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Forecasting Imports with Information from Abroad

Abstract

Globalization has led to huge increases in import volumes, but the literature on import forecasting is still in its infancy. We introduce the first leading indicator especially constructed for total import growth, the so-called 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 business and consumer confidence in the countries it trades with and its price competitiveness. In a pseudo out-of-sample, 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 import data. For Spain and the United Kingdom, our leading indicator works particularly well with the latest vintage of import data.

JEL-Codes: F010, F100, F170.

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 between economies and, therefore, has led to an increased importance of trade volumes for the growth of gross domestic product (GDP). In addition to a pronounced rise in exports of goods and services during the last decade, most industrialized countries have faced an increase in the ratio of imports to total output.[1] As import growth rates are extremely volatile, they also heavily influence fluctuations in GDP,[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 for import growth. In this paper, we close this gap and introduce the first leading indicator for imports 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, we follow 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. Our leading indicator, the Import Climate, weights the Export Climates of the domestic country's main trading partners with their share in domestic imports. In this paper, Import Climates are separately constructed for France, Germany, Italy, Spain, the United Kingdom, and the United States.

The forecasting power of the Import Climate is evaluated in a pseudo out-of-sample, real-time forecasting experiment for these six advanced economies with respect to the first release of import data. We compare our leading indicator to other relatively standard business cycle indicators such as sentiment indicators of the domestic country, new orders, or industrial production. Since survey-based indicators are usually viewed as short term predictors, we

[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.

[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.

generate forecasts for the current and the next quarter of total imports. We find that 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, our new leading indicator generates average forecast errors that are smaller than the volatility in quarterly import growth rates for all the countries. Therefore, the Import Climate not only performs well relative to other indicators, but also in absolute terms.

For Spain and the United Kingdom, the Import Climate is not always ranked first among the set of indicators. However, we find that 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, we find that our indicator is particularly well-suited for explaining the final import data vintage of these two economies.

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).[5] 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

[5] Marcellino *et al.* (2003) ask whether it is preferable to forecast each country of the Euro Area separately or predict the European aggregate directly. They find that country-specific models perform better than forecast models that use aggregate data.

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

The remainder of the paper is organized as follows. Section 2 presents the construction of our leading indicator. In Section 3 we describe our pseudo out-of-sample, real-time forecasting experiment, together with other potential import predictors. We discuss the results in Section 4. Section 5 concludes.

2. Construction of the Leading Indicator

In this section, we develop our new leading indicator for imports, the so-called Import Climate. We first discuss the theoretical background of the indicator and then present its construction.

2.1. Theoretical Background

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 $\Delta\gamma^k_{d,t}$ is the change in the share of country d in total exports of k and ΔX^k_t 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:

$$\begin{aligned}\mathrm{E}\left(\Delta M^d_{t+h|t}\right) = \sum_{k=1}^{K} \Big\{ & \mathrm{E}\left(w^d_{k,\tau+h-1|t}\right) \times \left[\mathrm{E}\left(\Delta\gamma^k_{d,t+h|t}\right) + \mathrm{E}\left(\Delta X^k_{t+h|t}\right)\right] \\ & + \mathrm{Cov}\left(w^d_{k,\tau+h-1|t}, \left[\Delta\gamma^k_{d,t+h|t} + \Delta X^k_{t+h|t}\right]\right)\Big\} \ . \end{aligned} \tag{3}$$

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. A well-accepted source for expectation data is surveys of firms and consumers. The first-best source of information would be to directly measure import expectations, $\mathrm{E}\left(\Delta M^d_{t+h|t}\right)$. However, to the best of our knowledge, information on expectations about total imports is not available. Therefore, we turn from the left- to the right-hand side of Equation (3) and use survey data to approximate each term.

To do so, we require two assumptions. First, we observe that import shares are relatively constant over time. Therefore, expectations about future import shares, $\mathrm{E}\left(w^d_{k,\tau+h-1|t}\right)$, are proxied by previous year values, $w^d_{k,\tau-1|t}$. 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 broadly consistent with the data. With these two assumptions, Equation (3) simplifies to:

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

The following section contains a more detail description of how we model expectations on export development.

2.2. 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, $\mathrm{E}\left(\Delta X_{t+h|t}^k\right)$, 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.[6] This functional relationship describes the Export Climate of country k, XC_t^k.[7] Substituting XC_t^k for $\mathrm{E}\left(\Delta X_{t+h|t}^k\right)$ in Equation (4) yields:

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

We base the Export Climates on business and consumer confidence indicators from 39 countries;[8] the data are from the European Commission, the OECD, and various national sources. The confidence indicators are standardized to have the same mean and standard deviation. Note that each country-specific Import Climate is based on the Export Climates of the remaining 38 countries, for example, the Import Climate of Germany depends, among others, on the Export Climate of France and vice versa. The shares η_j^k are calculated as the volume of exports of consumption goods from country k to j divided by 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.

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. 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.

[6] 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.

[7] 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.

[8] 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.

To approximate the price competitiveness of trading partner k's economy, PC_t^k, we use the real effective exchange rate (REER) for a broad number of industrial countries provided by the European Commission. 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 and has a publication lag of one quarter. In contrast, the REER based on consumer prices is available monthly with a publication lag of only one month; therefore, we rely on this variable.

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

$$\Delta X_{1,t}^k = c_1^k + \sum_{i=0}^{4} \alpha_{1,i}^k PC_{t-i}^k + \varepsilon_{1,t}^k \,,$$
$$\Delta X_{2,t}^k = c_2^k + \sum_{i=0}^{4} \alpha_{2,i}^k PC_{t-i}^k + \sum_{m=0}^{4} \beta_{2,m}^k \left\{ \sum_{j \neq k}^{J} \nu_j^k \left[\eta_j^k CC_{t-m}^j + (1-\eta_j^k) BC_{t-m}^j \right] \right\} + \varepsilon_{2,t}^k \,.$$

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. Both models are estimated with ex-post data for the sample period 1996:Q1 to 2016:Q4.[9] 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).

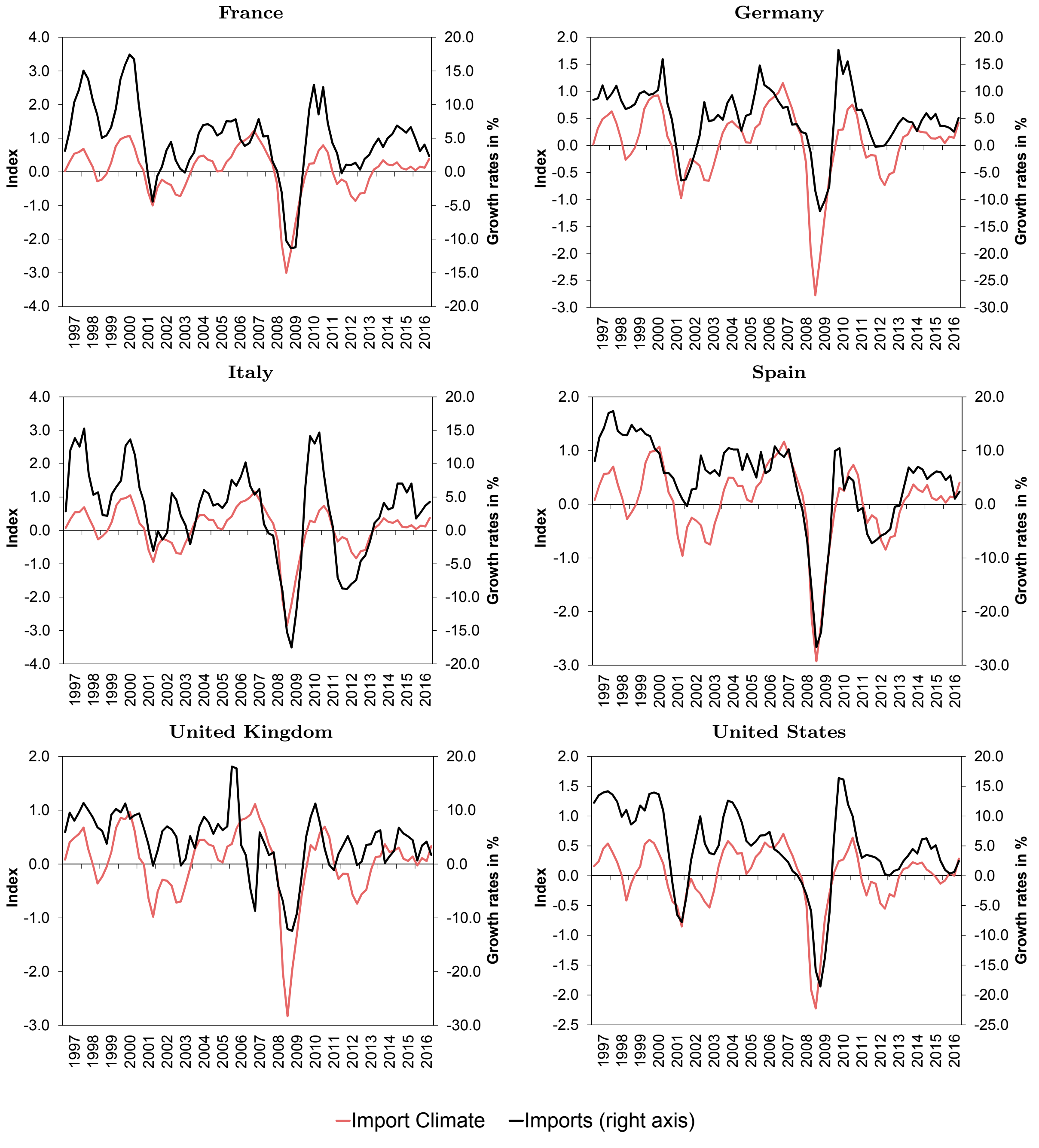
Finally, we compute the monthly Import Climate by aggregating the individual Export Climates, XC_t^k, using the import share of each trading partner k in the domestic country's total imports from the previous year, $w_{k,\tau-1}^d$. Note that these total imports equal the sum of imports from the remaining 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 U.N. 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%.

Figure 1 plots the Import Climates – aggregated to a quarterly frequency by taking three month averages – together with the growth rates of real imports 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

[9] Most of the predictors that we use in the subsequent forecast experiment are not available in real-time or only for a relative short period of time. Therefore, we also base the computation of the Import Climate on the latest available data to ensure a fair comparison across indicators.

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



Note: 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

Note: 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.

3. Empirical Approach

In the following, we introduce the forecasting model and the evaluation of the forecast performance. We also discuss other potential predictors for forecasting import growth.

3.1. Forecasting Model

To assess the forecasting performance of the indicator in a pseudo out-of-sample, real-time setup, we use the following general forecasting model,

$$\Delta M^l_{t+h|t} = \alpha^l + \sum_{p=0}^{P} \beta^l_p x^l_{t-n-p|t} + \varepsilon^l_{t|t} \ , \tag{5}$$

where $\Delta M_{t+h|t}$ is the h-period-ahead forecast of quarter-on-quarter real import growth that is based on the information available at time t. We specifically look at total imports for the six countries separately; the series are seasonally and price adjusted and, with the exception of the United States, also calendar adjusted.[10] The import series are available in real-time, that is, we rely on 48 vintages for the period 1996:Q1 to 2016:Q4 taken from Deutsche Bundesbank, OECD, and the Federal Reserve Bank of Philadelphia. x^l is one single predictor from the set l of potential indicators. The forecast horizon h is restricted to $h \in \{0, 1\}$ quarters, whereby $h = 0$ is the nowcast. P indicates the maximum number of lags. The choice of the optimal lag number of lags is based on the Bayesian Information Criterion.[11] The constants α^l and the coefficients β^l_p are estimated by OLS.

We estimate the model in real-time taking into account that information from some of the quarterly indicators for t are not yet available due to publication lags n. We proceed similarly with our monthly predictors, including the Import Climate, which are averaged to

[10]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).

[11]We also tested autoregressive distributed lag models in which we include lagged values of total import growth next to the specific indicator. However, we do not use this class of model because the forecast errors are larger than those from Model (5).

a quarterly frequency by relying only on those monthly values that are available at t. We run the forecasting experiment with two different timing assumptions. The baseline 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. As a robustness check, we use an alternative timing assumption where the forecasts are calculated at the end of each quarter. Both timing assumptions are associated with different publication lags of the indicators that might change the results; therefore, both timings will be discussed in the results section.[12] 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 forecast for 2005:Q3. 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.

The forecasts derived from Model (5) 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),

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

where T_h denotes the number of forecasts produced for each horizon. To assess the relative performance of an indicator compared to a well-specified benchmark model, we calculate the relative RMSFE or Theil's U as the ratio between the RMSFE of an indicator model and a BIC-optimized AR(p)-model.

Furthermore, 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 autoregressive benchmark.

3.2. Other Potential Predictors

To judge the relevance of our results for applied forecasting of import growth, we compare the Import Climate with other commonly used predictors. In the following, we distinguish between qualitative indicators that are based on surveys and quantitative predictors mainly extracted from official statistics.

[12] Table 5 in Appendix A provides more detail on the publication structure of the indicators.

3.2.1. Qualitative Indicators

We use the following survey-based indicators that should be related to import growth; all of them are seasonally adjusted.

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 confidence indicators for the European countries are extracted from the Joint Harmonised EU Programme of Business and Consumer Surveys. For the United States, we use the Purchasing Managers' Index (PMI) by the Institute for Supply Management (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 information from the Joint Harmonised EU Programme of Business and Consumer Surveys. For the United States, we take consumer confidence 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 from the Joint Harmonised EU Programme of Business and Consumer Surveys. 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*).[13] 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,

[13] 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.

this import-specific indicator only captures raw materials, which represent merely a small fraction of total imports.

3.2.2. Quantitative Information

The existing forecasting literature finds that hard 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). We use revised data because most of the indicators are either not available in real-time for the whole evaluation period or not at all. All indicators are seasonally adjusted.

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.

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.

New Orders, Germany (*NO-G*): Germany is a special case as monthly new orders are 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*).

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 real effective exchange rate (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 consumer prices. Ca'Zorzi and Schnatz (2010) and Lehmann (2015) discuss these measures and conclude that it is an empirical matter which indicator is the most convincing. We test each measure separately and find that the REER based on export prices is the best predictor.

The number of indicators in the 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. Results

Table 2 presents the relative forecasting performance of the Import Climate for each country and both forecast horizons (see Appendix B 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 and the corresponding rank among the set of indicators for the baseline real-time forecasting experiment. 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. Column (6) shows the rank for the Import Climate when it is used to make a forecast at the end of each quarter.

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

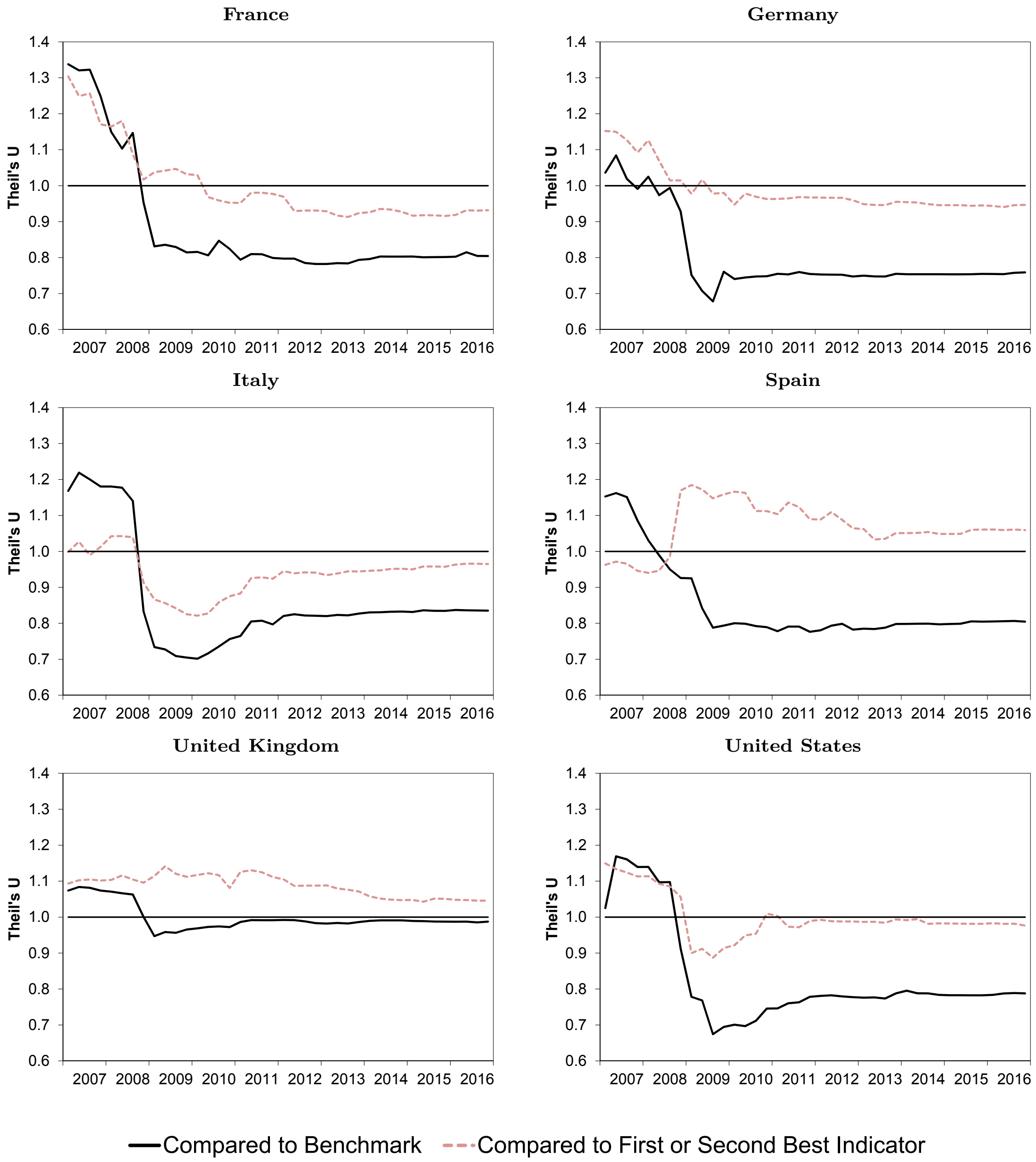
Note: The target series to forecast are real-time quarterly growth rates of total imports. The forecast is generated in the second month of each quarter and the forecast errors are computed with respect to the first release. $h = 0$ denotes the nowcast, $h = 1$ describes the forecast for the next quarter. 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.

For the nowcast, 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. In addition, we check whether the ranking of the Import Climate is driven by an exceptional good performance in a few periods. Figure 2 plots the Import Climate's RMSFE over time 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. 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 performance is driven by singular events.

When the forecasting experiment is conducted in the last month of the quarter instead of after the first release of national accounts figures, 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.

Turning to the forecast for the next quarter reveals that 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. Once again, we check

Figure 2: Forecasting Performance of the Import Climate over Time for $h = 0$

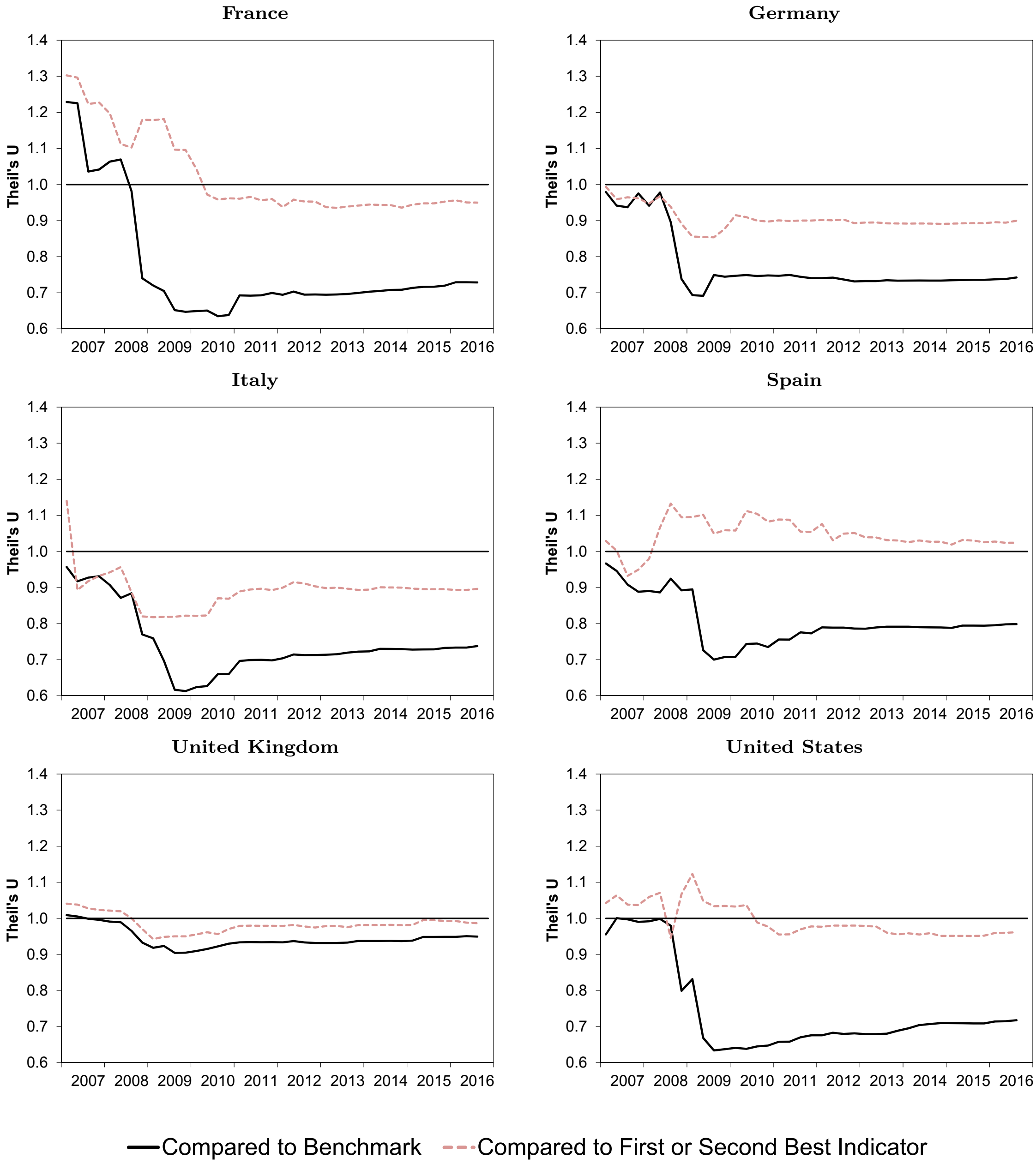


Note: The figure shows the relative root mean squared forecast errors of the Import Climate over time. The Import Climate's forecast errors are compared to the AR(p)-model (*Compared to Benchmark*) and to the second best indicator or, when the Import Climate is not, on average, the best predictor, to 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.

whether the good performance of the Import Climate is due to a few episodes. Similar to Figure 2, 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 does not depend on a few episodes.

Figure 3: Forecasting Performance of the Import Climate over Time for $h = 1$



Note: 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.

The finding that our new indicator performs better than other indicators for $h = 1$ is confirmed when we conduct the forecasting experiment at the end of a quarter when hard indicators are available for the first month of the respective quarter. 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.

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 3 presents the rank of the Import Climate among the set of indicators for both forecast horizons and both data releases (see Appendix B 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 3: 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

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 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.

Finally, the Import Climate also needs to be reliable in absolute terms in order to be useful in applied forecasting situations. From an objective perspective, the Import Climate has to generate RMSFEs that are smaller than the volatility in quarterly import growth rates. Table 4 presents the RMSFEs of the Import Climate together with the standard deviations (SD) in growth rates for the forecasting period of 2005 to 2016. For $h = 0$, the Import Climate's average forecast errors lie below the volatility in growth rates for all countries, confirming that the new indicator also has power in absolute terms. The same holds true for $h = 1$; the only exception being Spain, for which the RMSFE is above the standard deviation.

Table 4: Absolute Forecasting Performance of the Import Climate

Country	**RMSFE**		**SD**
	$h = 0$	$h = 1$	
France	1.45	1.42	1.93
Germany	1.96	1.85	2.30
Italy	1.88	2.06	2.45
Spain	3.29	3.58	3.36
United Kingdom	2.78	2.84	3.23
United States	1.96	2.10	2.30

Note: The target series to forecast are real-time quarterly growth rates of total imports. The standard deviations (SD) are calculated for the realized import growth rates for the forecasting period 2005:Q2 to 2016:Q4. $h = 0$ denotes the nowcast, $h = 1$ describes the forecast for the next quarter.

We thus conclude that the Import Climate exhibits remarkable leading indicator properties for forecasting import growth and is an improvement on available standard indicators. For applied forecasting situations, the Import Climate is a promising alternative as it produces smaller forecast errors compared to the volatility of the import series.

5. Conclusion

Import forecasting is typically accompanied by large forecast errors due to both the relative high volatility of imports and the lack of reliable leading indicators. This paper introduces the first leading indicator for import forecasting: the Import Climate. The novelty of our approach is to model imports from a foreign perspective. Instead of using domestic information, our indicator extracts the forecasting signals from abroad. Changes in today's import demand of the domestic country are mirrored in changes in the expected export development of the trading partners. In turn, the expected export development of each of the trading partners is explained by survey data information relating to its trading partners and its price competitiveness. The indicators of expected export development are combined to create the domestic country's Import Climate. In a real-time forecasting experiment involving six advanced economies, we show that the Import Climate 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. With respect to the size of absolute forecast errors, the Import Climate's RMSFEs are almost always smaller than the standard deviation of import growth, making the indicator useful for applied forecasting.

A growing literature suggests that forecasting individual GDP components separately and then aggregating them yields smaller forecast errors than forecasting GDP directly. We hypothesize that disaggregated GDP forecasts can be further improved by finding new leading indicators for all demand-side subcomponents. Our paper is the first to introduce a leading indicator for imports, in contrast to other work that investigates how to improve forecasting exports and private consumption. However, to the best of our knowledge, there are no studies on forecasting investment or government consumption. Therefore, future research in this area should concentrate on constructing new leading indicators for these two components and 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 5: 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	Industrial Confidence Indicator for France, Germany, Italy, Spain, and UK (in percentage points)	M/Q	1/0	0/0	L	European Commission
PMI	Purchasing Managers' Index for the US (in percentage points)	M/Q	1/0	0/0	L	Institute for Supply Management
CCI	Consumer Confidence Indicator for France, Germany, Italy, Spain, and UK (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
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
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

Continued on next page...

Table 5: Data Properties and Sources (cont.)

Variable	Description	F	PL 2	PL 3	T	Source
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-XPI37-Q	Domestic price and cost competitiveness against 38 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. Complete Forecasting Results

Table 6: Forecasting Results 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

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.

Table 7: Forecasting Results 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

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.

Table 8: Forecasting Results 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

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.

Table 9: Forecasting Results 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

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.

Table 10: Forecasting Results 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

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.

Table 11: Forecasting Results 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

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.