Nowcasting aggregate services trade

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# Introduction

The increasing importance of services trade in the global economy contrasts with the lack of timely data to monitor current trends. Monthly balance of payment data, which are the most timely source of services trade data, are published with a lag. This information gap poses challenges for policy-makers during times of economic volatility, as has become evident during the COVID-19 pandemic. This paper presents a nowcasting approach aimed at providing insights on current developments in aggregate services trade, as measured by the monthly balance of payments.

Existing trade-related nowcasting approaches often prioritise merchandise trade. While a limited set of contributions does consider services trade, the corresponding approaches estimate global trade flows ([1]). In contrast, this paper focuses on country-specific aggregate services imports and exports as recorded in the monthly balance of payments. The results presented in this abstract refer to the United States – the world’s largest importer and exporter of services. Yet, the approach was tested for all G7 countries and could generally be applied to all major advanced economies.

The methodology employs supervised machine learning to identify indicators of high predictive power. The approach combines traditional indicators of demand and supply, survey-based data capturing perceptions of economic prospects, as well as financial data and indicators of uncertainty. It also exploits Google Trends search data, a timely source of information available for a large set of economies.

# Methods

## Data

In a first step, four categories of potentially relevant predictors are defined (Table 1): (1) hard indicators, (2) soft and financial indicators, (3) indicators of uncertainty, (4) Google search requests. The first three categories rely on information from international organisations (Eurostat, OECD, IMF, World Bank, IEA) and scholars (policyuncertainty.com). Google data were provided by Google.

The first category also includes trade in goods, which is intertwined with services activities ([2], [3]). In the second category, survey-based measures, for example regarding business confidence, are often used as a predictor of economic activity and of the business climate. Available at high frequency, financial indicators reflect expectations of future developments ([4]). The third category comprises measures of uncertainty, including the economic policy uncertainty index (EPUI) ([5]). Based on newspaper sentiment analysis, the EPUI has been linked to changes in economic outcomes ([6]; [7]). Furthermore, the infectious disease volatility tracker was added ([8]).

Variables based on Google searches constitute the fourth category. Their strengths are timeliness and extensive country coverage. The data are daily and not revised over time. They provide a normalised measure of a search term’s relative popularity in a given period for a given country. Terms considered for this paper include searches focused on services (e.g. air transport) and searches related to the economic climate (e.g. judicial liquidation).

Table 1. Examples of predictors allocated to four categories

|  |  |
| --- | --- |
| Category | Examples of variables |
| Hard indicators | Unemployment rate, retail sales, car registrations, goods exports  |
| Soft and financial  | Business confidence, consumer confidence, stock market prices |
| Uncertainty | Infectious disease volatility tracker, economic policy uncertainty index |
| Google trend indicators | Searches related to advertising, hotels, air travel, judicial liquidation |

The time span was divided into two periods to estimate the model and assess its performance: the training period spans between January 2004 and June 2017; the out-of-sample period covers all observations from July 2017 to July 2020. The training sample was used to identify a parsimonious model and estimate its parameters. The subsequent evaluation of the models’ predictive accuracy relies on the out-of-sample period.

## Selection of predictors

The list of potentially relevant predictors across those four categories includes 98 variables. Yet, some might capture similar information and might be redundant. The selection of variables follows several steps. It first uses regressions to identify variables associated with services trade. It then employs supervised machine learning to refine the selection.

In order to identify variables displaying a strong link with services trade, different versions of univariate regressions linking changes in services trade to changes in a given predictor were estimated. As the impact of some variables might not be immediate, regressions using five different lag structures with a maximum lag of four months were run. Separate regressions were estimated for absolute changes (equation 1) and percentage changes (equation 2). All regressions were separately estimated using the month-on-month changes in exports as well changes in imports as the dependent variable. The number of statistically significant associations with the dependent variable was used to discard variables displaying a weak association with trade. 58 predictors were retained after this step.

(1) ∆Services\_trade= f() for p=0,1,2,3,4

(2) ) for p=0,1,2,3,4

As this list still contains variables likely to carry the same signals, a further step aimed at achieving a parsimonious model was implemented. Starting from the list of variables retained after the regressions, a supervised machine learning technique was used to identify the most relevant subset of predictors. The least absolute shrinkage and selection operator, known as Lasso ([9]), is a regularised regression method aimed at reducing model complexity. Capable of dealing with a large number of predictors, it provides a systematic, data-driven approach to model selection ([10]). Lasso minimises the mean squared error subject to a penalty on the sum of the absolute value of the coefficients.

In the equation above, which assumes all variables have been mean-centred, is the Lasso solution for the vector of parameters of interest. The first term on the right side corresponds to the least squares estimator. The second term introduces the penalisation, with λ determining the overall penalty level and representing predictor-specific penalty loadings. Through this penalisation, Lasso sets some coefficients to zero and removes all covariates whose estimated coefficients are zero from the model. It thereby helps to address the problem of overfitting. Lasso introduces a bias but simultaneously reduces the variance of the prediction. Given the bias-variance trade-off, this selection is likely to improve the performance relative to OLS and facilitates interpretation ([9]).

First, Lasso was applied separately to each category of indicators. For each category, the selection of indicators identified by Lasso was retained. The category-specific selections were combined in order to create two lists of predictors – one for imports and one for exports. In a second step, Lasso was applied to different variations of the variable list obtained after the first Lasso-based step: Different lags of the predictors from the four categories and versions with lags of the dependent variable were tested.

## 2.3 Bridge models used to fill missing observations

A further challenge relates to differences in reporting delay across variables. Two ways of addressing this aspect were explored: First, for a set of models a lag structure aligned with the reporting lags was imposed. Second, bridge equations were estimated to fill missing observations for variables with reporting delays. Linear regressions using Google variables and other high-frequency variables outperformed ARIMA and vector autoregression.

# Results

## Best-performing models

The models identified via Lasso were tested via linear regressions and vector autoregressions. Table 2 presents the results of the best models for US services exports (EXP-Model 1) and imports (IMP-Model 1). Both were estimated by linear regressions and combine variables from all four categories (see Table 3).

Table 2. Performance of best models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | RMSE as ratio of AR(4) RMSE | Forecast directional accuracy | Number of variables | Category |
| EXP-Model 1 | 0.885 | 74% | 13 | Mixed |
| IMP-Model 1 | 0.66 | 61% | 9 | Mixed |

Table 3. Variables included in best models

|  |  |  |
| --- | --- | --- |
| Category  | EXP-Model 1  | IMP-Model 1  |
| Hard | Exchange rate, goods imports, total goods exports of partner countries, unemployment rate, car registrations, manufacturing orders | Goods imports, goods exports |
| Soft and Financial | Share price index | Business conf. index |
| Uncertainty | Economic policy uncertainty index | Economic policy uncertainty index |
| Google | Business news, bus and rail, judicial liquidation | Air travel, sports |
| Lags of dependent variable | 2nd lag, 4th lag |  (none) |

The models’ performance was evaluated according to the root mean squared error (RMSE). The second column of Table 2 expresses the model’s RMSE as a ratio of the RMSE of a benchmark autoregressive model with four lags. For exports, the best model displays an RMSE corresponding to 88.5% of the RMSE of the AR(4) benchmark. Based on this measure, its predictive performance is hence 11.5% better than the benchmark. Regarding imports, the best model outperforms the AR(4) in terms of RMSE by 34%. The third column displays, for information, the directional accuracy. For roughly three quarters of the observations the export model accurately predicts the direction of change. Performances are somewhat lower for the import models.

## Ability to track impact of COVID-19 shock

The preferred models partially manage to track the unprecedented plunge in services trade following the COVID-19 shock. The average of the five best-performing models (consensus model) capture around 36% of the fall for both services exports and imports in the United States.

Figure 1 displays US services import outturns together with estimates provided by the best-performing export model (IMP-Model 1), the AR(4) benchmark and the “consensus model”. The latter is the average of the estimates of the five best models. The vertical red line indicates the start of the out-of-sample period in July 2017.



Figure 1. Services imports outturns, best-performing model, consensus and benchmark

# Conclusions

This paper develops an approach to nowcast monthly services trade data. It combines regressions and supervised machine learning to select variables and assesses resulting models according to their out-of-sample predictive performance. The models incorporate hard, soft, financial and uncertainty indicators. Google Trends search data help to improve the predictive power, either directly or by filling missing information in bridge equations. Selected models outperform autoregressive benchmarks. The average of the best models captures around 36% of the COVID-19-related fall for both US exports and imports.

The approach is subject to several caveats and there is scope for improvement. Thus, the approach could be directed toward sectoral analysis, looking at nowcasting specific categories of services trade. Similarly, the presence of non-linearities could be further investigated, especially regarding differential patterns during times of crisis.

# References

1. Martínez-Martín, J. and E. Rusticelli, “Keeping track of global trade in real time”, *International Journal of Forecasting (2020)*, [in](http://dx.doi.org/10.1016/j.ijforecast.2020.04.005) press.
2. Miroudot, S. and C. Cadestin, “Services In Global Value Chains: From Inputs to Value-Creating Activities”*, OECD Trade Policy Papers*, No. 197 (2017), OECD Publishing, Paris, <https://dx.doi.org/10.1787/465f0d8b-en>.
3. Ariu, A., et al., “The interconnections between services and goods trade at the firm-level”, *Journal of International Economics*, Vol. 116 (2019), pp. 173-188, <http://dx.doi.org/10.1016/j.jinteco.2018.10.005>.
4. Bańbura, M. et al., “Now-Casting and the Real-Time Data Flow”, in *Handbook of Economic Forecasting* (2013), Elsevier, <http://dx.doi.org/10.1016/b978-0-444-53683-9.00004-9>.
5. Baker, S., N. Bloom and S. Davis, “Measuring Economic Policy Uncertainty\*”, *The Quarterly Journal of Economics*, Vol. 131/4 (2016), pp. 1593-1636.
6. Biljanovska, N., F. Grigoli and M. Hengge, “Fear Thy Neighbor: Spillovers from Economic Policy Uncertainty”, *IMF Working Paper* WP/17/240 (2017).
7. Gulen, H. and M. Ion, “Policy Uncertainty and Corporate Investment”, *Review of Financial Studies,* Vol. 29/3(2015), pp. 523–564.
8. Baker, S. et al. (2020), “The Unprecedented Stock Market Reaction to COVID-19”, *The Review of Asset Pricing Studies* (2020), in press.
9. Tibshirani, R., “Regression Shrinkage and Selection Via the Lasso”, Journal of the Royal Statistical Society: Series B (Methodological), Vol. 58/1 (1996), pp. 267-288.
10. Hastie, T., R. Tibshirani and M. Wainwright, *Statistical Learning with Sparsity: The Lasso and Generalizations* (2015), Taylor and Francis.