrm{E}\left(\Delta X^{k}_{t+h|t}\right) . \quad (4)$$

Based on Equation (4), we construct the Import Climate. The data used for the implementation of the indicator as well as the data used in the forecast experiment are described in the next section.

3. Data Set

The description of the data consists of three parts.[5] First, we start by describing the target series that we forecast: total imports. Second, we connect the theoretical construction of the Import Climate to its empirical implementation. Third, we introduce further potential predictors for import growth to be able to judge the forecasting performance of the Import Climate.

[5] The Appendix contains detailed descriptions of all series that we use together with the sources from which the series are available.

Target Series

We forecast total imports for the six countries France, Germany, Italy, Spain, the United Kingdom, and the United States. All series are available on at quarterly frequency and are seasonally, price and, with the exception of the United States, calendar adjusted. Each series is from national accounts statistics, which is the statistic that applied forecasts usually rely on. To ensure a realistic forecasting setup, we use real-time data vintages of the import series. In each vintage, we get a new value for the most recent quarter and revised values for the past quarters. Due to publication lags, the date of the vintage and the time period of the most recent quarter do not coincide. We obtain real-time import data for the United States from the Federal Reserve Bank of Philadelphia, for Germany from the Deutsche Bundesbank, and for the other countries from the OECD.[6]

Import-Weighted Foreign Export Climates: The Import Climate

To derive our leading indicator, the Import Climate for the domestic country, IC_t^d, we model the expected export development of country k from Equation (4), $\mathrm{E}\left(\Delta X_{t+h|t}^k\right)$, as a function of business (BC_t^j) and consumer confidence (CC_t^j) in its trading partners $j \neq k$ as well as by a measure of its price competitiveness, PC_t^k.[7] This functional relationship describes the Export Climate of country k, XC_t^k.[8] Substituting XC_t^k for $\mathrm{E}\left(\Delta X_{t+h|t}^k\right)$ in Equation (4) yields the full representation of the Import Climate:

$$\begin{aligned} IC_t^d &= \mathrm{E}\left(\Delta M_{t+h|t}^d\right) \\ &= \sum_{k=1}^{K} w_{k,\tau-1|t}^d \times XC_t^k \\ &= \sum_{k=1}^{K} w_{k,\tau-1|t}^d \times \left(\beta^k \times \left\{\sum_{j\neq k}^{J} \nu_j^k \left[\eta_j^k CC_t^j + (1-\eta_j^k) BC_t^j\right]\right\} + (1-\beta^k) \times PC_t^k\right). \end{aligned} \tag{5}$$

[6]The OECD does not publish exact values of import volumes but rounds the figures to full billions. This rounding means a loss of information. Since we are not aware of other real-time data resources, and since we want to keep our forecasting experiment as realistic as possible, we rely on the OECD data vintages.

[7]Alternatively, we approximate the expected export development by export expectations either from surveys of manufacturing firms or experts in country k. However, we find that these approximations systematically generate larger forecast errors than the Import Climate. Therefore, we do not further consider this type of survey data in this paper.

[8]Elstner *et al.* (2013) use the Export Climate to forecast German export growth and show that the indicator produces relatively low forecast errors. Lehmann (2018a) confirms the forecasting power of the Export Climate for a multitude of European countries.

We use data to construct monthly Export Climates for 39 countries.[9] In the following, we describe the data used for measuring BC_t^j, CC_t^j, and PC_t^k, each in turn. The business confidence of each country (BC_t^j) is approximated by an industrial confidence indicator. For the European countries, we use the industrial confidence indicators (ICI) from the European Commission which are harmonized across the member states (see European Commission, 2016, p.17). For most of the other countries outside Europe, we use the Business Confidence Index (BCI) provided by the OECD. To approximate business confidence in the United States and China, we rely on the Purchasing Managers' Index (PMI) from the Institute for Supply Management (ISM) and the National Bureau of Statistics China, respectively; for Thailand, we use the BCI provided by the Bank of Thailand.

The consumer confidence indicators (CC_t^j) are taken from the European Commission for the European countries and from the OECD for all remaining countries.[10] Both confidence indicators – business and consumer – are seasonally adjusted and standardized to have the same mean and standard deviation.

Proxies for the price competitiveness of a country (PC_t^k) are taken from the European Commission. We use the real effective exchange rate (REER) for a broad number of industrial countries. A country's REER is its nominal effective exchange rate, taking into account the ratio of foreign to domestic consumer prices (see European Commission, 2014). A better approximation of a country's price competitiveness would be a REER based on export prices, but this measure is available only quarterly. In contrast, the REER based on consumer prices is available monthly; therefore, we rely on this variable to be able to calculate the Import Climate at monthly frequency.

So far, we have introduced the three main data components of the Import Climate. In the following, we discuss the different weights (η_j^k, ν_j^k, β^k, and $w_{k,\tau-1|t}^d$) that are necessary to densify these components. First, the shares η_j^k, which weight the confidence indicators, are calculated as the ratio of the volume of exports of consumption goods from country k to j and the sum of exports of consumption and investment goods from k to j. The individual sums of each of the J trading partners are weighted by j's share in total exports of country k. Country-specific export data are extracted from the UN Comtrade Database. This database allows us to split a country's exports with respect to destination and broad economic categories (BEC).[11]

[9]The 39 countries comprise all member states of the European Union (except Croatia and Cyprus), Norway, the Russian Federation, Switzerland, Turkey, a selection of North and South American countries (Brazil, Canada, Mexico, and the United States), a number of Asian countries (China, Japan, and South Korea), and Australia and New Zealand.

[10]Note that the indicators within each group (business and consumer) are perfectly comparable, as they are based on a similar set of survey questions. A detailed description of the OECD indices can be found at: `https://data.oecd.org/leadind/business-confidence-index-bci.htm` and `https://data.oecd.org/leadind/consumer-confidence-index-cci.htm`; for the European indicators see European Commission (2016, p.18).

[11]As we are interested in consumer versus investment goods exports, we rely on the consumer goods definition by the UN. Based on this definition, consumer goods are mainly the sum of food and beverages

Second, the share ν_j^k denotes the importance of country j for country k's exports and is computed as the volume of exports from k to j divided by the total volume of exports of k; the data are taken from the IMF's Direction of Trade Statistics. An increase in the weighted sum of consumer and business confidence suggests an increase in exports of k to the domestic country. This assumes that trade fluctuations among the countries are synchronized to some extent because, in principle, a situation could arise in which k's exports only increase to j while exports to the domestic country remain unaffected. Thus, an increase in k's Export Climate does not have to be triggered by a higher demand from the domestic economy, which may introduce some noise to the indicator.

Third, the weights of the Export Climate's two components (the combined confidence indicators and the price competitiveness), described by β^k, are calculated from two separate regressions:

$$\Delta X_t^k = c_1^k + \sum_{i=0}^{4} \alpha_{1,i}^k PC_{t-i}^k + \varepsilon_{1,t}^k \,,$$

$$\Delta X_t^k = c_2^k + \sum_{i=0}^{4} \alpha_{2,i}^k PC_{t-i}^k + \sum_{m=0}^{4} \beta_{2,m}^k \left\{ \sum_{j \neq k}^{J} \nu_j^k \left[\eta_j^k CC_{t-m}^j + (1-\eta_j^k) BC_{t-m}^j \right] \right\} + \varepsilon_{2,t}^k \,.$$

The first regression describes trading partner k's export growth, ΔX_t^k, only by its price competitiveness. The second regression includes both the competitiveness and the confidence indicators. The competitiveness measures and the confidence indicators are aggregated to a quarterly frequency by computing three month averages. Both models are estimated with quarterly national accounts export data for the sample period 1996:Q1 to 2016:Q4. Then, the weight β^k is computed from the ratio of the adjusted R^2 of the first regression to that of the second model (see Kilian *et al.*, 2009).

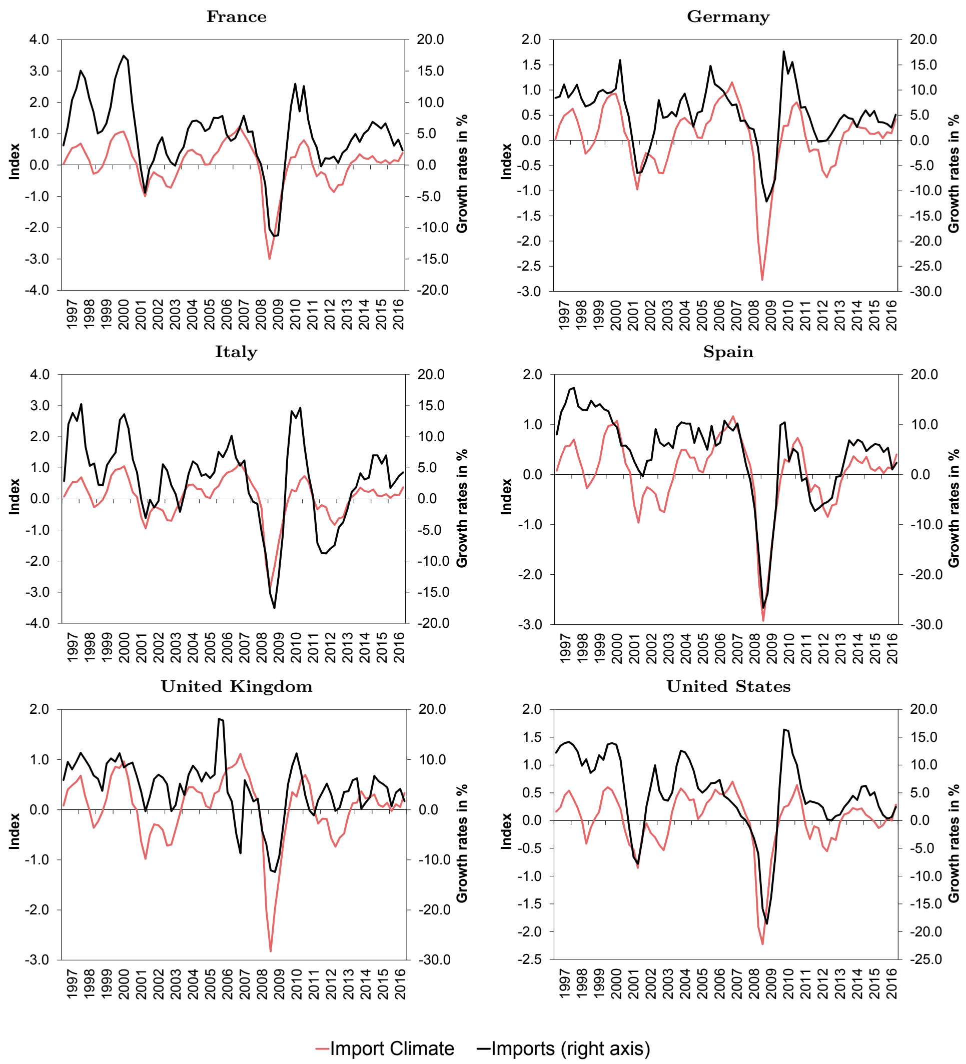
Finally, we compute the monthly and seasonally adjusted Import Climate by aggregating the individual Export Climates, XC_t^k, using the import share of each trading partner k in the domestic country's total imports from the previous year, $w_{k,\tau-1|t}^d$. The import data are taken from the IMF's Direction of Trade Statistics. Note that total imports equal the sum of imports from the remaining 38 trading partners. For each of the six countries for which we conduct our forecasting experiment, we construct an individual Import Climate that densifies the information from the Export Climates of 38 trading partners, respectively. According to UN Comtrade Data for 2016, we cover a large share in goods imports of each country: France: 67%, Germany: 89%, Italy: 83%, Spain: 80%, the United Kingdom: 87%, and the United States: 80%. Note that the Import Climate is not available in real-time.

for household consumption, processed fuels and lubricants, non-industrial transport equipment and consumer goods that are not specified in any other BEC. Investment goods are capital goods and industrial transport equipment. See also `https://unstats.un.org/unsd/tradekb/Knowledgebase/50090/Intermediate-Goods-in-Trade-Statistics`.

Even though survey data are not revised with new publications, real-time data are, to the best of our knowledge, not available for the price competitiveness measures as well as for the variables that are used to calculate the weights from Equation (5).

Figure 1 plots the Import Climates – aggregated to a quarterly frequency by taking three month averages – together with the growth rates of the final vintage of real imports from national accounts for each of the six countries for the period 1997:Q1 to 2016:Q4. Overall, the Import Climates fall during the burst of the dot-com bubble, then increase until 2007, drop again during the global financial crisis, and subsequently rebound. For each country, the Import Climate and import growth are contemporaneously highly correlated (see Table 1). The Import Climates also exhibit strong lead correlations with import growth. In sum, Figure 1 and the correlations suggest that the Import Climate may be well suited to forecast import growth for the countries at hand.

Figure 1: Import Climate and growth of total imports



Notes: Total imports are based on the latest vintage and are transformed into year-over-year growth rates.

Table 1: Cross-correlations of the Import Climate and import growth

Country	*Lead of the Import Climate (t-x quarters)*				
	0	1	2	3	4
France	0.81	0.80	0.62	0.33	-0.00
Germany	0.76	0.73	0.55	0.27	-0.07
Italy	0.80	0.72	0.49	0.18	-0.15
Spain	0.78	0.68	0.44	0.16	-0.08
United Kingdom	0.59	0.53	0.33	0.09	-0.11
United States	0.74	0.75	0.57	0.26	-0.08

Notes: The cross-correlations are calculated between the level of the respective Import Climate and the year-over-year growth rates for price-adjusted total imports.

Further Potential Predictors

To judge the relevance of the Import Climate for applied import forecasting, we need to compare its forecasting performance to the performance of other predictors. We select only such indicators that should be related to import dynamics by mirroring the more standard channel of domestic demand for foreign goods and services. This selection comprises both qualitative (e.g., from business and consumer surveys) as well as quantitative indicators (e.g., data from official statistics). All predictors are seasonally adjusted and already revised as most of the indicators are either not available in real-time for the whole evaluation period or not at all. The Appendix shows descriptive statistics of all the indicators used in this paper as well as cross-correlations of these indicators with the import growth rates.

Industrial Confidence Indicator (*ICI*): A higher confidence of domestic firms should lead to a higher degree of capacity utilization and an increase in domestic production. To raise production, firms need intermediate goods, some of which are purchased abroad, implying an increase in domestic demand for foreign intermediate goods. The monthly industrial confidence indicators for the European countries are provided by the European Commission. For the United States, we use the PMI by the ISM.

Consumer Confidence Indicator (*CCI*): When households become more confident in the state of the economy, they may increase consumption. Part of the additional consumption is satisfied by foreign consumption goods, which raises import demand. For the European countries, we use consumer confidence indicators provided by the European Commission. For the United States, we take indicators from both the Conference Board and the University of Michigan.

New Orders, Survey (*NO-S*): An increase in order volume increases production, albeit with some time lag. As stated above, higher production may be associated with a greater need for imported goods; thus, an increase in new orders may signal a higher import demand by domestic firms. For the European countries, we rely on two order questions provided by the European Commission. First, the firms are asked monthly about their current order-book levels (*NO-S-M*). Second, the survey includes a quarterly question on the development of new orders in recent months (*NO-S-Q*). For the United States, the ISM provides a monthly question on new orders (*NO-ISM*).

Country-Specific Surveys: In addition to indicators that are similar across countries, we also include indicators that are available only for some countries. A prominent leading indicator for economic activity in Germany is the ifo Business Climate (*ifo-BC*), which is the geometric mean of the assessment of the business situation (*ifo-BS*) and business expectations (*ifo-BE*).[12] We use all three indicators separately in our forecast experiment. For the United States, the ISM provides an indicator on firms' assessment of their current change in material imports (*ISM-imports*). However, this import-specific indicator only captures raw materials, which represent merely a small fraction of total imports.

Imports and Exports – Special Trade Classification (*IM-STC* and *EX-STC*): The most straightforward quantitative indicator is import in delimitation of special trade, which is available on a monthly basis and solely captures traded goods. We also use the monthly export series in delimitation of special trade. Exports can be a reliable import indicator because products that are sold on foreign markets often require imported intermediate goods or services during their production. Both indicators are measured in nominal terms and are provided by the OECD.

Industrial Production (*IP*): Industrial production is an important indicator for measuring economic activity on a monthly basis. We suggest that *IP* contains signals that predict imports, since an increase in production should go hand in hand with a higher demand for foreign goods and services. Also, the existing forecasting literature finds that hard, quantitative indicators measuring real economic activity are very important for forecasting quarterly macroeconomic aggregates (see, e.g., Bańbura and Rünstler, 2011; Giannone *et al.*, 2008; Heinisch and Scheufele, 2018b). Monthly industrial production is extracted from the OECD database.

New Orders, Germany (*NO-G*): In Germany monthly new orders are also available quantitatively. To the best of our knowledge, this indicator is not available over the whole period for the other countries. In the forecast exercise, we distinguish between domestic (*NO-G-D*), foreign (*NO-G-F*), and total new orders (*NO-G-T*). The series are provided by the German Federal Statistical Office.

[12] Lehmann (2018b) surveys the literature and finds that the ifo Business Climate is a reliable indicator for economic activity in Germany. Using machine-learning techniques, Carstensen *et al.* (2017) find that the ifo business expectations are one of the most informative indicators for the German business cycle.

Price Competitiveness (*PC*): In addition to the indicators describing the real economy, we also rely on a price measure. As imports are directly linked to the relative price competitiveness position of the domestic economy within the world market, information about relative prices should contain signals that may help forecast import growth. We use the REER based on export prices against 37 industrial countries (*PC-XPI37-Q*) released by the European Commission on a quarterly basis. Note that there are other quarterly *PC* measures that are based on different weights, such as the ratio of GDP deflators or unit labor costs. We test each measure separately and find that the REER based on export prices is the best predictor.

The number of predictors in the indicator set l differs across the six countries. For France, Italy, Spain, and the United Kingdom we rely on nine different indicators. For the United States, the indicator set comprises ten variables. The largest set is the one for Germany which captures 15 predictors.

4. Forecasting Approach

In the following, we present the forecasting model and how we evaluate the forecast quality of each indicator. To assess the forecasting performance of the indicator in a pseudo out-of-sample, real-time setup, we use the following general forecasting model:

$$\Delta M^l_{t+h|t} = \alpha^l + \sum_{p=0}^{P} \beta^l_p x^l_{t-n-p|t} + \varepsilon^l_{t|t} \ , \tag{6}$$

where $\Delta M_{t+h|t}$ is the h-period-ahead forecast of quarter-on-quarter real import growth.[13] Each single predictor from the set l of potential indicators is denoted as x^l. The forecast horizon h is restricted to $h \in \{0, 1\}$ quarters, whereby $h = 0$ is the nowcast.[14] P indicates the maximum number of lags. In each iteration step of the pseudo out-of-sample approach, the choice of the optimal number of lags is based on the Bayesian Information Criterion.[15] The parameters of the model, α^l and β^l_p, are estimated by OLS; $\varepsilon^l_{t|t}$ is the error term.

Our initial estimation period ranges from 1996:Q1 to 2005:Q1, which encompasses 37 observations. From this sample, we generate a nowcast for 2005:Q2 and a one-step-ahead

[13]For notational convenience we leave out the country index. For the United Kingdom, we additionally include dummy variables for 2006:Q1, 2006:Q2, and 2006:Q3 because the trade figures were heavily affected by the introduction of the reverse charge derogation during this time (Office for National Statistics, 2015).

[14]We also tested the performance of the indicators for two-, three-, four- and eight-quarter-ahead forecasts and present the results in the Appendix. We confirm the finding in the literature that survey-based indicators lose their quality with longer forecast horizons.

[15]We also tested two variants of Model (6): (i) we keep the number of lags fixed in each iteration step with $p \in \{1, ..., 8\}$ and (ii) we apply autoregressive distributed lag models in which we include lagged values of total import growth next to the specific indicator. Both models generated forecast errors that are larger than those from the baseline model.

forecast for the following quarter. The estimation window is recursively expanded until 2016:Q2 so that the total evaluation period runs from 2005:Q2 to 2016:Q4. We apply a direct-step forecasting scheme, thus, the forecast for the next quarter does not depend on the nowcast.

The country-specific models are specified such that only available information in quarter t enter the estimation procedure and the subsequent calculated forecast. This is ensured in two ways. First, we use real-time data for imports as described in Section 3. Therefore, we take into account that the forecaster is not able to observe revisions ex-ante. In sum, we rely on 48 vintages for total imports for the period 1996:Q1 to 2016:Q4. Second, we consider indicator-specific publication lags n. All monthly indicators enter the forecasting model as quarterly averages. We take into account that at the time of the forecast not all monthly values of a quarter are known. Therefore, the quarterly aggregation of the monthly indicators for quarter t is based on either the first month, the first and second months, or all three months. Indicators, that are only available quarterly, enter the equation directly with their specific publication lags: the survey on new orders has no publication lag, whereas the price competitiveness measure is only available with a time lag of one quarter. The Appendix provides detailed information on the publication lag of each indicator.

We run the forecasting experiment with two different timing assumptions. The first timing assumes that the forecasts are produced right after the release of new figures from national accounts. This is usually the case in the second month of the quarter. The second timing assumes that forecasts are calculated at the end of each quarter. Both timing assumptions are also associated with different publication lags of the indicators, which may change the results. Therefore, both timings will be discussed in the results section.

The forecasts derived from Model (6) are compared to the first release of import growth which is available at $t+h+m$, where m denotes the publication lag of national account figures. In applied forecasting, the precision of the forecast is often evaluated with respect to the first release (see, e.g., Heinisch and Scheufele, 2018b). We assess the overall absolute performance of indicator l at horizon h based on the root mean squared forecast error (RMSFE),

$$RMSFE_h^l = \sqrt{\frac{1}{T_h} \sum_{t \in T_h} \left(\Delta \widehat{M}_{t+h|t}^l - \Delta M_{t+h|t+h+m} \right)^2}, \tag{7}$$

where T_h denotes the number of forecasts produced for each horizon. To assess the relative performance of an indicator, we calculate the relative RMSFE or Theil's U as the ratio of the RMSFE of the indicator model and a specific benchmark. As benchmark we use a BIC-optimized AR(p)-model. We apply the Diebold-Mariano test (Diebold and Mariano, 1995), modified via the small-sample correction proposed by Harvey *et al.* (1997), to analyze whether the forecast errors from the indicator model differ significantly from those obtained from the BIC-optimized AR(p)-model.

In addition to the BIC-optimized AR(p)-benchmark, we also tested other benchmarks: (i) a random walk (RW), (ii) the sample mean (SM) that is observable at time t, (iii) different autoregressive specifications and (iv) models that result from the algorithm proposed by Hyndman and Khandakar (2008). Whereas the first two benchmarks produce on average larger forecast errors than the BIC-optimized AR(p)-model, the results from the latter two are very similar to our chosen benchmark. Therefore, we decided to present only the comparison to the BIC-optimized AR(p)-benchmark, but the results are available upon request.

5. Results

Baseline Results

Table 2 presents the relative forecasting performance of the Import Climate for each country and the two forecast horizons (see the Appendix for the full list of results). Columns (1) and (2) define the forecast horizon and the country considered. Columns (3) and (4) show the Theil's U of the Import Climate compared to the BIC-optimized AR(p)-benchmark and the corresponding rank among the set of indicators. Here, the forecast is generated in the second month of a quarter, right after the release of new national account figures but before the first-month publication of hard indicators such as industrial production. Whenever the rank of the Import Climate is different from 1, Column (5) lists the Theil's U of the best indicator. All Theil's U values, which are in bold, indicate significant differences between the forecast errors of the indicator model and the benchmark model at least at the 10% level according to the Diebold-Mariano test. Column (6) shows the rank for the Import Climate when the forecasts are produced at the end of each quarter.

For the nowcast and the first timing assumption, the Import Climate is the best indicator for forecasting import growth for France, Germany, Italy, and the United States. For these countries, the Import Climate's RMSFE relative to the RMSFE of the second-best indicator is 0.95 on average, that is, the Import Climate performs 5% better than the second-best predictor. For Spain and the United Kingdom, the Import Climate is in fifth and third place, respectively, but its performance is not much worse than that of the best indicator, which is consumer confidence for the United Kingdom and industrial confidence for Spain. For Spain, the Theil's U for the Import Climate is 0.80, whereas the best indicator yields 0.76; for the United Kingdom, these two values are 0.89 and 0.84, respectively. Overall, improvements over the AR(p) benchmark range from 24% for Germany to 1% for the United Kingdom and are in most cases statistically significant.

Turning to the forecast for the next quarter and the first timing assumption, the Import Climate's forecasting power becomes even better relative to the nowcasting setup. With the exception of Spain, the Import Climate is always ranked first; for the five countries, the Import Climate's RMSFE relative to that of the second-best indicator is 0.94 on average, which corresponds to a 6% improvement in the Import Climate's forecasting performance. In the case of Spain, however, the best-performing indicator – consumer confidence – is, on average, better by only 2.4%. In sum, the Import Climate's improvement over the AR(p) benchmark varies between 28% for the United States and 5% for the United Kingdom; again, most of these improvements are statistically significant.

Table 2: Relative forecasting performance of the Import Climate

(1)	(2)	(3)	(4)	(5)	(6)
Horizon	*Country*	*Theil's U*	*Rank*	*Theil's U*	*Rank 3rd Month*
		Import Climate		Best Indicator	Import Climate
$h = 0$	France	**0.80**	1	–	4
	Germany	**0.76**	1	–	3
	Italy	0.84	1	–	3
	Spain	**0.80**	5	**0.76**	7
	United Kingdom	0.99	3	0.94	6
	United States	**0.79**	1	–	3
$h = 1$	France	**0.73**	1	–	1
	Germany	**0.74**	1	–	1
	Italy	**0.74**	1	–	1
	Spain	0.80	2	0.78	3
	United Kingdom	0.95	1	–	1
	United States	**0.72**	1	–	1

Notes: The target series to forecast are real-time quarterly growth rates of total imports. The forecast is generated in the second month of each quarter and the forecast errors are computed with respect to the first release. $h = 0$ denotes the nowcast, $h = 1$ describes the forecast for the following quarter. Theil's U values in bold indicate that the forecast error of the respective indicator is significantly different from the error of the AR(p) benchmark model at least at the 10% level. The ranks from the column labeled *3rd Month* are based on a forecasting experiment conducted at the end of each quarter. The number of variables in the indicator set is as follows: France: 9, Germany: 15, Italy: 9, Spain: 9, United Kingdom: 9, and United States: 10.

Turning to the last column, we check the performance of the Import Climate when the forecast is conducted in the last month of the quarter. Now, hard indicators are available for the first month of the respective quarter. For $h = 0$, the Import Climate is still among the top four performing indicators for most of the countries. Hard indicators – such as industrial production or monthly import figures – perform better to some extent, but the differences in the relative RMSFEs between our indicator and the hard indicators are small. This result is not surprising as the literature on GDP nowcasting finds that the forecasting power of hard indicators is better than that of survey data once a hard indicator is released for the first month of a quarter (see, e.g., Bańbura and Rünstler, 2011; Giannone *et al.*, 2008; Heinisch and Scheufele, 2018a,b). We confirm this finding for total imports. For $h = 1$, we find that our new indicator still performs better than other indicators. For France, Germany, Italy, the United Kingdom, and the United States, the Import Climate produces the lowest RMSFEs. In Spain, our new indicator is ranked third. Industrial production is slightly better than the Import Climate; however, the differences are small.

Discussion

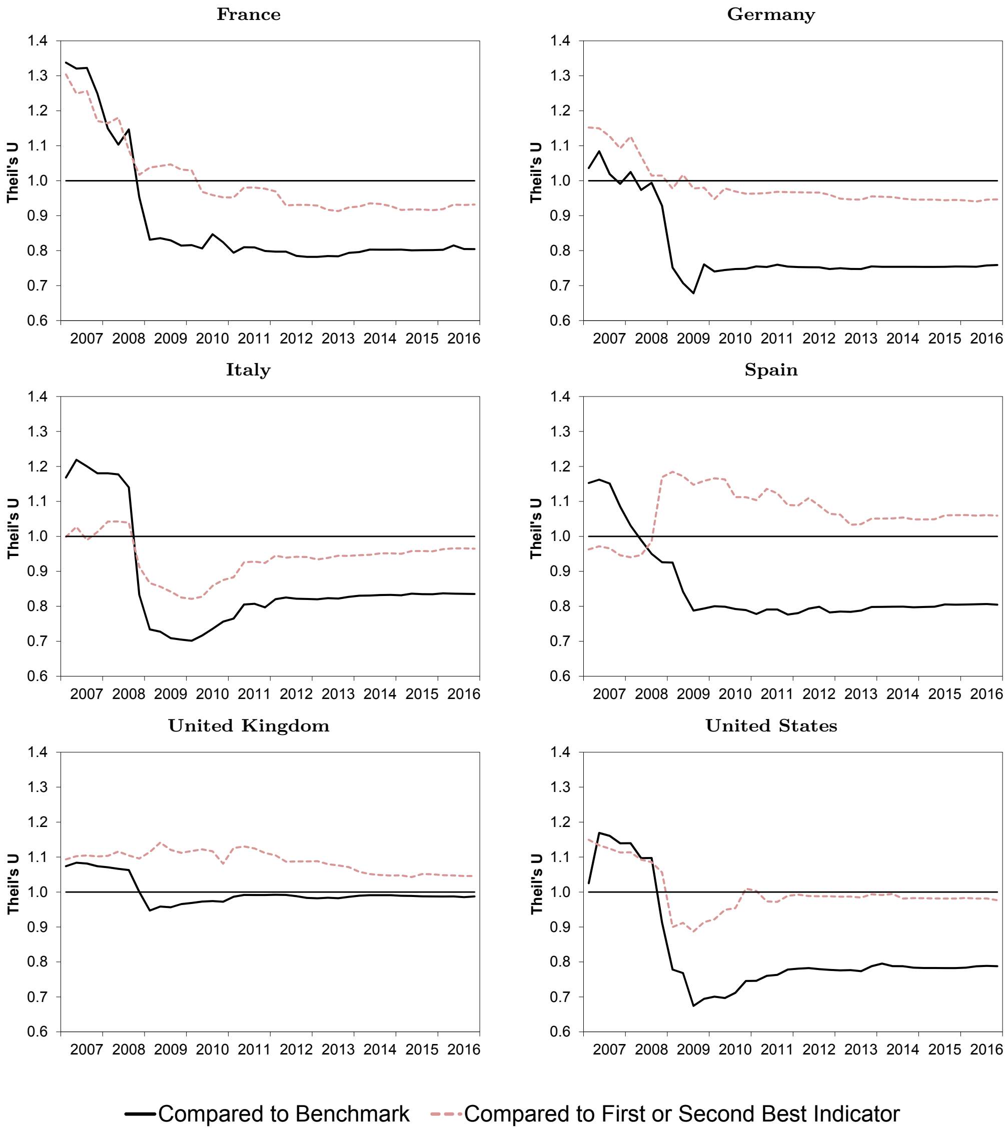
The aim of this section is to analyze how robust our baseline results are and whether the Import Climate is a reliable tool for applied forecasting. First, we look at the Import Climate's performance over time, thereby checking whether the good average forecasting performance found in the baseline section is solely driven by a few events. Second, we check whether the Import Climate's forecast errors are less dispersed than the volatility of the import series to see whether our indicator represents a clear added value to applied forecasting. Third, we investigate why the Import Climates' performance for Spain and the United Kingdom is not as good as the performance for the other countries. Fourth, we check whether our indicator produces lower forecast errors than more sophisticated methods such as factor models or forecast combinations.

Forecasting Performance Over Time

The good performance of the Import Climate in the baseline could be driven by exceptional good performances in a few periods. As the RMSFE represent averages over the entire forecasting period, outliers may distort the performance of the benchmark or that of the other indicators, which may bias the true relative performance of the Import Climate. Another reason is that the relative forecasting quality of different models may change over time (see Giacomini and Rossi, 2010). By focusing on averages over the entire sample period, the forecasting performance of the Import Climate over time cannot be evaluated. Figure 2 plots the Import Climate's RMSFE time-path for the nowcast relative to (i) the benchmark model and (ii) the second best indicator or, when the Import Climate is not, on average, the best predictor, to the indicator ranked first. The RMSFEs are based on an expanding window; the initial period is eight quarters. We chose the expanding window for two reasons. First, the impact of single events vanishes as the number of forecasts rises, since less weight is attached to each observation. Second, one can easily interpret the time-path of the expanding window RMSFEs. If there is a trend in the time-path, the relative forecasting performance either improves or deteriorates. In contrast, if the time-path remains constant, we can interpret this behavior as evidence for a steady forecasting performance.

Compared to the benchmark model, the Import Climate performs better for all countries since the Financial Crisis of 2008/09 (solid lines). The Import Climate's RMSFEs are lower than those of the second-best predictor for France, Germany, Italy, and the United States in almost all of the periods after the Financial Crisis (dashed lines). In contrast, for the United Kingdom, the Import Climate performs worse than the first-best indicator during the whole evaluation period, for Spain since 2008. However, the Import Climate's performance catches up in both cases. In sum, there is no evidence that the Import Climate's good forecasting performance in the nowcast setup is driven by singular events, because the relative RMSFEs remain constant after the financial crisis.

Figure 2: Forecasting performance of the Import Climate over time for $h = 0$

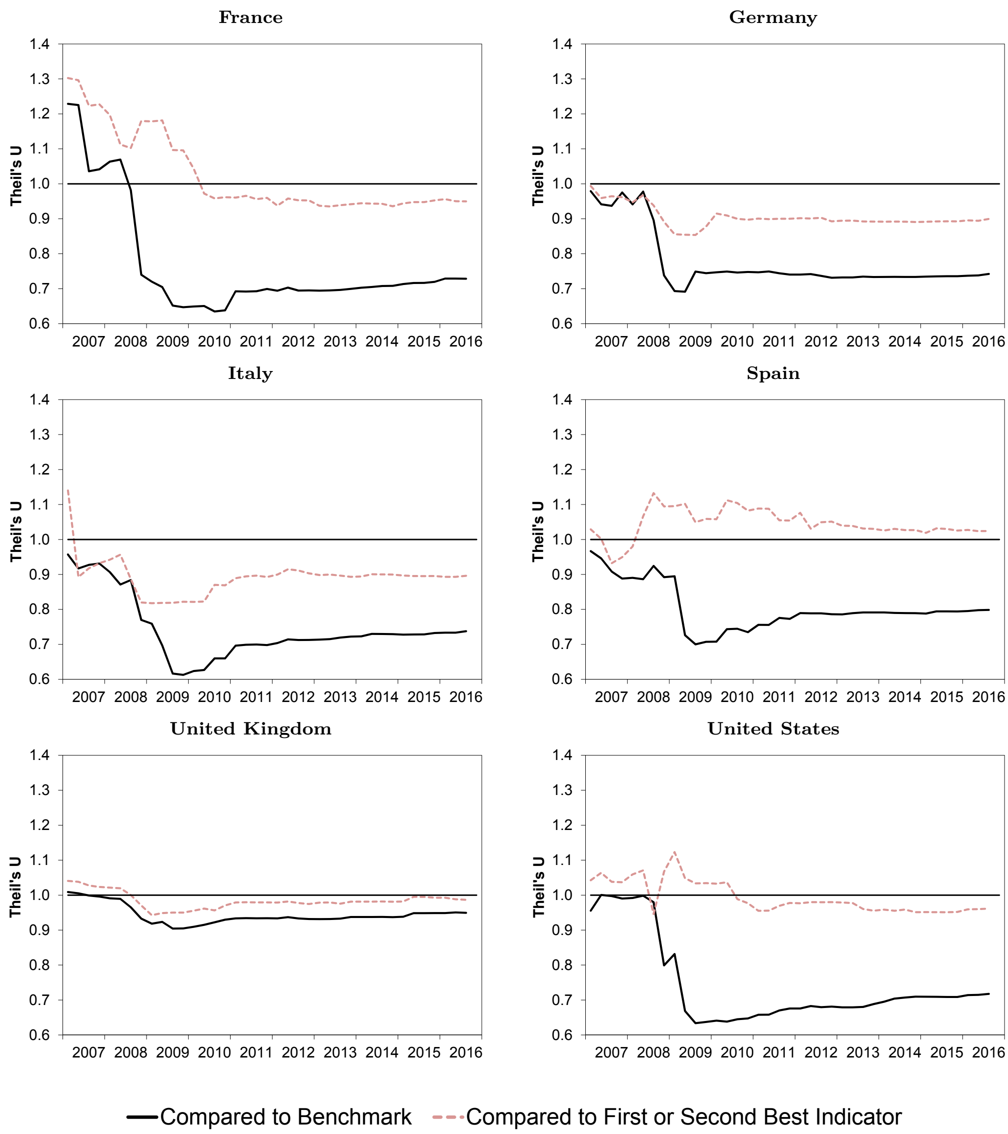


Notes: The figure shows the relative root mean squared forecast errors of the Import Climate over time. The Import Climate's forecast errors are compared to the AR(p)-model (*Compared to Benchmark*) and to the second best indicator or, when the Import Climate is not, on average, the best predictor, to the best-performing indicator (*Compared to First or Second Best Indicator*). The root mean squared forecast errors are based on an expanding window, the initial period is eight quarters.

For one-quarter-ahead predictions, Figure 3 plots the relative RMSFEs over time. With the exception of France and the United Kingdom, the Import Climate's RMSFEs are always lower than those of the benchmark model (solid lines); in the former two countries, the Import Climate performs worse up to the outbreak of the Financial Crisis. Compared to the second-best predictor, the Import Climate's performance is always better for Germany, better for Italy and the United Kingdom with the exception of the beginning of the evaluation period, and better for France and the United States since 2010 (dashed lines). In contrast, the Import Climate's RMSFEs for Spain are only lower than those of the first-best indicator in 2007. However, the relative performance of the Import Climate steadily improves since

2011. Overall, the good performance of the Import Climate for $h = 1$ does not depend on a few episodes, because the relative RMSFEs remain rather stable over time.

Figure 3: Forecasting performance of the Import Climate over time for $h = 1$



Notes: The figure shows the relative root mean squared forecast errors of the Import Climate over time. The Import Climate's forecast errors are compared to the AR(p)-model (*Compared to Benchmark*) and to the second best indicator or, when the Import Climate is not, on average, the best predictor, to the best-performing indicator (*Compared to First or Second Best Indicator*). The root mean squared forecast errors are based on an expanding window, the initial period is eight quarters.

Dispersion of Forecast Errors

In the previous sections, we showed that the Import Climate performs well relative to other indicators. In order to represent an added value to applied forecasting, we now check whether the noise-to-signal (NTS) ratio of our new indicator is below one. The NTS ratio is the ratio of the dispersion of forecast errors produced by the Import Climate and the dispersion of the quarterly import growth rates. Table 3 presents the NTS ratio for the two forecast horizons and the six countries. For $h = 0$, the NTS ratio is always below one, confirming that the new indicator truly provides additional information. The same holds for $h = 1$. However, the performance for Spain is not as good as for the other countries as the NTS Ratio is close to one. We elaborate more on the Spanish case in the next section.

Table 3: Noise-to-Signal ratio of the Import Climate

Country	*NTS Ratio*	
	h = 0	*h = 1*
France	0.73	0.71
Germany	0.86	0.81
Italy	0.72	0.77
Spain	0.91	0.99
United Kingdom	0.89	0.90
United States	0.77	0.85

Notes: The noise-to-signal ratio is the ratio of the dispersion of forecast errors of the Import Climate and the dispersion of the quarterly growth rates of total imports. The calculation is based on the forecasting period from 2005:Q2 to 2016:Q4 and the first timing assumption. $h = 0$ denotes the nowcast, $h = 1$ describes the forecast for the following quarter.

Forecasting Performance for Spain and the United Kingdom

Why is the Import Climate not the best performing indicator for Spain and the United Kingdom? One possible explanation is that the import data from earlier vintages may be relatively inaccurate for both countries and thus have been heavily revised over time. To check the accuracy of the import data, we first calculate for each quarter and vintage the absolute revision in quarterly growth rates compared to the latest release for 2016:Q4. Second, for each quarter we average these revisions over all vintages, which yields cross-vintage absolute revisions. Third, we compute the mean absolute revision as the average of all cross-vintage absolute revisions. This mean absolute revision is 1.1 and 0.7 percentage points for Spain and the United Kingdom, respectively, and thus larger compared to the other countries (France: 0.3 p.p., Germany: 0.4 p.p., Italy: 0.6 p.p., United States: 0.2 p.p.). The standard deviation in cross-vintage absolute revisions is also larger for these two countries compared to the remaining four countries.

Based on the finding that the import data for Spain and the United Kingdom are relatively heavily revised, we repeat our forecast experiment for the latest vintage and check whether our indicator properly reflects the "true underlying development" in both countries. The forecasts are generated in the second month of a quarter to make them comparable to those of the baseline forecast experiment. Table 4 presents the rank of the Import Climate among the set of indicators for both forecast horizons and both data releases (see the Appendix for the relative RMSFEs). For the nowcast and both countries, the Import Climate's rank improves when moving from the real-time data to the latest vintage. For the forecast for the next quarter, the Import Climate remains ranked first for the United Kingdom and becomes the best-performing indicator for Spain. These results suggest that, overall, the Import Climate is particularly well-suited to forecast the "true" import development in Spain and the United Kingdom.

Table 4: Comparison of rankings for real-time data and latest vintage

Horizon	*Spain*		*United Kingdom*	
	Real-time	Latest	Real-time	Latest
$h = 0$	5	2	3	2
$h = 1$	2	1	1	1

Notes: The target series to forecast are quarterly growth rates of total imports with respect to either the first release (*Real-time*) or the latest vintage (*Latest*). The forecast is generated in the second month of each quarter. $h = 0$ denotes the nowcast, $h = 1$ describes the forecast for the next quarter. The number of variables in the indicator set is as follows: France: 9, Germany: 15, Italy: 9, Spain: 9, United Kingdom: 9, and United States: 10.

Comparison to Sophisticated Forecasting Methods

So far, we analyzed the Import Climate's performance with the help of an (autoregressive) distributed lag model. With this methodological approach we showed that the Import Climate produces lower forecast errors than other indicators. In the following, we check whether this finding also holds when we employ more sophisticated methods, namely factor models and forecast combinations.

Both forecasting approaches densify the amount of information. This is done either ex-ante by collapsing a large set of indicators into a limited set of factors or ex-post by combining forecasts from a large set of single predictions. The first approach applies static or dynamic factors models (see, among many others, Forni *et al.*, 2005; Marcellino *et al.*, 2003; Stock and Watson, 2002), while the second method focuses on pooling strategies or combinations of model outcomes (see, among others, Drechsel and Maurin, 2011; Eickmeier and Ziegler, 2008; Stock and Watson, 2006; Timmermann, 2006).

Representing the first method, we apply a standard principal components analysis with one single factor. We specify two factor models in pseudo real-time in which the factor is derived from different indicator sets: all indicators without the Import Climate (PCA) and the Import Climate is also part of the indicator set (PCA-IC). By applying both indicator set specifications, we are able to show whether the Import Climate also improves the forecast accuracy of the PCA-factor. Both factors, each in turn, enter the forecasting model and replace the specific indicator $x^l_{t-n-p|t}$ in Equation (6). We avoid the ragged-edge problem by averaging the monthly indicators to the quarterly frequency before calculating the factors. This averaging, in addition to the generation of forecasts and forecast errors, is analogous to the procedure described in Section 4.

For the second forecast method we pool the forecasts from model (6). In each iteration step of the model, the forecasts for a specific horizon are combined as following: either they are averaged or we calculate the median forecast of the sorted indicator predictions. The latter has the advantage that it is more robust to outliers. The average and the median forecast are the representative forecasts from the indicator set and evaluated subsequently. The indicator set consists of either all indicators without the Import Climate (Mean, Median) or the total number of indicators (Mean-IC, Median-IC).

Table 5 compares the Theil's U values of the Import Climate from Table 2 with those obtained from the more sophisticated models. We present the results from the first timing assumption, that is, the forecast takes place in the second month of the quarter. Forecast errors in bold face indicate that these values are statistically significantly different from the AR(p)-benchmark. For each country-horizon-combination, the model(s) with the lowest Theil's U value(s) are underlined.

Table 5: Forecasting performance of the sophisticated methods

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Horizon	*Model*	*Theil's U*					
		FR	DE	IT	ES	UK	US
$h = 0$	Import Climate	**0.80**	**0.76**	0.84	**0.80**	0.99	**0.79**
	PCA[a]	**0.81**	**0.80**	0.80	**0.77**	0.94	**0.74**
	PCA-IC[b]	**0.80**	**0.81**	0.79	**0.76**	0.93	**0.75**
	Mean[a]	**0.80**	**0.83**	**0.90**	**0.77**	0.95	**0.82**
	Mean-IC[b]	**0.79**	**0.82**	**0.89**	**0.77**	0.95	**0.81**
	Median[a]	**0.80**	**0.81**	**0.91**	**0.77**	0.98	**0.79**
	Median-IC[b]	**0.80**	**0.81**	**0.90**	**0.77**	0.98	**0.79**
$h = 1$	Import Climate	**0.73**	**0.74**	**0.74**	0.80	0.95	**0.72**
	PCA[a]	0.88	1.01	0.90	**0.85**	1.02	0.76
	PCA-IC[b]	0.83	0.99	0.85	**0.83**	1.00	0.75
	Mean[a]	**0.85**	0.93	**0.85**	**0.80**	**0.96**	0.79
	Mean-IC[b]	**0.83**	0.91	**0.84**	0.79	**0.96**	**0.78**
	Median[a]	**0.87**	**0.91**	**0.85**	**0.81**	**0.96**	0.79
	Median-IC[b]	**0.85**	**0.90**	**0.84**	**0.80**	**0.96**	0.77

Notes: The target series to forecast are real-time quarterly growth rates of total imports. The forecast is generated in the second month of each quarter and the forecast errors are computed with respect to the first release. $h = 0$ denotes the nowcast, $h = 1$ describes the forecast for the following quarter. Theil's U values in bold indicate that the forecast error of the respective indicator or model is significantly different from the error of the AR(p) benchmark at least at the 10% level. The best model(s) per country-horizon-combination are underlined. The number of variables in the indicator set is as follows: France: 9, Germany: 15, Italy: 9, Spain: 9, United Kingdom: 9, and United States: 10. The Import Climate is either excluded from (a) or included in the set of indicators (b).

For the nowcast, the Import Climate is either the best predictor (Germany) or among the best performing models (France, Italy, United States). The sophisticated models perform better for Spain and the United Kingdom. Nevertheless, in these two countries the best method is always the one that is based on the indicator set including the Import Climate.

For $h = 1$, the Import Climate clearly underpins its high forecast accuracy as it performs better than the sophisticated models for France, Germany, Italy, the United Kingdom and the United States. Note that the Import Climate outperforms the best sophisticated model particularly for France, Germany and Italy. Here, our indicator produces relative errors that are 10 or more percentage points lower than those of the best sophisticated method. In contrast, in Spain the Import Climate is ranked second. However, the best method – the combination method that averages all the forecasts – includes the Import Climate in the information set.

6. Conclusion

This paper introduces the first leading indicator for import forecasting: the Import Climate. In a real-time forecasting experiment involving six advanced economies, we show that this indicator produces the lowest forecast errors compared to a wide range of standard business cycle indicators for nowcasts and one-quarter-ahead forecasts for most of our selected countries. For Spain and the United Kingdom, our indicator works particularly well with the latest data vintage.

There is a growing literature suggesting that forecasting individual GDP components separately and then aggregating them yields smaller forecast errors than forecasting GDP directly. Since the construction of new leading indicators is one promising way to increase the forecast accuracy of demand-side sub-components of GDP, disaggregated GDP forecasts could be further improved by finding reliable indicators for all components. Our paper is the first to introduce a new leading indicator for imports, in contrast to other work that investigates how leading indicators improve the forecast of exports and private consumption. However, to the best of our knowledge, there are no studies that evaluate the performance of leading indicators for the forecast of investment and government consumption. Therefore, future research in this area should close this gap in order to reevaluate the question of whether short-term GDP forecasting can be further improved by the application of component-specific predictors.

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A. Data Set Description

Table 6: Data Properties and Sources

Variable	Description	F	PL 2	PL 3	T	Source
	Target series					
Total Imports	Sum of imported goods and services (in %)	Q	1	1	GR	OECD, Deutsche Bundesbank, Federal Reserve of Philadelphia
	New indicator					
Import Climate	Weighted foreign export climates of 38 trading partners and domestic price and cost competitiveness (index)	M/Q	2/0	1/0	L	European Commission, national sources, own calculations
	Qualitative Indicators					
ICI-EU	Industrial Confidence Indicator for the European countries (in percentage points)	M/Q	1/0	0/0	L	European Commission
PMI-US	Purchasing Managers' Index for the US (in percentage points)	M/Q	1/0	0/0	L	Institute for Supply Management
BCI-Other-Countries	Business Confidence Index for most of the other countries outside Europe (in percentage points)	M/Q	1/0	0/0	L	OECD
PMI-China	Purchasing Managers' Index for China (in percentage points)	M/Q	1/0	0/0	L	National Bureau of Statistics China
BCI-Thailand	Business Confidence Index for Thailand (in percentage points)	M/Q	1/0	0/0	L	Bank of Thailand
CCI-EU	Consumer Confidence Indicator for the European Countries (in percentage points)	M/Q	1/0	0/0	L	European Commission
CCI-Michigan	Consumer Confidence Indicator for the US (in percentage points)	M/Q	1/0	0/0	L	University of Michigan
CCI-Conf-Board	Consumer Confidence Indicator for the US (in percentage points)	M/Q	1/0	0/0	L	Conference Board
CCI-Other-Countries	Consumer Confidence Indicator for the countries outside Europe (in percentage points)	M/Q	1/0	0/0	L	OECD
NO-S-M	Survey on current order-books level for France, Germany, Italy, Spain, and UK (in percentage points)	M/Q	1/0	0/0	L	European Commission
NO-S-Q	Survey on development of new orders in recent month for France, Germany, Italy, Spain, and UK (in percentage points)	Q	0	0	L	European Commission

Continued on next page...

Table 6: Data Properties and Sources (cont.)

Variable	Description	F	PL 2	PL 3	T	Source
NO-ISM	Survey on new orders for the US (in percentage points)	M/Q	1/0	0/0	L	Institute for Supply Management
ifo-BS	ifo Business Survey: assessment of the current business situation in Germany (in percentage points)	M/Q	1/0	0/0	L	ifo Institute
ifo-BE	ifo Business Survey: business expectations for the next six months in Germany (in percentage points)	M/Q	1/0	0/0	L	ifo Institute
ifo-BC	ifo Business Survey: business climate in Germany (in percentage points)	M/Q	1/0	0/0	L	ifo Institute
ISM-Imports	US firms' assessment of their current change in material imports (in percentage points)	M/Q	1/0	0/0	L	Institute for Supply Management
	Quantitative Indicators					
IM-STC	Total imports of goods based on the special trade classification (in %)	M/Q	3/1	2/0	GR	OECD
EX-STC	Total exports of goods based on the special trade classification (in %)	M/Q	3/1	2/0	GR	OECD
IP	Production in manufacturing (in %)	M/Q	3/1	2/0	GR	OECD
NO-G-D	Domestic new orders Germany (in %)	M/Q	3/1	2/0	GR	Federal Statistical Office of Germany
NO-G-F	Foreign new orders Germany (in %)	M/Q	3/1	2/0	GR	Federal Statistical Office of Germany
NO-G-T	Total new orders Germany (in %)	M/Q	3/1	2/0	GR	Federal Statistical Office of Germany
PC-CPI37-M	Domestic price and cost competitiveness against 37 industrial countries based on consumer prices (index)	M	3/1	2/0	L	European Commission
PC-XPI37-Q	Domestic price and cost competitiveness against 37 industrial countries based on export prices (index)	Q	1	1	L	European Commission

Notes: Frequency (*F*), Publication lags second month of a quarter (*PL 2*), Publication lags third month of a quarter (*PL 3*), Transformation (*T*), Quarterly (*Q*), Monthly (*M*), Levels (*L*), Growth rates (to the previous month or quarter, *GR*). If the original series is available monthly and aggregated to a quarterly frequency, this is abbreviated by *M/Q*. In the columns headed by *PL 2* and *PL 3*, the first number denotes the publication lag of the monthly series and the second number the publication lag of the monthly series aggregated to a quarterly frequency.

B. Descriptive Statistics

Table 7: Descriptive Statistics – France

Indicator	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Import growth (in %, p.p.)	1.15	1.84	-6.46	5.01
Import Climate	0.01	0.73	-3.00	1.23
ICI	-6.36	9.29	-37.07	13.73
CCI	-17.50	8.08	-35.67	1.17
NO-S-M	7.01	7.62	-28.61	22.27
NO-S-Q	2.21	17.38	-56.00	37.20
IM-STC (in %, p.p.)	1.06	3.36	-11.18	8.76
EX-STC (in %, p.p.)	0.84	3.03	-10.57	7.08
IP (in %, p.p.)	-0.03	1.45	-7.68	2.76
PC-XPI37-Q (in %, p.p.)	-0.15	1.07	-2.60	2.30

Note: The descriptive statistics are based on the full sample (1996:Q1 to 2016:Q4).

Table 8: Descriptive Statistics – Germany

Indicator	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Import growth (in %, p.p.)	1.25	2.21	-6.05	7.06
Import Climate	-0.00	0.66	-2.78	1.12
ICI	-6.85	10.82	-40.67	14.50
CCI	-7.07	9.22	-31.37	9.07
NO-S-M	-15.26	17.27	-62.03	15.97
NO-S-Q	2.67	14.86	-45.70	43.20
ifo-BC	5.36	14.28	-43.47	27.13
ifo-BS	7.90	20.87	-52.00	41.13
ifo-BE	-1.55	10.43	-39.73	18.17
IM-STC (in %, p.p.)	1.29	3.37	-12.46	10.42
EX-STC (in %, p.p.)	1.41	2.94	-13.93	8.11
IP (in %, p.p.)	0.49	2.23	-13.67	5.71
NO-G-D (in %, p.p.)	0.52	3.52	-16.52	9.08
NO-G-F (in %, p.p.)	1.37	4.53	-19.44	10.20
NO-G-T (in %, p.p.)	0.91	4.58	-15.68	10.79
PC-XPI37-Q (in %, p.p.)	-0.18	1.17	-2.94	2.75

Note: The descriptive statistics are based on the full sample (1996:Q1 to 2016:Q4).

Table 9: Descriptive Statistics – Italy

Indicator	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Import growth (in %, p.p.)	0.69	2.42	-7.69	5.13
Import Climate	0.02	0.69	-2.85	1.16
ICI	-4.28	7.89	-31.07	11.30
CCI	-15.85	8.71	-38.80	1.07
NO-S-M	-18.77	14.90	-66.07	7.03
NO-S-Q	-1.23	14.81	-53.60	22.40
IM-STC (in %, p.p.)	1.08	3.78	-15.28	9.12
EX-STC (in %, p.p.)	1.00	3.12	-14.71	7.04
IP (in %, p.p.)	-0.15	1.98	-10.56	2.81
PC-XPI37-Q (in %, p.p.)	0.15	1.13	-2.75	3.07

Note: The descriptive statistics are based on the full sample (1996:Q1 to 2016:Q4).

Table 10: Descriptive Statistics – Spain

Indicator	**Statistic**			
	Mean	*Std. Dev.*	*Min.*	*Max.*
Import growth (in %, p.p.)	1.07	2.93	-13.50	7.16
Import Climate	0.02	0.71	-2.92	1.17
ICI	-7.12	8.95	-36.97	6.07
CCI	-12.05	11.22	-45.13	4.37
NO-S-M	-14.02	17.05	-59.73	9.43
NO-S-Q	4.84	7.32	-20.60	16.80
IM-STC (in %, p.p.)	1.52	4.41	-15.88	11.96
EX-STC (in %, p.p.)	1.53	3.55	-15.84	8.83
IP (in %, p.p.)	0.03	1.76	-8.81	3.38
PC-XPI37-Q (in %, p.p.)	0.12	0.83	-1.92	2.10

Note: The descriptive statistics are based on the full sample (1996:Q1 to 2016:Q4).

Table 11: Descriptive Statistics – United Kingdom

Indicator	**Statistic**			
	Mean	*Std. Dev.*	*Min.*	*Max.*
Import growth (in %, p.p.)	1.04	2.54	-10.76	9.03
Import Climate	0.01	0.66	-2.83	1.11
ICI	-7.62	10.46	-43.17	10.17
CCI	-6.40	8.42	-31.00	6.90
NO-S-M	-14.91	14.87	-59.40	8.73
NO-S-Q	-1.79	16.24	-54.70	25.30
IM-STC (in %, p.p.)	1.16	2.87	-7.15	8.31
EX-STC (in %, p.p.)	0.86	3.96	-19.44	12.77
IP (in %, p.p.)	-0.06	1.06	-4.74	2.10
PC-XPI37-Q (in %, p.p.)	0.01	2.17	-6.73	6.33

Note: The descriptive statistics are based on the full sample (1996:Q1 to 2016:Q4).

Table 12: Descriptive Statistics – United States

Indicator	**Statistic**			
	Mean	*Std. Dev.*	*Min.*	*Max.*
Import growth (in %, p.p.)	1.17	2.22	-9.67	4.77
Import Climate	-0.01	0.51	-2.23	0.70
PMI	-0.03	0.97	-3.50	1.77
CCI-Michigan	87.23	13.09	57.67	110.13
CCI-Conf-Board	0.08	1.03	-2.30	1.87
NO-ISM	9.67	13.13	-43.17	38.67
ISM-Imports	4.98	8.45	-32.03	19.33
IM-STC (in %, p.p.)	1.40	4.14	-19.60	9.26
EX-STC (in %, p.p.)	1.14	3.70	-14.89	7.66
IP (in %, p.p.)	0.38	1.33	-5.61	2.51
PC-XPI37-Q (in %, p.p.)	0.23	2.77	-4.61	12.33

Note: The descriptive statistics are based on the full sample (1996:Q1 to 2016:Q4).

C. Cross-Correlations

Table 13: Cross-correlations of the Indicators for France

Indicator	**Lead of the Indicator (t-x quarters)**				
	0	*1*	*2*	*3*	*4*
Import Climate	0.81	0.80	0.62	0.33	-0.00
ICI	0.86	0.74	0.49	0.18	-0.12
CCI	0.65	0.60	0.45	0.22	0.01
NO-S-M	0.68	0.82	0.82	0.65	0.37
NO-S-Q	0.85	0.72	0.47	0.16	-0.11
IM-STC	0.90	0.75	0.48	0.16	-0.13
EX-STC	0.89	0.80	0.56	0.24	-0.05
IP	0.85	0.81	0.61	0.32	0.03
PC-XPI37-Q	-0.48	-0.51	-0.47	-0.38	-0.23

Notes: The cross-correlations are calculated between the indicators and the year-over-year growth rates for price-adjusted total imports.

Table 14: Cross-correlations of the Indicators for Germany

Indicator	**Lead of the Indicator (t-x quarters)**				
	0	*1*	*2*	*3*	*4*
Import Climate	0.76	0.74	0.56	0.27	-0.07
ICI	0.70	0.58	0.34	0.02	-0.29
CCI	0.42	0.29	0.09	-0.15	-0.41
NO-S-M	0.62	0.39	0.09	-0.20	-0.44
NO-S-Q	0.69	0.71	0.60	0.38	0.09
ifo-BC	0.70	0.62	0.43	0.14	-0.19
ifo-BS	0.57	0.38	0.10	-0.20	-0.46
ifo-BE	0.60	0.68	0.66	0.48	0.17
IM-STC	0.93	0.74	0.44	0.12	-0.19
EX-STC	0.85	0.74	0.47	0.13	-0.19
IP	0.85	0.76	0.48	0.13	-0.21
NO-G-D	0.82	0.81	0.62	0.29	-0.06
NO-G-F	0.79	0.85	0.68	0.39	0.03
NO-G-T	0.81	0.85	0.66	0.35	-0.01
PC-XPI37-Q	-0.53	-0.43	-0.24	-0.08	0.05

Notes: The cross-correlations are calculated between the indicators and the year-over-year growth rates for price-adjusted total imports.

Table 15: Cross-correlations of the Indicators for Italy

Indicator	**Lead of the Indicator (t-x quarters)**				
	0	*1*	*2*	*3*	*4*
Import Climate	0.80	0.72	0.49	0.18	-0.15
ICI	0.83	0.68	0.43	0.12	-0.17
CCI	0.49	0.47	0.45	0.40	0.31
NO-S-M	0.78	0.57	0.31	0.02	-0.23
NO-S-Q	0.83	0.64	0.37	0.05	-0.19
IM-STC	0.87	0.72	0.44	0.12	-0.19
EX-STC	0.75	0.60	0.31	-0.03	-0.34
IP	0.90	0.77	0.50	0.15	-0.18
PC-XPI37-Q	-0.36	-0.31	-0.23	-0.13	0.01

Notes: The cross-correlations are calculated between the indicators and the year-over-year growth rates for price-adjusted total imports.

Table 16: Cross-correlations of the Indicators for Spain

Indicator	Lead of the Indicator (t-x quarters)				
	0	*1*	*2*	*3*	*4*
Import Climate	0.78	0.68	0.44	0.16	-0.08
ICI	0.88	0.80	0.64	0.43	0.25
CCI	0.76	0.77	0.71	0.58	0.42
NO-S-M	0.82	0.69	0.53	0.34	0.19
NO-S-Q	0.83	0.80	0.68	0.46	0.25
IM-STC	0.75	0.58	0.36	0.15	-0.01
EX-STC	0.50	0.35	0.14	-0.05	-0.17
IP	0.94	0.88	0.70	0.49	0.29
PC-XPI37-Q	-0.08	-0.02	0.01	0.00	0.03

Notes: The cross-correlations are calculated between the indicators and the year-over-year growth rates for price-adjusted total imports.

Table 17: Cross-correlations of the Indicators for the United Kingdom

Indicator	Lead of the Indicator (t-x quarters)				
	0	*1*	*2*	*3*	*4*
Import Climate	0.59	0.53	0.33	0.09	-0.11
ICI	0.33	0.28	0.13	-0.07	-0.19
CCI	0.49	0.56	0.53	0.41	0.27
NO-S-M	0.30	0.18	-0.00	-0.18	-0.27
NO-S-Q	0.28	0.19	0.05	-0.15	-0.27
IM-STC	0.56	0.34	0.03	-0.22	-0.38
EX-STC	0.54	0.33	0.04	-0.19	-0.38
IP	0.69	0.59	0.35	0.14	-0.03
PC-XPI37-Q	0.31	0.38	0.42	0.41	0.35

Notes: The cross-correlations are calculated between the indicators and the year-over-year growth rates for price-adjusted total imports.

Table 18: Cross-correlations of the Indicators for the United States

Indicator	Lead of the Indicator (t-x quarters)				
	0	*1*	*2*	*3*	*4*
Import Climate	0.74	0.75	0.57	0.26	-0.08
PMI	0.61	0.77	0.73	0.52	0.22
CCI-Michigan	0.59	0.59	0.54	0.45	0.31
CCI-Conf-Board	0.55	0.51	0.42	0.30	0.17
NO-ISM	0.37	0.60	0.67	0.58	0.35
ISM-Imports	0.60	0.69	0.63	0.44	0.19
IM-STC	0.83	0.72	0.42	0.07	-0.20
EX-STC	0.64	0.53	0.25	-0.09	-0.35
IP	0.91	0.82	0.60	0.31	0.05
PC-XPI37-Q	-0.13	-0.24	-0.23	-0.08	0.10

Notes: The cross-correlations are calculated between the indicators and the year-over-year growth rates for price-adjusted total imports.

D. Complete Forecasting Results: Short Horizons

Table 19: Forecasting Results Short Horizons – France

Indicator	**Real-Time 2nd Month**		**Real-Time 3rd Month**		**Latest 2nd Month**	
	h = 0	*h = 1*	*h = 0*	*h = 1*	*h = 0*	*h = 1*
AR(p)	1.80	1.95	1.80	1.95	1.94	2.04
Import Climate	**0.80**	**0.73**	**0.82**	**0.70**	**0.81**	0.78
Qualitative Indicators						
ICI	0.87	0.84	0.87	0.82	**0.79**	0.86
CCI	0.92	0.93	0.91	0.93	0.90	0.95
NO-S-M	0.86	0.77	0.88	**0.74**	**0.77**	0.77
NO-S-Q	**0.87**	0.92	**0.87**	0.92	**0.89**	0.97
Quantitative Indicators						
IM-STC	0.96	0.96	**0.59**	0.94	0.98	0.98
EX-STC	0.94	0.95	**0.69**	0.91	0.96	0.99
IP	0.96	1.12	0.81	0.99	0.93	1.19
PC-XPI37-Q	1.08	0.97	1.08	0.97	1.10	1.02
Forecast Combination and Factor Models						
Mean[a]	**0.80**	**0.85**	**0.70**	**0.82**	**0.79**	**0.88**
Mean-IC[b]	**0.79**	**0.83**	**0.70**	**0.79**	**0.78**	**0.86**
Median[a]	**0.80**	**0.87**	**0.73**	**0.85**	**0.78**	**0.88**
Median-IC[b]	**0.80**	**0.85**	**0.72**	**0.83**	**0.77**	**0.87**
PCA[a]	**0.81**	0.88	**0.71**	0.84	**0.81**	0.93
PCA-IC[b]	**0.80**	0.83	**0.73**	0.82	**0.80**	0.91
Other Benchmarks						
Random Walk	1.16	1.19	1.16	1.19	1.16	1.15
Sample Mean	1.01	0.95	1.01	0.95	1.02	0.99

Note: The target series to forecast are quarterly growth rates of total imports with respect to either the first release (*Real-Time*) or the latest vintage (*Latest*). The forecasts are based on a forecast experiment either conducted at the second month (*2nd Month*) or at the end of each quarter (*3rd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

Table 20: Forecasting Results Short Horizons – Germany

Indicator	Real-Time 2nd Month		Real-Time 3rd Month		Latest 2nd Month	
	h = 0	*h = 1*	*h = 0*	*h = 1*	*h = 0*	*h = 1*
AR(p)	2.59	2.49	2.59	2.49	2.29	2.28
Import Climate	**0.76**	**0.74**	**0.76**	**0.74**	**0.73**	**0.74**
Qualitative Indicators						
ICI	0.88	**0.83**	0.88	0.82	0.89	**0.79**
CCI	0.93	0.99	0.94	0.97	0.96	0.98
NO-S-M	0.86	0.87	0.86	0.87	**0.81**	0.83
NO-S-Q	**0.83**	0.91	**0.83**	0.91	0.82	0.92
ifo-BC	0.90	0.89	0.90	0.87	0.93	0.88
ifo-BS	0.86	0.86	0.84	0.84	0.84	0.83
ifo-BE	0.86	0.92	0.86	0.92	0.89	0.95
Quantitative Indicators						
IM-STC	0.95	1.02	**0.77**	0.98	1.00	1.00
EX-STC	0.91	1.05	0.84	1.03	0.91	1.02
IP	1.15	1.20	**0.75**	1.18	0.96	1.10
NO-G-D	0.87	1.09	**0.74**	0.97	0.88	1.09
NO-G-F	**0.80**	1.08	**0.76**	0.89	**0.78**	1.04
NO-G-T	**0.82**	1.00	**0.81**	0.94	**0.83**	1.03
PC-XPI37-Q	0.98	1.04	0.98	1.04	1.00	1.02
Forecast Combination and Factor Models						
Mean^a	**0.83**	0.93	**0.78**	0.88	**0.80**	0.89
Mean-IC^b	**0.82**	0.91	**0.77**	0.87	**0.79**	**0.88**
Median^a	**0.81**	**0.91**	**0.80**	0.88	**0.80**	**0.90**
Median-IC^b	**0.81**	**0.90**	**0.80**	0.87	**0.80**	**0.88**
PCA^a	**0.80**	1.01	**0.83**	0.88	0.85	1.05
PCA-IC^b	**0.81**	0.99	**0.84**	0.86	0.84	0.97
Other Benchmarks						
Random Walk	1.33	1.29	1.33	1.29	1.18	1.30
Sample Mean	0.97	1.02	0.97	1.02	1.01	1.01

Note: The target series to forecast are quarterly growth rates of total imports with respect to either the first release (*Real-Time*) or the latest vintage (*Latest*). The forecasts are based on a forecast experiment either conducted at the second month (*2nd Month*) or at the end of each quarter (*3rd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

Table 21: Forecasting Results Short Horizons – Italy

Indicator	**Real-Time 2nd Month**		**Real-Time 3rd Month**		**Latest 2nd Month**	
	h = 0	*h = 1*	*h = 0*	*h = 1*	*h = 0*	*h = 1*
AR(p)	2.25	2.80	2.25	2.80	2.33	2.92
Import Climate	0.84	**0.74**	0.80	**0.71**	0.80	**0.72**
Qualitative Indicators						
ICI	**0.87**	**0.82**	**0.83**	**0.82**	**0.85**	**0.80**
CCI	1.10	0.94	1.09	0.94	1.07	0.94
NO-S-M	0.91	0.83	0.87	**0.81**	**0.86**	**0.82**
NO-S-Q	0.95	0.93	0.95	0.93	0.93	0.92
Quantitative Indicators						
IM-STC	**1.07**	0.93	**0.76**	0.89	**1.05**	**0.91**
EX-STC	1.03	0.90	0.89	0.88	1.03	**0.89**
IP	0.93	1.01	0.75	0.81	1.07	1.01
PC-XPI37-Q	**1.15**	0.97	**1.15**	0.97	**1.13**	0.97
Forecast Combination and Factor Models						
Mean^a	**0.90**	**0.85**	**0.83**	**0.82**	**0.91**	**0.85**
Mean-IC^b	**0.89**	**0.84**	**0.82**	**0.80**	**0.89**	**0.83**
Median^a	**0.91**	**0.85**	**0.83**	**0.84**	**0.93**	**0.84**
Median-IC^b	**0.90**	**0.84**	**0.82**	**0.82**	**0.91**	**0.83**
PCA^a	**0.80**	0.90	**0.67**	**0.75**	**0.81**	0.84
PCA-IC^b	**0.79**	0.85	**0.67**	**0.74**	**0.79**	0.82
Other Benchmarks						
Random Walk	1.12	1.15	1.12	1.15	1.05	1.04
Sample Mean	1.15	0.92	1.15	0.92	1.12	0.91

Note: The target series to forecast are quarterly growth rates of total imports with respect to either the first release (*Real-Time*) or the latest vintage (*Latest*). The forecasts are based on a forecast experiment either conducted at the second month (*2nd Month*) or at the end of each quarter (*3rd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

Table 22: Forecasting Results Short Horizons – Spain

Indicator	**Real-Time 2nd Month**		**Real-Time 3rd Month**		**Latest 2nd Month**	
	h = 0	*h = 1*	*h = 0*	*h = 1*	*h = 0*	*h = 1*
AR(p)	4.08	4.48	4.08	4.48	3.78	4.88
Import Climate	**0.80**	0.80	**0.82**	0.79	0.83	0.70
Qualitative Indicators						
ICI	**0.76**	**0.81**	**0.74**	**0.79**	0.78	0.70
CCI	**0.77**	0.78	**0.78**	**0.77**	0.83	0.72
NO-S-M	**0.79**	0.84	**0.76**	0.82	0.84	0.74
NO-S-Q	**0.81**	0.90	**0.81**	0.90	0.86	0.88
Quantitative Indicators						
IM-STC	0.92	0.88	**0.73**	0.87	0.99	0.78
EX-STC	0.99	0.87	**0.86**	0.88	1.01	0.74
IP	**0.77**	0.95	**0.71**	**0.74**	1.02	0.99
PC-XPI37-Q	0.94	0.83	0.94	0.83	0.92	0.73
Forecast Combination and Factor Models						
Mean[a]	**0.77**	**0.80**	**0.73**	**0.77**	0.82	0.73
Mean-IC[b]	**0.77**	**0.79**	**0.73**	**0.76**	0.81	0.71
Median[a]	**0.77**	**0.81**	**0.73**	**0.79**	0.82	0.71
Median-IC[b]	**0.77**	**0.80**	**0.73**	**0.78**	0.81	0.71
PCA[a]	**0.77**	**0.85**	**0.66**	**0.80**	**0.75**	0.88
PCA-IC[b]	**0.76**	**0.83**	**0.66**	**0.79**	**0.73**	0.81
Other Benchmarks						
Random Walk	1.07	1.10	1.07	1.10	0.98	0.91
Sample Mean	0.94	0.87	0.94	0.87	0.95	0.74

Note: The target series to forecast are quarterly growth rates of total imports with respect to either the first release (*Real-Time*) or the latest vintage (*Latest*). The forecasts are based on a forecast experiment either conducted at the second month (*2nd Month*) or at the end of each quarter (*3rd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

Table 23: Forecasting Results Short Horizons – United Kingdom

Indicator	**Real-Time 2nd Month**		**Real-Time 3rd Month**		**Latest 2nd Month**	
	h = 0	*h = 1*	*h = 0*	*h = 1*	*h = 0*	*h = 1*
AR(p)	2.82	2.99	2.82	2.99	3.06	3.05
Import Climate	0.99	0.95	0.98	0.95	0.98	0.97
Qualitative Indicators						
ICI	1.02	1.02	1.03	1.03	1.00	1.01
CCI	0.94	0.97	0.95	0.96	0.95	1.00
NO-S-M	1.04	1.03	1.05	**1.04**	1.00	1.00
NO-S-Q	**1.03**	1.01	**1.03**	1.01	0.99	1.01
Quantitative Indicators						
IM-STC	1.03	0.98	0.95	1.00	1.00	1.01
EX-STC	1.02	0.96	0.92	0.98	0.99	1.00
IP	1.00	1.06	0.95	0.98	1.02	1.06
PC-XPI37-Q	0.97	1.13	0.97	1.13	0.99	1.05
Forecast Combination and Factor Models						
Mean^a	0.95	**0.96**	**0.91**	**0.96**	0.95	0.98
Mean-IC^b	0.95	**0.96**	**0.91**	**0.96**	0.95	0.98
Median^a	0.98	**0.96**	0.97	0.97	0.96	0.98
Median-IC^b	0.98	**0.96**	0.96	**0.96**	0.95	0.97
PCA^a	0.94	1.02	0.96	1.01	0.94	1.01
PCA-IC^b	0.93	1.00	0.95	0.99	0.94	1.00
Other Benchmarks						
Random Walk	1.23	1.31	1.23	1.31	1.28	1.49
Sample Mean	1.03	0.98	1.03	0.98	1.00	1.01

Note: The target series to forecast are quarterly growth rates of total imports with respect to either the first release (*Real-Time*) or the latest vintage (*Latest*). The forecasts are based on a forecast experiment either conducted at the second month (*2nd Month*) or at the end of each quarter (*3rd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

Table 24: Forecasting Results Short Horizons – United States

Indicator	Real-Time 2nd Month		Real-Time 3rd Month		Latest 2nd Month	
	h = 0	*h = 1*	*h = 0*	*h = 1*	*h = 0*	*h = 1*
AR(p)	2.49	2.93	2.49	2.93	2.00	2.78
Import Climate	**0.79**	**0.72**	**0.78**	0.70	0.77	0.69
Qualitative Indicators						
PMI	0.85	0.75	0.85	0.70	0.83	0.69
CCI-Michigan	1.13	0.98	1.10	0.95	**1.32**	0.99
CCI-Conf-Board	1.02	0.89	1.01	0.89	**1.18**	0.89
NO-ISM	**0.81**	0.77	**0.82**	**0.74**	0.85	0.74
ISM-Imports	0.81	0.85	**0.79**	0.81	0.88	0.81
Quantitative Indicators						
IM-STC	0.87	0.95	**0.75**	0.86	0.93	0.89
EX-STC	1.09	0.99	1.03	1.03	1.14	0.94
IP	0.91	1.00	**0.67**	**0.78**	0.93	0.99
PC-XPI37-Q	1.21	1.02	1.21	1.02	**1.36**	1.01
Forecast Combination and Factor Models						
Mean[a]	**0.82**	0.79	**0.79**	**0.76**	0.85	0.76
Mean-IC[b]	**0.81**	**0.78**	**0.78**	**0.75**	0.83	0.75
Median[a]	**0.79**	0.79	**0.77**	**0.76**	0.81	0.75
Median-IC[b]	**0.79**	0.77	**0.77**	**0.74**	0.80	0.72
PCA[a]	**0.74**	0.76	**0.68**	**0.68**	0.72	0.71
PCA-IC[b]	**0.75**	0.75	**0.69**	**0.67**	0.72	0.69
Other Benchmarks						
Random Walk	1.11	1.19	1.11	1.19	1.03	1.07
Sample Mean	1.08	0.92	1.08	0.92	1.24	0.91

Note: The target series to forecast are quarterly growth rates of total imports with respect to either the first release (*Real-Time*) or the latest vintage (*Latest*). The forecasts are based on a forecast experiment either conducted at the second month (*2nd Month*) or at the end of each quarter (*3rd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

E. Complete Forecasting Results: Longer Horizons

Table 25: Forecasting Results Longer Horizons – France

Indicator	Real-Time 2nd Month			
	h = 2	*h = 3*	*h = 4*	*h = 8*
AR(p)	1.98	1.95	1.96	1.88
Import Climate	0.87	0.93	0.98	1.21
Qualitative Indicators				
ICI	0.90	0.94	0.97	**1.04**
CCI	0.96	0.98	0.99	**1.07**
NO-S-M	**0.85**	**0.93**	1.00	1.03
NO-S-Q	0.93	0.92	0.93	1.04
Quantitative Indicators				
IM-STC	**0.93**	**0.92**	**0.93**	1.01
EX-STC	0.95	**0.94**	**0.94**	1.00
IP	1.03	**0.93**	**0.91**	1.06
PC-XPI37-Q	0.98	1.01	1.01	1.01
Forecast Combination and Factor Models				
Mean[a]	**0.90**	**0.92**	**0.93**	1.01
Mean-IC[b]	**0.89**	**0.91**	**0.92**	1.02
Median[a]	**0.92**	**0.92**	**0.92**	1.01
Median-IC[b]	**0.91**	**0.92**	**0.92**	1.01
PCA[a]	0.93	0.94	0.92	1.02
PCA-IC[b]	0.92	0.93	0.92	1.03
Other Benchmarks				
Random Walk	1.32	1.38	1.39	1.37
Sample Mean	0.95	0.97	0.97	1.03

Note: The target series to forecast are quarterly growth rates of total imports with respect to the first release (*Real-Time*). The forecasts are based on a forecast experiment conducted at the second month of each quarter (*2nd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

Table 26: Forecasting Results Longer Horizons – Germany

Indicator	Real-Time 2nd Month			
	h = 2	*h = 3*	*h = 4*	*h = 8*
AR(p)	2.54	2.60	2.59	2.78
Import Climate	0.92	0.91	0.93	0.95
Qualitative Indicators				
ICI	0.90	0.89	0.95	0.96
CCI	0.95	0.86	0.93	1.05
NO-S-M	0.94	**0.90**	0.94	0.91
NO-S-Q	0.97	0.98	1.03	0.99
ifo-BC	0.88	0.89	**0.91**	0.95
ifo-BS	0.91	0.88	0.92	0.96
ifo-BE	0.93	0.91	0.93	0.96
Quantitative Indicators				
IM-STC	1.03	0.98	1.00	**0.93**
EX-STC	1.02	0.97	0.95	**0.94**
IP	1.03	0.94	0.95	1.02
NO-G-D	**1.05**	1.00	0.96	1.04
NO-G-F	1.02	0.94	0.98	0.94
NO-G-T	1.02	0.98	1.01	**0.94**
PC-XPI37-Q	1.02	1.01	1.02	**0.93**
Forecast Combination and Factor Models				
Mean[a]	0.92	0.90	0.93	**0.93**
Mean-IC[b]	0.92	0.90	0.92	**0.93**
Median[a]	0.94	0.90	0.94	**0.93**
Median-IC[b]	0.93	0.90	0.94	**0.92**
PCA[a]	0.94	0.90	0.93	**0.94**
PCA-IC[b]	0.93	0.90	0.93	**0.94**
Other Benchmarks				
Random Walk	1.50	1.33	1.64	1.51
Sample Mean	1.00	0.98	0.98	0.93

Note: The target series to forecast are quarterly growth rates of total imports with respect to the first release (*Real-Time*). The forecasts are based on a forecast experiment conducted at the second month of each quarter (*2nd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

Table 27: Forecasting Results Longer Horizons – Italy

Indicator	**Real-Time 2nd Month**			
	h = 2	*h = 3*	*h = 4*	*h = 8*
AR(p)	2.92	2.82	2.68	2.59
Import Climate	**0.81**	**0.89**	0.98	1.08
Qualitative Indicators				
ICI	0.86	0.97	1.05	1.06
CCI	0.93	0.98	1.00	1.00
NO-S-M	0.89	1.00	1.09	1.13
NO-S-Q	0.89	**0.93**	1.01	1.09
Quantitative Indicators				
IM-STC	0.90	**0.92**	0.96	1.01
EX-STC	0.85	**0.90**	**0.91**	1.06
IP	0.92	0.96	0.96	1.05
PC-XPI37-Q	0.95	0.98	1.03	0.98
Forecast Combination and Factor Models				
Mean^a	**0.85**	**0.90**	**0.94**	1.03
Mean-IC^b	**0.84**	**0.89**	**0.94**	1.03
Median^a	0.86	**0.93**	0.95	1.04
Median-IC^b	0.86	**0.93**	0.94	1.04
PCA^a	**0.86**	0.94	0.98	**1.04**
PCA-IC^b	**0.85**	0.93	0.98	**1.05**
Other Benchmarks				
Random Walk	1.21	1.31	1.45	1.50
Sample Mean	0.89	0.93	0.98	1.03

Note: The target series to forecast are quarterly growth rates of total imports with respect to the first release (*Real-Time*). The forecasts are based on a forecast experiment conducted at the second month of each quarter (*2nd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

Table 28: Forecasting Results Longer Horizons – Spain

Indicator	**Real-Time 2nd Month**			
	h = 2	*h = 3*	*h = 4*	*h = 8*
AR(p)	4.66	4.64	3.96	4.10
Import Climate	0.86	0.90	1.18	1.15
	Qualitative Indicators			
ICI	0.82	0.90	**1.13**	1.20
CCI	0.77	0.87	1.14	1.03
NO-S-M	0.84	0.92	1.19	1.38
NO-S-Q	0.92	0.84	1.02	1.09
	Quantitative Indicators			
IM-STC	0.83	0.85	1.00	1.01
EX-STC	0.84	0.84	1.00	1.00
IP	0.88	0.95	1.20	1.13
PC-XPI37-Q	0.83	0.85	1.00	1.01
	Forecast Combination and Factor Models			
Mean^a	0.80	0.84	1.01	1.06
Mean-IC^b	0.80	0.84	1.02	1.06
Median^a	0.82	0.84	1.00	1.04
Median-IC^b	0.82	0.83	1.00	1.06
PCA^a	0.85	0.91	1.08	1.07
PCA-IC^b	0.84	0.88	1.08	1.10
	Other Benchmarks			
Random Walk	1.07	1.11	1.30	1.33
Sample Mean	0.84	0.86	1.02	1.03

Note: The target series to forecast are quarterly growth rates of total imports with respect to the first release (*Real-Time*). The forecasts are based on a forecast experiment conducted at the second month of each quarter (*2nd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

Table 29: Forecasting Results Longer Horizons – United Kingdom

Indicator	Real-Time 2nd Month			
	h = 2	*h = 3*	*h = 4*	*h = 8*
AR(p)	2.96	3.03	2.94	2.41
Import Climate	0.99	1.02	1.10	1.16
Qualitative Indicators				
ICI	1.03	1.03	1.23	1.07
CCI	1.06	0.99	1.02	1.05
NO-S-M	**1.04**	1.05	1.09	1.09
NO-S-Q	1.00	1.02	**1.04**	**1.05**
Quantitative Indicators				
IM-STC	0.98	0.96	0.98	1.14
EX-STC	0.96	**0.93**	1.00	1.10
IP	**1.03**	0.98	1.00	1.00
PC-XPI37-Q	1.23	1.07	1.00	0.99
Forecast Combination and Factor Models				
Mean[a]	1.00	0.97	1.01	1.01
Mean-IC[b]	1.00	0.98	1.02	1.02
Median[a]	0.99	0.97	1.00	1.01
Median-IC[b]	0.99	0.97	1.00	1.01
PCA[a]	**1.02**	1.01	1.03	1.03
PCA-IC[b]	1.02	1.01	1.04	1.05
Other Benchmarks				
Random Walk	1.29	1.40	1.39	1.17
Sample Mean	1.00	0.99	1.00	1.05

Note: The target series to forecast are quarterly growth rates of total imports with respect to the first release (*Real-Time*). The forecasts are based on a forecast experiment conducted at the second month of each quarter (*2nd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

Table 30: Forecasting Results Longer Horizons – United States

Indicator	**Real-Time 2nd Month**			
	h = 2	*h = 3*	*h = 4*	*h = 8*
AR(p)	2.85	2.94	2.96	2.82
Import Climate	**0.90**	0.92	0.92	**1.06**
		Qualitative Indicators		
PMI	0.94	0.93	0.91	1.01
CCI-Michigan	1.03	1.07	1.04	1.04
CCI-Conf-Board	1.00	1.00	0.98	1.02
NO-ISM	0.96	0.94	0.93	1.00
ISM-Imports	1.00	1.00	1.10	1.05
		Quantitative Indicators		
IM-STC	0.97	0.92	0.86	1.05
EX-STC	1.00	0.90	0.84	1.03
IP	0.99	1.03	0.99	1.00
PC-XPI37-Q	1.09	1.03	0.99	1.03
		Forecast Combination and Factor Models		
Mean[a]	0.93	0.94	0.93	1.00
Mean-IC[b]	0.92	0.93	0.92	1.01
Median[a]	0.94	0.94	0.92	1.00
Median-IC[b]	0.94	0.93	0.91	1.00
PCA[a]	0.97	0.95	0.92	0.99
PCA-IC[b]	0.95	0.93	0.91	1.00
		Other Benchmarks		
Random Walk	1.24	1.27	1.43	1.36
Sample Mean	0.96	0.94	0.95	1.03

Note: The target series to forecast are quarterly growth rates of total imports with respect to the first release (*Real-Time*). The forecasts are based on a forecast experiment conducted at the second month of each quarter (*2nd Month*). All numbers shown are relative root mean squared forecast errors with the exception of the AR(p)-model. The AR-numbers represent forecast errors in percentage points. The relative root mean squared forecast errors in bold indicate that the indicator model performs better than the benchmark at least to the 10% significance level based on the Diebold-Mariano test. The Import Climate is either excluded from (a) or included in the set of indicators (b).

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