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Nowcasting and forecasting economic activity in Denmark using payment system data

Kristian Nørgaard Bentsen
knb@nationalbanken.dk
DANMARKS NATIONALBANK

Denis Gorea
dego@nationalbanken.dk
DANMARKS NATIONALBANK

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Abstract
We show that payment system data can help predict economic activity in Denmark by employing mixed-data sampling (MIDAS) regression methods to forecast quarterly macroeconomic variables using high-frequency data. Among a set of frequently used predictors of economic activity, payment system data delivers some of the best nowcasts and one-quarter-ahead forecasts of GDP. Forecast combinations that blend monthly payment system data with other high-frequency predictors also score high in terms of their nowcasting performance. However, the forecasting performance of the payment system data deteriorates during the first half of 2020, as changes in the payment behavior recorded in the payment system data are not large enough to explain the sharp drop in economic activity during the first wave of the covid-19 pandemic.

Resume
Vi viser, at data fra betalingssystemer kan hjælpe med at forudsige den økonomiske aktivitet i Danmark ved at anvende MIDAS-regressionsmetoder til at forecaste kvartalsvise makroøkonomiske variable ved hjælp af højfrekvente data. Blandt en række data, der ofte anvendes til at forudsige økonomisk aktivitet, leverer betalingssystemdata nogle af de bedste BNP-nowcasts, samt BNP-forecasts for det kommende kvartal. Forecast-kombinationer, der kombinerer månedlige betalingssystemdata med andre højfrekvente data, scorer også højt med hensyn til deres forudsigelsesevne. Anvendeligheden af betalingssystemdata til at forudsige den økonomiske aktivitet forværres dog i første halvdel af 2020, da ændringer i betalingsadfærden registreret i betalingssystemdata ikke er store nok til at forklare det kraftige fald i økonomisk aktivitet under den første bølge af covid-19-pandemien.

Keywords
Payment systems; forecasting.

JEL classification
C53; E17; E42.

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The authors alone are responsible for any remaining errors.

Nowcasting and forecasting economic activity in Denmark using payment system data*

Kristian Nørgaard Bentsen†
Denis Gorea‡

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Abstract

We show that payment system data can help predict economic activity in Denmark by employing mixed-data sampling (MIDAS) regression methods to forecast quarterly macroeconomic variables using high-frequency data. Among a set of frequently used predictors of economic activity, payment system data delivers some of the best nowcasts and one-quarter-ahead forecasts of GDP. Forecast combinations that blend monthly payment system data with other high-frequency predictors also score high in terms of their nowcasting performance. However, the forecasting performance of the payment system data deteriorates during the first half of 2020, as changes in the payment behavior recorded in the payment system data are not large enough to explain the sharp drop in economic activity during the first wave of the covid-19 pandemic.

JEL classification codes: C53, E17, E42.

Keywords: Payment Systems, Forecasting, Aggregate Dynamics.

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†Danmarks Nationalbank: *knb@nationalbanken.dk.*

‡Danmarks Nationalbank: *dego@nationalbanken.dk.*

1 Introduction

Central banks around the world increasingly use high-frequency data to nowcast and forecast policy-relevant macroeconomic variables such as the gross domestic product (GDP). The strong push among policy makers to use such data for near-term predictions is mainly driven by the need to monitor economic activity at dates when quarterly macroeconomic series are not readily available. In this sense, payment system data (PSD) offers a timely source of information on economic transactions that is available in-house at most central banks. This data source is highly reliable because it does not suffer constant revisions and is typically available at a daily frequency.

In this paper, we investigate to what extent PSD can be used to monitor and forecast short-term economic conditions in Denmark by comparing its nowcasting and forecasting performance with that of other high-frequency indicators used in the literature. Our payment system data is based on customer-initiated interbank payments from Danmarks Nationalbank's real-time gross settlement system, Kronos, as well as on retail payments settled via Finance Denmark's Clearing Systems (Sumclearing, Intradagclearing and Straksclearing), which are operated by Nets. To estimate the relationship between these high-frequency series (i.e., interbank payments and retail payments) and the low-frequency GDP data, we employ a popular econometric method that incorporates variables of different frequencies in a single regression model — the Mixed Data Sampling (MIDAS) regression model. This model was first introduced by Ghysels et al. (2004) and has gained popularity ever since due to its parsimonious parameterization and efficiency gains relative to conventional distributed lag models.

We start by contrasting the forecasting performance of PSD to the one of industrial production (IP), a popular high-frequency data series used to predict macroeconomic variables.[1] We find that PSD predictions dominate IP predictions both in terms of nowcasts and one-quarter-ahead forecasts. Among the PSD series that we use in this paper, data from the Kronos system performs better than IP in terms of nowcasts, while one-quarter-ahead forecasts using data from the Clearing Systems deliver lower root mean squared errors compared to forecasts constructed using IP data. Moreover, PSD outperforms IP data when it comes to predicting private and government consumption,

[1] In this paper, we measure the *predictive performance* of PSD in a MIDAS model by computing the root mean squared errors for forecasts generated by the model. We also use the Diebold-Mariano test and the out-of-sample R-squared to assess the relative performance of forecasts across combinations of a set of high-frequency variables that includes PSD.

money supply and fixed capital formation. In addition to comparisons to the IP data, we also investigate how the PSD predictions compare to a larger set of high-frequency series, such as consumer prices and residential construction, and find that the PSD series are among the best single-variable model predictors in our set of high-frequency variables irrespective of the forecast horizon. Moreover, forecasts based on PSD in combination with those based on IP deliver the best predictions in terms of nowcasting. These results are robust to a batch of statistical tests and alterations of our baseline model in terms of the size of estimation windows, both in the case of rolling window and recursive window estimation, as well as when different vintages of GDP data are used in our forecasting exercises. We also find that the daily PSD is a better predictor of the quarterly GDP than daily stock market data.

The forecasting performance of our MIDAS regressions that use PSD deteriorates somewhat during the first two quarters of 2020, a period marked by the first wave of the covid-19 pandemic and the ensuing lockdown. During this period, the PSD series employed in our analysis did not exhibit significant drops which the model could rely upon to predict the sharp drop in economic activity that followed the virus outbreak. We find that other high-frequency series, such as car registrations and unemployment rates, are better at predicting the evolution of GDP in an evaluation sample that includes the first half of 2020.

Our results compare favorably with the growing literature using payment systems data to forecast economic activity. Carlsen and Storgaard (2010) use data on debit card payments (Dankort) to forecast retail sales in Denmark and show that the out-of-sample predictions of their PSD match well results from an autoregressive model. Aastveit et al. (2020) nowcast Norwegian household consumption using MIDAS regressions with predictors sampled at monthly and weekly frequency and find that debit card data is an accurate predictor of consumption, including during periods of high uncertainty such as the covid-19 pandemic. Galbraith and Tkacz (2018) assess how PSD can contribute to more accurate GDP nowcasts using Canadian data and find that debit card data helps reduce nowcast errors for GDP and retail sales. Duarte et al. (2017) employ MIDAS regression models and data collected from automated teller machines and points-of-sale systems to nowcast and forecast quarterly private consumption in Portugal. Similar to our results, they show that PSD for Portugal delivers better nowcasting results than typical indicators and, to a lesser extent, better one-quarter-ahead forecasts. Gil et al. (2018) and Bodas et al. (2019) use data on card transactions to successfully forecast private consumption and retail trade in Spain. Aprigliano et al. (2019) find that a mixed-frequency factor model based on payment systems data can reliably predict Italian GDP and its main components.

Our paper also borrows heavily from the methodological literature on the estimation of mixed-frequency models. Armesto et al. (2010) provide a short summary of some of the common methods used to tackle such mixed-frequency setups, with a special emphasis on the MIDAS framework. This framework has been applied extensively to study how various high-frequency data series can be used to forecast economic activity, such as: the real-time forecasting of the US federal government budget (Ghysels and Ozkan, 2015), the forecasting of GDP growth using daily financial data (Andreou et al., 2013), the nowcasting of euro area GDP (Kuzin et al., 2011), and the forecasting of the monthly real price of oil (Baumeister et al., 2015). Another strand of the literature dealing with mixed-frequency data has focused on developing dynamic factor models to nowcast low-frequency variables using high-frequency series (see Giannone et al., 2008; Doz et al., 2011; Bok et al., 2018; Grenestam and Schmith, 2021). These models rely on Kalman filtering techniques to handle the frequency differences in the data and to update estimates of the common factors. Lastly, Bayesian vector autoregression methods have been also shown to be successful at nowcasting economic activity with high-frequency data. Carriero et al. (2015) and Giannone et al. (2015) show that this framework can greatly reduce the number of data transformations needed to estimate mixed-frequency models due to the innate probabilistic nature of these methods that center around Bayesian inference.

The rest of the paper is organized as follows. Section 2 describes the payment systems infrastructure in Denmark. Section 3 introduces the MIDAS regression model used in our nowcasting and forecasting exercises. Section 4 discusses our main results. Section 5 lists several robustness checks that reinforce our results. Section 6 describes how our main results change when we try to forecast economic activity during the covid-19 global pandemic. Section 7 concludes the paper.

2 Danish payment system data

The Danish payments infrastructure is based on a network of systems that enables economic agents to exchange payments. Examples of payments processed within these systems are large-value interbank payments, securities transactions, retail payments and foreign exchange transactions. In this paper, we use payment system data that is likely to have the strongest connection to real economic activity, namely customer-initiated interbank transactions and retail payments. Both sources are described in detail below.

Customer-initiated interbank transactions from Kronos. Our first data source for the PSD series is based on the customer-initiated interbank transactions from the payment system Kronos.[2] Kronos is a Real-Time Gross Settlement (RTGS) system for payments in Danish kroner, and one of its main functions is the settlement of large-value, time-critical interbank payments. Kronos is both operated and owned by the Danish central bank. Interbank payments in Kronos can be initiated by the banks themselves or by their customers. The customer-initiated payments are typically initiated to cover a very large purchase of goods from private actors, for example buying a car from abroad, and are more likely to be tied to economic activity than other interbank payments. Therefore, we only use this data in our analysis going forward. The distinction is made by filtering data using information from the SWIFT payment message type. Data from Kronos is available from May 2002 on a daily basis and consists of total gross transactions in terms of value and number of payments.

Retail payments from the Clearing Systems. The second data source is based on retail payments from Finance Denmark's Clearing Systems. Retail payments are payments between consumers, firms and public authorities, e.g. by payment card or credit transfers. Retail payments are settled through Finance Denmark's three systems: Sumclearing, Intradagclearing and Straksclearing. The three systems were not introduced simultaneously, but were a result of payment innovation that gradually reduced the settlement time for retail payments. Intradagclearing made it possible to ex-

[2]The current RTGS system was introduced in August 2018 and is called Kronos2, while the former system was called Kronos. The time series in this analysis uses data from both systems in a consistent way, and we use the name Kronos to refer to the joint series.

change a payment from one bank to another within the same day, while Straksclearing introduced instant credit transfers in Denmark. All systems are still active today and handle different types of retail payments. Finance Denmark is the system owner of the Clearing Systems, while Nets is the operator of the system. Danmarks Nationalbank provides the final settlement in Kronos.[3] Data from Sumclearing is available from December 2008, while data from Intradagclearing and Straksclearing is available from February 2014 and November 2014, respectively. Intradagclearing was in fact introduced in November 2013 and, therefore, there is a three-month data gap. In this period, the sum of all retail payments from the three different systems is not consistent with the period before or after, since a lot of retail payments migrated from Sumclearing to Intradagclearing when the Intradagclearing was launched. As a consequence, data from this period is excluded from our analysis. Data from Straksclearing, on the other hand, is available from the launch date. Data from the Clearing Systems is available on a daily basis and contains total gross transactions in terms of value and number of payments.

3 Estimation

There are increasingly many econometric methods for estimating models that rely on high-frequency time series to forecast low-frequency data. In this paper, we use the Augmented Distributed Lag MIDAS model, introduced by Andreou et al. (2013), to test whether payment system data can be considered as a timely indicator of economic activity. Our model has an autoregressive component of order one and is expressed as follows:

$$y^L_{t_L+h} = a_h + \lambda_h y^L_{t_L} + b_h C(L^{\frac{1}{m}}; \theta_h) x^H_{t_L} + \varepsilon^L_{t_L+h} \tag{1}$$

where y and x are the low and high-frequency variables, respectively. We use nine lags for the independent variables.[4] The forecasting horizon h is set to zero in the case of the nowcasting exercises in this paper, and to one for the one-quarter-ahead forecasting exercises. More specifically,

[3] While payments data from the Clearing Systems offers a good proxy for payments related to consumption, it also includes transactions that do not necessarily reflect consumption activity. An example of this are transactions of customers redistributing transfers across accounts.

[4] We experimented with different lag structures for the independent variable and found that using nine lags led to the lowest forecast RMSE in our set models.

this implies that we will use the high-frequency regressors x from the three months that belong to quarter $t+1$ when nowcasting y_{t+1}. Similarly, when computing the one-quarter-ahead forecast for y_{t+1}, we will use the high-frequency regressors x from the three months that belong to quarter t.

Both the dependent and the independent variables are log differences of the respective time series, unless specified otherwise. In all of our empirical exercises described below, the frequency of the dependent variable is quarterly, while the frequency of the independent variables is either monthly or daily. $C(L^{\frac{1}{m}};\theta) = \sum_{i=0}^{N} c(i;\theta)L^{i/m}$ is a polynomial function of weights on each of the lagged regressors, and $C(1;\theta) = \sum_{j=0}^{N} c(j;\theta) = 1$.

We take an agnostic approach on the preferred polynomial specification $C(\cdot)$ by considering a plethora of functional forms: (i) unrestricted — in which coefficients are estimated without constraints; (ii) normalized beta probability density function with a zero and non-zero last lag; (iii) normalized exponential Almon lag polynomial; (iv) Almon lag polynomial; and (v) step polynomial.[5] Appendix A provides more details on these functional forms. We use non-linear least squares to estimate each model and determine the best forecast fit by computing the root mean squared error (RMSE) for each polynomial function, as well as other measures of predictive performance described in Appendix B. Our computation routine follows closely the one in Qian (2020).

Table 1 lists the data series used to estimate the model in equation 1. Our main dependent variable describing economic activity is the gross domestic product, but we also explore whether PSD can be used to predict other macroeconomic aggregates such as private and government consumption, money supply, production in total manufacturing, and gross fixed capital formation. Besides industrial production and PSD, our set of high-frequency regressors includes the consumer price index, the unemployment rate among all persons, a series for works started in the residential construction business, a series for energy production and distribution, the number of passenger car registrations, total retail trade, a business confidence indicator, and an index series describing the evolution of the local stock market.

[5] The unrestricted polynomial structure in a MIDAS framework was pioneered by Foroni et al. (2015).

Table 1: Data description and sources

Variable names	Description	Frequency	Source
GDP	total gross domestic product; CP, SA	Q	OECD
Private Consumption	private final consumption expenditure; CP, SA	Q	OECD
Government Consumption	government final consumption expenditure; CP, SA	Q	OECD
M1	narrow money; SA	Q	OECD
Production Manufacturing	production in total manufacturing; SA	Q	OECD
Fixed Capital Formation	gross fixed capital formation; CP, SA	Q	OECD
Industrial Production	production of total industry; SA	M	OECD
CPI	consumer price index	M	OECD
Unemployment Rate	unemployment rate, all persons; SA	M	OECD
Residential Construction	residential construction, work started; SA	M	OECD
Energy Production	production and distribution of electricity, gas, etc.; SA	M	OECD
Car Registrations	passenger car registrations; SA	M	OECD
Retail Trade	total retail trade; SA	M	OECD
Business Confidence	business tendency surveys, confidence indicator; SA	M	OECD
Stock Prices	stock market index, OMX Copenhagen 20	D	NASDAQ OMX
Kronos (Val. & Vol.)	total gross customer-initiated interbank payments	D	DN
Clearing Systems (Val. & Vol.)	total gross retail payments	D	DN and Nets

Notes: Variables that are sourced from the OECD were retrieved from FRED, Federal Reserve Bank of St. Louis. The symbols "CP" and "SA" in the column titled "Description" stand for constant prices and seasonally adjusted. The symbols "Q", "M" and "D" in the column titled "Frequency" stand for quarterly, monthly, and daily respectively. Symbol "DN" in column "Source" stands for Danmarks Nationalbank. Clearing Systems is the sum of retail payments across Sumclearing, Intradagclearing and Straksclearing.

4 Nowcasting and forecasting exercises

We start by comparing the nowcasting and forecasting performance of the payment system data to the one of the industrial production index. IP is frequently used to predict economic activity and has been shown to have high predictive power in earlier studies (see Koenig et al., 2003). The PSD series that we focus on in this paper are the value and volume of customer-initiated daily interbank transactions recorded in the Kronos system, as well as the total value and volume of payments across Sumclearing, Intradagclearing and Straksclearing, which we refer to in our figures and tables as the Clearing Systems sample.[6] To ensure comparability with the IP series and adjust

[6]We excluded the observations between October 2013 and January 2014 in the Clearing Systems sample from our analysis, in line with the explanation provided in section 2. This deliberate data omission solves the issue of different

for the daily and weekly seasonality in the data, we aggregate the PSD series to a monthly value by summing up all values and volumes in a given month. We also explore whether the mean values of our Kronos and Clearing Systems series have higher predictive power than the sum of recorded values.

As described above, we estimate equation 1 for each of the five polynomial specifications $C(\cdot)$ and compute the respective forecast RMSE. The nowcasts that we report in this paper are based on regressions using the high-frequency variables in the month of the forecast quarter. For example, the nowcast of GDP growth in quarter Q4 are computed using monthly Kronos data in months 10 to 12. Figure 1 reports our results for the nowcasting exercise. Each bar in the chart is the range between minimum and maximum RMSE computed across different polynomial weighting functions applied to the high-frequency regressors. Our Kronos estimation sample starts in May 2002 and ends in December 2019. The sample size is determined by the availability of the Kronos data.[7] Our Clearing Systems sample starts in December 2008 and ends in December 2019. This sample is constructed to fit the starting and ending points of our retail payments data from Sumclearing, Intradagclearing and Straksclearing. In both samples, estimation starts 12 months after the beginning of each sample (due to the lag structure of our empirical model) and ends in the last quarter of 2015. We use the last three years of each sample (i.e., 2016-2019) to compute our forecasts and model RMSE.

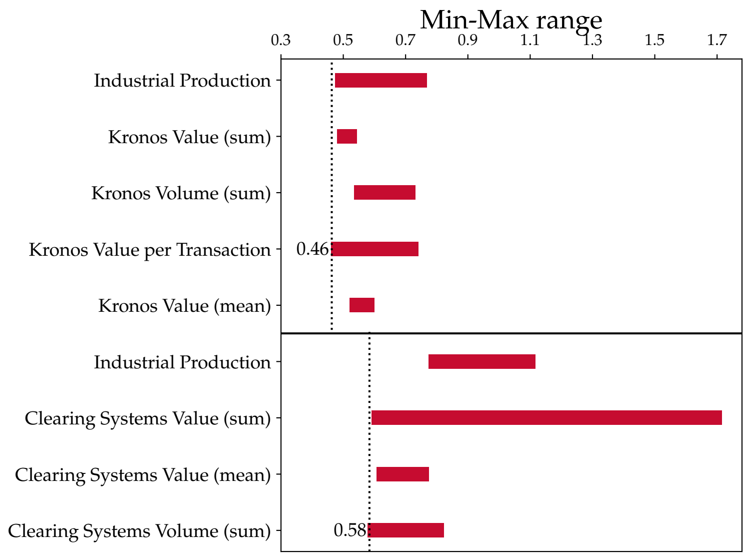
As shown in figure 1, the model that nowcasts quarterly changes in GDP using monthly changes in IP delivers an RMSE of 0.47, which is slightly above the RMSE of the model using Kronos data of 0.46. The RMSE min-max range is rather large for industrial production in our first sample, highlighting that the polynomial functions put significantly different weights on the lags of this independent variable. Among the group of Kronos predictors, the value per transaction delivers the lowest RMSE in this subgroup.[8] Among the Clearing Systems sample predictors, IP nowcasts are dominated by the ones generated using Clearing Systems data series in terms of RMSE perfor-

reporting scales in the volume series that are due the introduction of Intradagclearing in 2013.

[7] Section 6 describes how our results change when we extend our sample to include data from the first two quarters of 2020.

[8] Value per transaction is computed as the ratio between total monthly value of payments to total monthly volume of payments. While value per transaction delivers better predictions, total value and volume of payments are similar, if not better, indicators of economic activity when it comes to economic intuition, as more transactions and higher value of payments are indicative of more economic activity.

Figure 1: Root mean squared error for GDP nowcasting



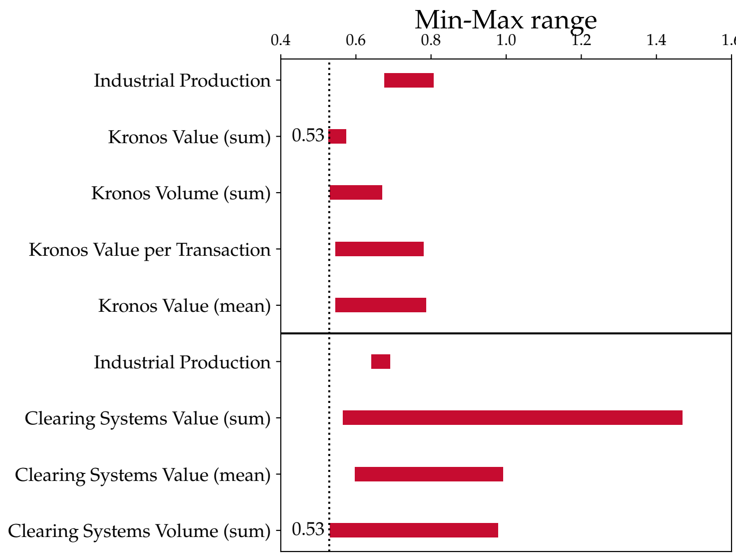
Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. Nowcasts are zero-quarters-ahead forecasts.

mance. The minimum RMSE obtained across the Clearing Systems models is larger for this sample compared to the Kronos sample (0.58 vs. 0.46). Overall, the PSD series seem to dominate IP in terms of their nowcasting performance. In light of this finding, it is important to note that PSD comes at a much higher frequency than IP and could be used in weekly/daily versions of a MIDAS model to create nowcasts in periods when timeliness of projections provides more value to policymakers than accuracy.

Figure 2 plots our results for the case when we forecast GDP growth using high-frequency data with a lag of one quarter.[9] Similar to our results in figure 1, IP is the worst performing predictor of GDP as measured by forecast RMSE in both our samples. In the first sample, Kronos data on total value of transactions has the best predictive power (RMSE of 0.53), while in our second sample the sum of volumes of payments in a given calendar month processed through the Clearing Systems delivers a similar RMSE of 0.53. Total volume of Clearing Systems payments is a close second, but there seems to be more forecast disagreement in terms of weighting functions for this case, as the

[9]Most forecasts reported in this paper are one-quarter-ahead forecasts, unless specified otherwise. In section 5, we also report how our conclusions change when we extend the forecast horizon to up to six quarters ahead.

Figure 2: Root mean squared error for GDP forecasting



Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. Forecast horizon is equal to one quarter.

Min-Max range is rather wide.

Summing up, results reported in figures 1 and 2 suggest that payment system data could be used for nowcasting and forecasting purposes, as they seem to outperform the predictions of a MIDAS model that employs data on industrial production — a popular predictor of economic activity used in the literature. In addition to GDP, we also study whether other macroeconomic aggregates can be forecast using PSD. Table 2 reports the minimum RMSE across model specifications used to plot the Min-Max ranges in figures 1 and 2. We use the Kronos sample in the nowcasting exercises, since, as we have shown in figure 1, these PSD series seem to outperform IP in terms of their RMSE. For one-quarter-ahead forecasts, we use the Clearing Systems sample instead, in line with our evidence in figure 2, though the RMSE for Clearing Systems data is only slightly lower than the one obtained using Kronos data in this case.[10] Out of the PSD series considered in figures 1 and 2, we report in table 2 only results for the one of these series that delivers the lowest RMSE.

[10] We also computed the forecasting performance of our models using Kronos data between 2009 and 2019, in line with the time period for the Clearing Systems sample. Figures 14 and 15 replicate figures 1 and 2 for this shorter time period. Our results suggest that there is little difference in terms of forecasting performance during the shorter period between using Kronos data vs. using Clearing Systems data as our independent variable.

Table 2: Forecasting macroeconomic aggregates using payment system data

	GDP	Private Consumption	Government Consumption	M1	Production Manufacturing	Fixed Capital Formation
			Nowcasting			
Industrial Production	0.47	0.82	0.73	1.13	1.65	3.64
Kronos	0.46	0.79	0.69	0.62	3.63	3.98
			Forecasting			
Industrial Production	0.64	0.92	0.93	1.12	2.90	4.11
Clearing Systems	0.53	0.86	0.67	0.60	2.42	3.66

Notes: The numbers reported in the table are minimum forecast RMSE for single-variable models where the forecast variable is the one described in each column and the high-frequency variable is the ones listed in each row. Kronos stands for the best predictor in terms of RMSE out of the series listed in figure1, rows two to five. Similarly, Clearing Systems stands for the best predictor among the set of series listed in figure1, rows seven to nine. Forecast horizon is equal to one quarter for the lower panel of the table above, while nowcasting stands for zero-quarters ahead forecasting.

Table 2 describes how successful the PSD series are at forecasting private consumption, government consumption, money supply (M1), manufacturing production, and fixed capital formation. We find that, in terms of nowcasting, Kronos data delivers lower RMSE compared to IP for private consumption, government consumption, and money supply, and higher RMSE for manufacturing production and fixed capital formation. While results for nowcasting are not uniform across different measures of economic activity, one-quarter-ahead predictions using the Clearing Systems series significantly dominate the performance delivered by forecasts that use IP data across all the macroeconomic aggregates in terms of forecast RMSE.

Next, we compare the nowcasting and forecasting performance of PSD to other popular high-frequency indicators used in the literature. Table 3 reports our results for RMSE of model predictions of GDP growth rates from a set of nine high-frequency indicators. As in table 2, we report the mimimum RMSE across the set of functional forms for the weighting polynomial $C(\cdot)$ in equation 1. Kronos data delivers the best nowcast RMSE, followed closely by industrial production and energy production. Results are somewhat different when we consider forecasting at the three-month horizon. Clearing Systems data is the fourth-best predictor in terms of RMSE at this horizon, somewhat behind the forecast RMSE of the residential construction series (0.53 vs. 0.44).[11] Overall,

[11]The residential construction data has been subject to major revisions in 2019. We used the latest vintage available of that data in our analysis. While revisions might not influence the results of our static exercise when we use only one

Table 3: Predicting GDP growth using various high-frequency indicators

		Nowcasting	Forecasting
(1)	Clearing Systems / Kronos	0.46	0.53
(2)	Industrial Production	0.47	0.64
(3)	CPI	0.50	0.50
(4)	Unemployment Rate	0.61	0.62
(5)	Residential Construction	0.48	0.44
(6)	Energy Production	0.47	0.63
(7)	Car Registrations	0.83	0.74
(8)	Retail Trade	0.65	0.53
(9)	Business Confidence	0.48	0.48

Notes: The numbers reported in the table are minimum forecast RMSE for models where the dependent variable is GDP and the independent variables are the ones described in each row. Clearing Systems / Kronos stands for the best predictor in terms of RMSE out of the series listed in figure1 (nowcasting) and 2 (forecasting). For each high-frequency indicator and horizon, we estimate equation 1 for all specifications of the weighting polynomial function and record the minimum RMSE. The forecast horizon is equal to one quarter for the right column of the table above, while nowcasting stands for a zero-quarter-ahead forecast.

our results in this section suggest that there is a strong case to be made for using PSD to forecast economic activity at very short forecasting horizons.

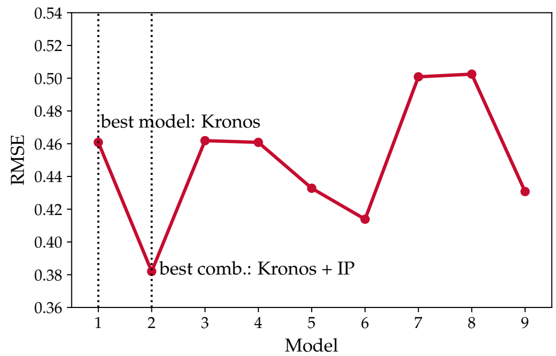
5 Robustness

In this section, we present the results of several extensions of our main empirical exercise described in the previous section. We start by constructing forecast combinations based on the high-frequency predictors listed in table 3 and analyzing which of these can improve forecast accuracy relative to our baseline models in which only one high-frequency predictor is used to forecast GDP growth. We then employ other tests than RMSE to check whether the forecast performance of the combined models is indeed above the one of single-variable models.[12] We also show how our main results

vintage for all high-frequency and low-frequency data, they are likely to cause significant biases when forecasting is done using flash data for series that undergo major revisions.

[12]Models that are referred to as *single-variable* in the text also include the AR(1) component of equation 1. We also tested the forecasting performance in terms of RMSE of an AR(1) model that has no high-frequency regressors and found that this model underperforms relative to the MIDAS models that include PSD as additional explanatory variables. For example, in the Kronos sample, we obtain an RMSE of 0.62 for one-quarter-ahead forecasts delivered by an AR(1) model vs. an RMSE of 0.53 using Kronos data.

Figure 3: GDP nowcasting combinations



Notes: The numbers on the x-axis are the model numbers listed in the first column of table 3. The dotted line marked with the text "best model" stands for the best single-variable model in terms of RMSE in table 3. In the case of the best single-variable model, we report on the y-axis the forecast RMSE of that model. In the case of other models (1 to 9, except for 3, in the figure above), we report on the y-axis the RMSE for the forecast combination of the best model (i.e., Kronos) and the other single-variable models (i.e., for unit 2 of the x-axis above, the y-coordinate is the RMSE of the forecast combination between Kronos data and the IP model). Nowcasts are zero-quarter ahead forecasts.

change when using rolling and recursive window samples instead of our benchmark fixed window approach. Finally, we study whether daily PSD series can be used to forecast GDP by contrasting their forecasting performance to the one of another popular daily predictor of economic activity used in the literature — stock market data.

We check whether forecast combinations can lead to better predictions than forecasts of single high-frequency variable models by computing the predicted values for GDP based on each of the models summarized in table 3 (i.e., models that deliver the lowest RMSE across the sample of weighting polynomial functions $C(\cdot)$). We then use the best single-variable model for each horizon and combine the predicted GDP from this model with predicted values from the rest of the models described in table 3. We next assign different weights to each single-variable forecast to get a forecast combination of two variables. We follow an agnostic approach and compute forecast combinations using a set of different criteria for weights assigned to each single forecast as follows: (i) equal weights; (ii) weights based on the Bayesian information criteria of each regression model; (iii) weights based on the Akaike information criteria of each regression model; (iv) weights based on mean squared forecast error; and (v) weights based on the discounted mean squared forecast error (with a discount of 0.9).[13] Once the forecast combinations for a pair of single high-frequency models is computed

[13] Appendix C describes these weighting schemes in greater detail.

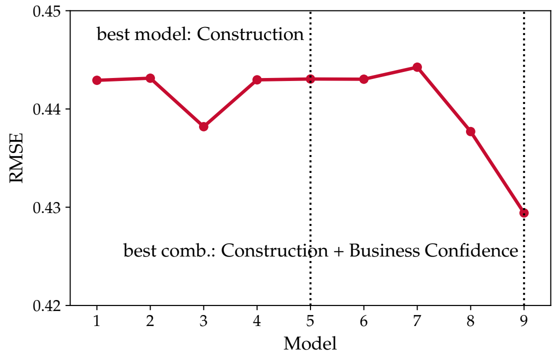
according to each of the five weighting criteria, we compute the minimum RMSE for each set of such combined forecasts.

Figure 3 summarizes our results for the best nowcast combinations. As shown in table 3, the model that uses Kronos data to predict GDP delivers the best single-variable model forecast, with an RMSE of 0.46. Figure 3 also shows that the combination of forecasts based on Kronos and industrial production (model 2) leads to a significantly lower RMSE of about 0.38 compared to the best single-variable model. Other combinations of the high-frequency series listed in table 3 with Kronos data also lead to minor improvements in terms of forecast RMSE relative to the one of the single-variable model, though some series such as car registrations and retail trade underperform the single-variable model when combined. To sum up, Kronos data delivers the best single-variable model prediction when it comes to nowcasting, and one can also increase the predictive power of single-variable models significantly when using IP in forecast combinations with Kronos data.

Figure 4 plots the minimum RMSE for one-quarter-ahead forecast combinations. The best single-variable model prediction for this horizon is obtained when using residential construction data as the predictor of GDP. In terms of forecast combinations, the only model that leads to a significant improvement in lowering the RMSE compared to the single-variable model is the one that combines the forecast using business confidence with the residential construction forecast. PSD data improves the performance of the single-variable model only mildly when it comes to one-quarter-ahead forecast combinations.

To further check how the forecasting performance of joint combinations differs from the one of single-variable models, we compute two more statistics that measure the predictive power of nowcast and forecast combinations. The first statistics that we use is the Diebold-Mariano test (Diebold and Mariano, 1995), which compares forecast errors for the best single-variable model and the best forecast combination across the pair of models described in figures 3 and 4. The Diebold-Mariano test is a conservative measure when applied to short-horizon forecasts, as is the case of forecasts presented in this paper. We supplement this test with a less conservative statistical measure that has been used in the literature to compare forecasts across models — the out-of-sample R-squared (see Campbell and Thompson, 2008, and Faccini et al., 2019). This test evaluates whether the variance explained by the best forecast combination is higher or lower than the variance explained by

Figure 4: GDP forecast combinations



Notes: The numbers on the x-axis are the model numbers listed in the first column of table 3. The dotted line marked with the text "best model" stands for the best single-variable model in terms of RMSE in table 3. In the case of the best single-variable model, we report on the y-axis the forecast RMSE of that model. In the case of other models (1 to 9, except for 5, in the figure above), we report on the y-axis the RMSE for the forecast combination of the best model (Construction) and the other single-variable model (i.e., for unit 9 of the x-axis above, the y-coordinate is the RMSE of the forecast combination between residential construction and business confidence data). The forecast horizon is equal to one quarter.

the best single-variable model.

Table 4 summarizes our results for these two tests. It first lists the best single-variable model and the best forecast combination across the three horizons which we reported earlier in table 3 and figures 3 and 4. As described above, when it comes to nowcasting, the single-variable model using high-frequency data from the Kronos system leads to the best nowcasts in terms of RMSE. Combining this forecast with the one from the model using industrial production leads to better performance in terms of RMSE (figure 3), but the Diebold-Marino test fails to reject the null hypothesis of no difference between forecasts of the single-variable model and the forecast combination. Furthermore, the less conservative test of out-of-sample R-squared is negative, which implies that the forecast combination also underperforms the single-variable model in terms of nowcasting GDP. The same conclusions hold true for the Diebold-Mariano test and the out-of-sample R-squared in the case of one-quarter-ahead forecasting. According to the Diebold-Mariano test, we fail to find any improved forecasting performance of the combined model (residential construction + business confidence) relative to the single-variable model (residential construction), and also do not find that the combined model outperforms the single-variable model in terms of out-of-sample R-squared.

We next report how our baseline results in figures 1 and 2 change when we use rolling and recursive

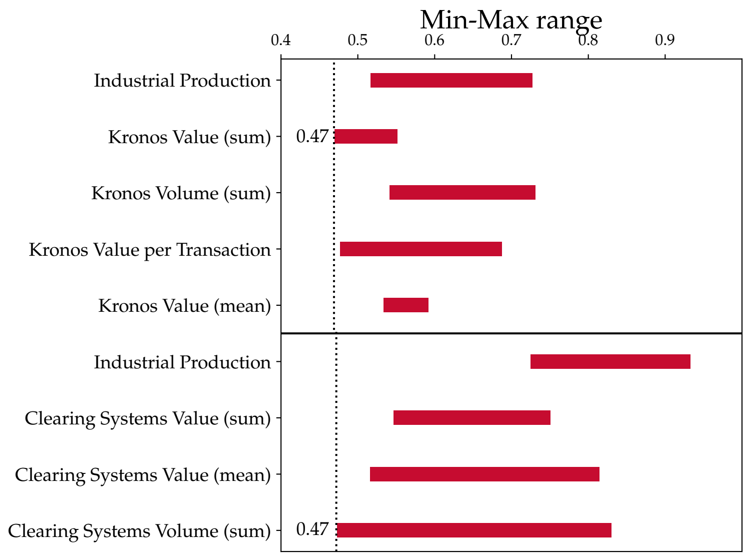
Table 4: Additional tests of the forecasting performance of combined models

	Nowcasting	Forecasting
(1) Best single-variable model	Kronos	Residential Construction
(2) Best forecast combination	Kronos + Industrial Production	Residential Construction + Business Confidence
(3) Diebold-Mariano Test	-0.20 no significant difference	-0.52 no significant difference
(4) Out-of-sample R-squared	-0.41 underperform	-0.01 underperform

Notes: The first row in the table above lists the best model at nowcasting/forecasting GDP as reported in table 3. The second row lists the best forecast combination as reported in figures 3 and 4. The last two rows of the table report the results of the Diebold-Mariano test and the out-of-sample R-squared test that confirm/contradict the superior performance of forecast combinations relative to single-variable high-frequency models. The forecast horizon is equal to one quarter for the right column of the table above, while nowcasting stands for a zero-quarter-ahead forecast.

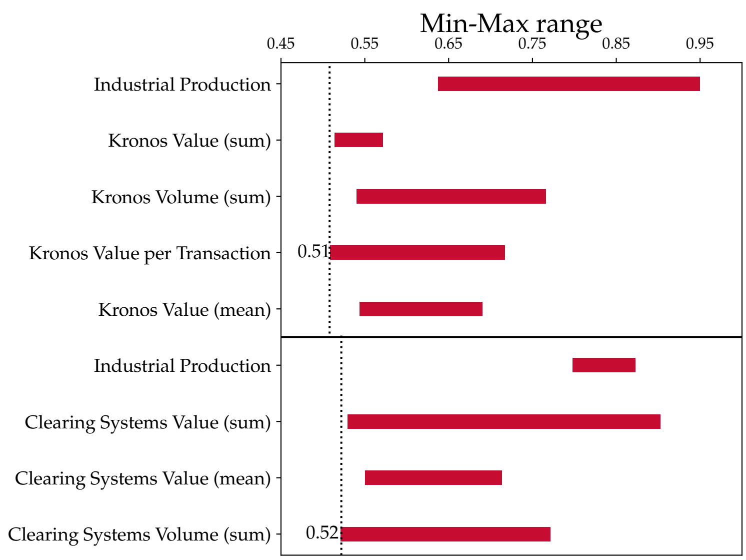
regression windows instead of our fixed-window approach that was used to obtain all the results up to this point. Rolling window regressions execute estimation over multiple consecutive windows of the same length with a step size of one month, while recursive window regressions keep the starting date fixed and increase the size of the window by one month until the sample end date. Figure 5 (7) shows that results for rolling (recursive) window models are very much in line with our fixed-window results in figure 1 in the case of the nowcasting exercise. Kronos data still delivers the best RMSE, and the performance of Clearing Systems data improves somewhat relative to the fixed-window results. Figures 6 and 8 repeat the exercise for the case when the forecasting horizon is set to one quarter, underscoring the results in figure 2. Overall, our results suggest that the method we apply to our estimation window does not seem to alter significantly the forecasting performance of our high-frequency models, as both the Kronos data and the Clearing Systems data seem to outperform IP in terms of their forecasting capability.

Figure 5: Root mean squared error for GDP nowcasting (rolling window)



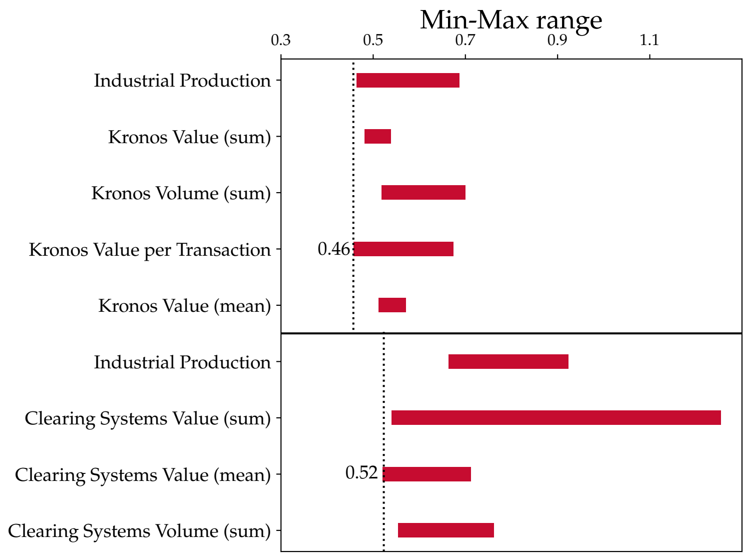
Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. Nowcasts are zero-quarter-ahead forecasts.

Figure 6: Root mean squared error for GDP forecasting (rolling window)



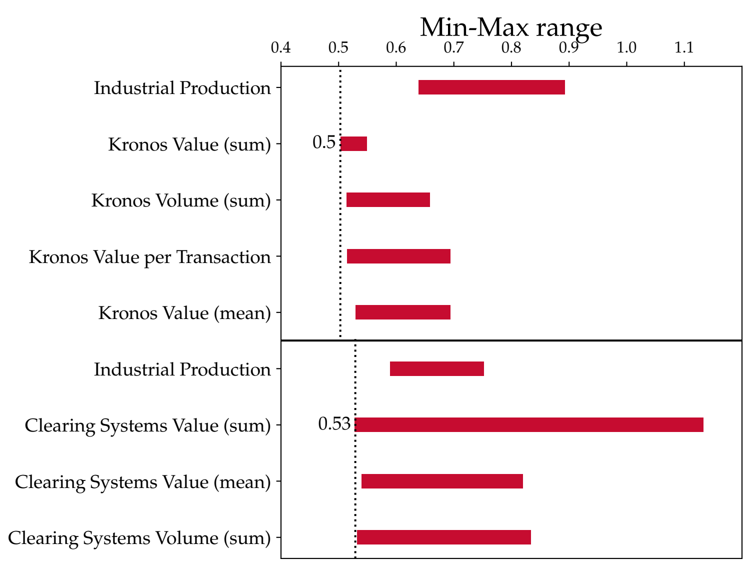
Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. The forecast horizon is equal to one quarter.

Figure 7: Root mean squared error for GDP nowcasting (recursive window)



Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. Nowcasts are zero-quarter-ahead forecasts.

Figure 8: Root mean squared error for GDP forecasting (recursive window)



Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. The forecast horizon is equal to one quarter.

Our next robustness check involves estimating the benchmark model for cases when the independent variable comes at an even higher frequency than the monthly frequency used in our benchmark case. We repeat the exercises that produced figures 1 and 2, except that we now use daily changes in stock prices instead of monthly changes in IP as our reference high-frequency predictor.[14] For simplicity, we only report our results for daily regressions in the case of the Kronos sample. We set the lag for the independent high-frequency variable to be equal to 15 days. Figure 9 shows that Kronos data outperforms stock prices when it comes to both nowcasting and forecasting exercises. Interestingly, the RMSE for nowcasting using daily Kronos data on value per transaction is somewhat larger than the one using monthly data (figure 1). Forecasting one quarter ahead seems to deliver similar RMSE for Kronos data in both the monthly and daily regressions, with a slight edge in favor of the daily series. Min-Max ranges for regressions using daily data are somewhat larger than the ones for monthly data, suggesting that there is little similarity between the weighting functions in terms of how much weight they assign to given lags in the 15-day set.

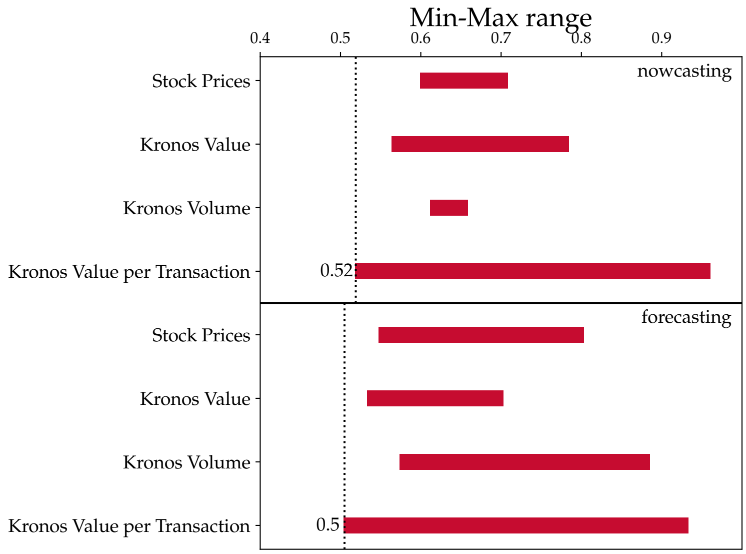
In addition to the robustness checks presented above, we also experimented with using Sumclearing and Straksclearing data separately to predict Danish GDP, as opposed to summing them up in one Clearing Systems series.[15] Figures 10 and 11 of the Appendix report our results for these two data series across the forecasting horizons considered in this paper (i.e., zero and one quarter). Unlike in our benchmark case (lower panels of figures 1 and 2), industrial production dominates Straksclearing data in terms of nowcasting and forecasting, but does not perform equally as well as the Sumclearing data. This suggests that when it comes to the Clearing Systems data used to plot figures 1 and 2, the improvement relative to IP in terms of forecasting performance stems from the Sumclearing data. We also explored whether using data on older vintages of GDP data series would alter our conclusions in terms of the forecasting performance of our PSD series. Figures 12 and 13 of the Appendix repeat the exercise in figures 1 and 2 by replacing the dependent variable with vintage GDP data, as opposed to data based on the latest update of the historical series for Danish GDP.[16] Our conclusions do not change as a consequence of this alteration, but the RMSE

[14]Gomez-Zamudio and Ibarra (2017) show that daily financial data, including stock prices, can help improve GDP forecasting in MIDAS regression models.

[15]Our regression models that use the Straksclearing data are based on a sample that starts in 2014 and ends in 2017, while the rest of the data, from 2018 to 2019, is used to assess forecast performance.

[16]The vintage data for each quarter is based on the flash (real-time) estimate of GDP reported as the first value for that particular quarter. Flash estimates are likely to suffer from estimation bias and, as a consequence, are frequently

Figure 9: Root mean squared error for GDP nowcasting/forecasting (fixed window, daily high-frequency variables)



Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. The independent variables are expressed as daily log changes. Forecast horizon is equal to one quarter for the lower panel in the chart above, while nowcasting stands for a zero-quarter ahead forecast.

deteriorate when we use real-time data, implying that the data revisions tend to make the GDP series more aligned with the evolution of high-frequency PSD, which do not suffer any revisions.

We also checked if sample size differences influence our conclusions drawn based on figures 1 and 2. In figures 14 and 15, we re-estimate our models in the Kronos sample by restricting the starting date of that sample to coincide with the one in the Clearing Systems sample. The performance of the Kronos models deteriorates somewhat relative to our benchmark case, but our conclusions still hold, namely that Kronos data is better in terms of its nowcasting performance relative to IP, while Clearing Systems data is slightly better at forecasting GDP growth than Kronos data, even in a shorter sample. Lastly, we check how the forecasting performance of PSD changes as we increase the forecast horizon from zero to six quarters. The period of estimation for all models is set to 2009-2015 in line with our Clearing Systems data, so that we have a consistent comparison across both the PSD and the other high-frequency series. We contrast the forecasting performance

updated by statistical agencies after the quarters in which they were released.

of PSD across horizons to the best forecast among all other high-frequency variables in figure 16. The model that uses Clearing Systems data dominates the one using Kronos data in terms of one-quarter and two-quarter-ahead forecast RMSE. Better nowcasts and medium-term forecasts (three to six quarters ahead) are produced using Kronos data instead. Other high-frequency variables lead to lower forecast RMSE than PSD, but the difference in forecasts seems to decrease significantly as we increase the forecast horizon to two quarters and above.

Summing up, the robustness tests reported in this section support our main findings that the PSD series are a useful predictor of GDP growth in Denmark and can complement other high-frequency series to deliver better nowcasting and forecasting performance.

6 Forecasting during the covid-19 pandemic

All our estimates of the forecasting performance of PSD presented above are based on an evaluation sample that starts in 2016 and ends in 2019. The choice of our sample end date was motivated by the nature of the covid-19 pandemic shock that hit in 2020 — an extremely irregular event that led to a significant drop in economic activity. This irregularity makes out-of-sample predictions difficult as our models were estimated on data with no drops of a similar size or nature prior to 2016. Moreover, the pandemic shock had an outsized effect on some economic sectors (i.e. tourism and hospitality), while other sectors have been spared during the first couple of quarters of 2020.

Nonetheless, we check how our models perform during these trying times by extending the evaluation sample to include data from the first two quarters of 2020. Table 5 repeats the exercise reported in table 3 based on the new forecast evaluation sample (i.e., 2016-2020). Payment system data are no longer among the best predictors of economic activity, as changes in unemployment and car registrations seem to dominate other high-frequency variables in terms of their nowcasting and forecasting performance, respectively. Furthermore, the forecast RMSE reported in this table are significantly higher than the ones in table 3, highlighting the challenges that our models have in replicating the drop in economic activity in 2020. We also tested whether the forecasting performance of single-variable models can be improved upon by combining individual forecasts. Table 6 reports in rows (1) and (2) the best single-variable models, as well as the best combinations that lead

Table 5: Predicting GDP growth using various high-frequency indicators (incl. 2020)

		Nowcasting	Forecasting
(1)	Kronos	1.79	1.77
(2)	Industrial Production	1.71	1.89
(3)	CPI	1.82	1.80
(4)	Unemployment Rate	1.66	1.87
(5)	Residential Construction	1.85	1.86
(6)	Energy Production	1.79	1.82
(7)	Car Registrations	1.67	1.70
(8)	Retail Trade	1.85	1.74
(9)	Business Confidence	1.86	1.76

Notes: The numbers reported in the table are minimum forecast RMSE for models where the dependent variable is GDP and the independent variables are the ones described in each row. Kronos stands for the best predictor in terms of RMSE out of the Kronos series listed in figure 1. For each high-frequency indicator and horizon, we estimate equation 1 for all specifications of the weighting polynomial function and record the minimum RMSE. The forecast horizon is equal to one quarter for the right column of the table above, while nowcasting stands for a zero-quarter-ahead forecast.

to lower RMSE than single-variable models. Car registrations, unemployment and business confidence are the high-frequency series that seem to be the most informative in terms of the evolution of Danish GDP during the extended evaluation sample. Table 6 also reports the Diebold-Mariano test and the out-of-sample R-squared in rows (3) and (4), two more measures that contrast the differences in forecast performance between the combined and the single-variable model forecasts. Similar to table 4, the combined forecasts do not lead to much of an improvement relative to the single-variable models.

In light of the relatively poor forecasting performance of our MIDAS models reported in table 5, we also explored how the MIDAS models used in this paper compare to another model employed currently by Danmarks Nationalbank to forecast Danish GDP during the covid-19 pandemic. Figures 17 and 18 of the Appendix show the evolution of GDP growth in the data and the model nowcast and forecast generated by our benchmark MIDAS model, based on the best performing combined forecasts and the factor model in Grenestam and Schmith (2021).[17] Figure 17 shows that

[17]The evidence presented in table 6 suggests that the forecast combinations do not improve significantly on the forecasting performance of single-variable models. Nonetheless, we used the forecast combinations as our MIDAS model benchmarks in figures 17 and 18 instead of single-variable models because the combinations lead to a somewhat lower RMSE over the evaluation sample, which is the metric of comparison that we rely on when contrasting our model to the

Table 6: Additional tests of the forecasting performance of combined models (incl. 2020)

	Nowcasting	Forecasting
(1) Best single-variable model	Unemployment	Car Registrations
(2) Best Forecast Combination	Unemployment rate + Car Registrations	Car Registrations + Business Confidence
(3) Diebold-Mariano Test	-0.19 no significant difference	-0.24 no significant difference
(4) Out-of-sample R-squared	0.00 underperform	-0.03 underperform

Notes: The first row in the table above lists the best model at nowcasting/forecasting GDP as reported in table 3. The second row lists the best forecast combination as reported in figures 3 and 4. The last two rows of the table report the results of the Diebold-Mariano test and the out-of-sample R-squared test that confirm/contradict the superior performance of forecast combinations relative to single-variable high-frequency models. The forecast horizon is equal to one quarter for the right column of the table above, while nowcasting stands for a zero-quarter-ahead forecast.

the two models deliver somewhat comparable results in terms of their nowcast RMSE, with an edge in favor of the factor model, while figure 18 shows that the factor model is significantly better at predicting the evolution of GDP at this forecasting horizon. Both models struggle to replicate the drop in economic activity observed in 2020 ex ante because they are estimated conservatively using a sample ending prior to 2016. In an exercise that is not reported in the paper, we also compared the performance of the two models when the evaluation sample ended in 2019 and found that our MIDAS model results are similar to the ones produced by the factor model in terms of their nowcast and forecast RMSE. As described in section 4, the set of high-frequency regressors performing best in our MIDAS models in the shorter evaluation sample, 2016-2019, features prominently the payment systems data series.

factor model.

7 Conclusion

In this paper, we show that payment system data can be used to improve forecasts of economic activity in Denmark. We use mixed-data sampling regression models to estimate the impact of various high-frequency (monthly) data on low-frequency (quarterly) data such as the gross domestic product, private and public consumption. We find that payment system data is among the best predictors of these macroeconomic variables from a set of high-frequency variables that includes industrial production, consumer prices, the unemployment rate, and many others. In the case of nowcasting, payment system data in combination with data on industrial production deliver the best outcome in terms of minimizing the forecast root mean squared error, dominating the best single-variable model that uses payment system data. For one-quarter-ahead forecasts, models using data on residential construction and business confidence deliver the best performing forecast combination.

Our results on the predictive performance of payment system data are robust in terms of changing the way the estimation and forecast windows are constructed, for both rolling window and recursive window estimation. We also show that a daily series of payments system data is a better predictor of the quarterly gross domestic product than daily stock market data. Overall, our results suggest that central banks should seriously consider readily available payment system data in their forecasting toolkits, as these timely sources of information seem to be reliable predictors of economic activity in normal times. During the covid-19 pandemic, other high-frequency data series seem to provide better forecasts of economic activity in Denmark, as there were few changes in our payment system data that could have hinted at the upcoming changes in economic activity.

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Appendix

A Polynomial weights

We use the following functional forms for the polynomial specification $C(L^{\frac{1}{m}};\theta) = \sum_{i=0}^{N} c(i;\theta)L^{i/m}$ in equation 1:

1. Unrestricted: $C(L^{\frac{1}{m}};\theta) = \sum_{i=0}^{N} c(i;\theta)L^{i/m}$

2. Normalized beta probability density function:
   $C(L^{\frac{1}{m}};\theta) = \sum_{i=0}^{N} c(i;\theta)L^{i/m} = \sum_{i=0}^{N}\left(\frac{x_i^{\theta_1-1}(1-x_i)^{\theta_2-1}}{\sum_{i=1}^{N} x_i^{\theta_1-1}(1-x_i)^{\theta_2-1}} + \theta_3\right)L^{i/m}$, where $x_i = i/(N+1)$ and $\theta_3 = 0$ for the case of zero last lag

3. Normalized exponential Almon lag polynomial:
   $C(L^{\frac{1}{m}};\theta) = \sum_{i=0}^{N} c(i;\theta)L^{i/m} = \sum_{i=0}^{N} \frac{e^{\theta_1 i+\theta_2 i^2}}{\sum_{i=1}^{N} e^{\theta_1 i+\theta_2 i^2}} L^{i/m}$

4. Almon lag polynomial: in equation 1, $b_h C(L^{\frac{1}{m}};\theta_h)$ is replaced by $b_h c(i;\theta) = \sum_{p=0}^{P} \theta_p i^p$, and the sum of weights is not equal to one

5. Step polynomial: $b_h c(i;\theta) = \theta_1 I_{i\in[a_0,a_1]} + \sum_{p=2}^{P} \theta_p I_{i\in(a_{p-1},a_p]}$,
   where $a_0 = 1 < a_1 < ... < a_P = N$ and $I_{i\in[a_{p-1},a_p]} = \begin{cases} 1, & a_{p-1} \leq i \leq a_p \\ 0 & \text{otherwise} \end{cases}$

B Measures of predictive performance

Our main measure of predictive performance in this paper is the forecast root mean squared error, which is computed as follows: $RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}$, where n is the number of periods in the forecast path, and i is the period number. $\hat{y}_i$ is the forecast value in period i.

We also use the Diebold-Mariano test to check whether forecast combinations are significantly better than MIDAS models with only one high-frequency variable. This test is computed as follows:

$$DM = \frac{\bar{d}}{\sqrt{[\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k]/n}}$$

where $\bar{d} = \frac{1}{n}\sum_{i=1}^{n} d_i$, $d_i = \left[(y_i - \hat{\hat{y}}_i)^2 - (y_i - \hat{y}_i)^2\right]$ and $\hat{\hat{y}}_i$ is the forecast value of the combined forecast. If $\mu = E[d_i] = 0$ (the null hypothesis of no difference between forecasts), then $DM \sim N(0, 1)$.

Lastly, we compute the out-of-sample R-squared as follows: $R^2 = 1 - \frac{var(\hat{\hat{y}}_i - y_i)}{var(\hat{y}_i - y_i)}$. A value of above zero for the out-of-sample R-squared suggests that the combined model outperforms the single high-frequency model, while a value below zero implies underperformance.

C Weighting schemes for forecast combinations

We use different weighting schemes to compute out-of-sample forecast combinations $f_{t+h|t} = \sum_{i=1}^{n} w_{i,t}^{h} \hat{y}_{i,t+h|t}^{L}$. $w_{i,t}$ is set according to the following criteria:

1. Equal weights: $w_{i,t} = \frac{1}{n}$

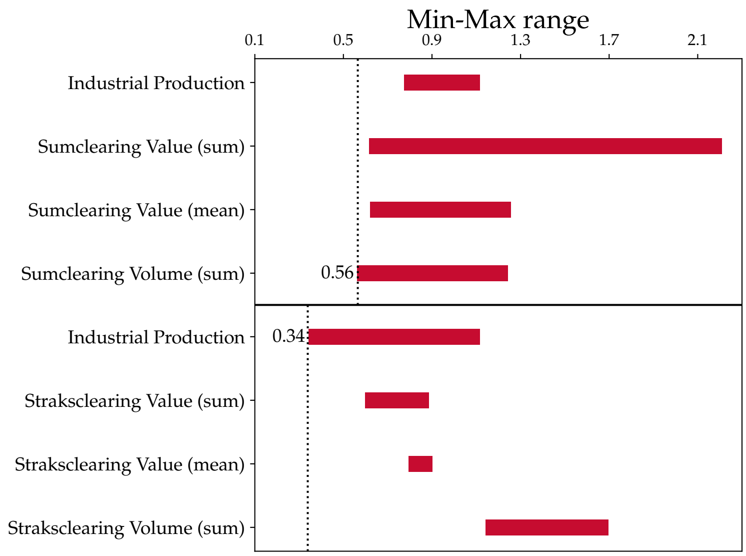
2. Bayesian information criterion weights: $w_{i,t} = \frac{\exp(-BIC_i)}{\sum_{i=1}^{n}\exp(-BIC_i)}$

3. Akaike information criterion weights: $w_{i,t} = \frac{\exp(-AIC_i)}{\sum_{i=1}^{n}\exp(-AIC_i)}$

4. Mean squared forecast error weights:
   $w_{i,t} = \frac{m_{i,t}^{-1}}{\sum_{i=1}^{n} m_{i,t}^{-1}}$, where $m_{i,t} = \sum_{i=T_0}^{t} \delta^{t-1}\left(y_{s+h}^{h} - \hat{y}_{i,s+h|s}\right)^2$, T_0 is the first out-of-sample observation and $\delta = 1$

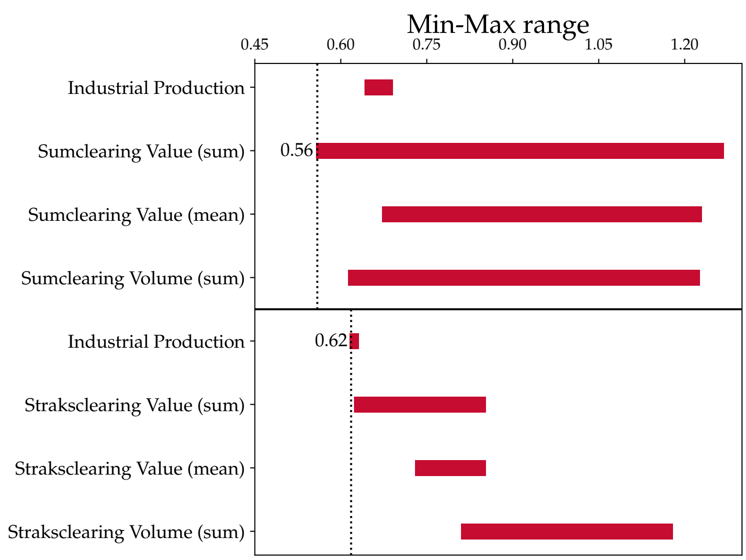
5. Discounted mean squared forecast error:
   $w_{i,t} = \frac{m_{i,t}^{-1}}{\sum_{i=1}^{n} m_{i,t}^{-1}}$, where $m_{i,t} = \sum_{i=T_0}^{t} \delta^{t-1}\left(y_{s+h}^{h} - \hat{y}_{i,s+h|s}\right)^2$, T_0 is the first out-of-sample observation and $\delta = 0.9$

Figure 10: Root mean squared error for GDP nowcasting



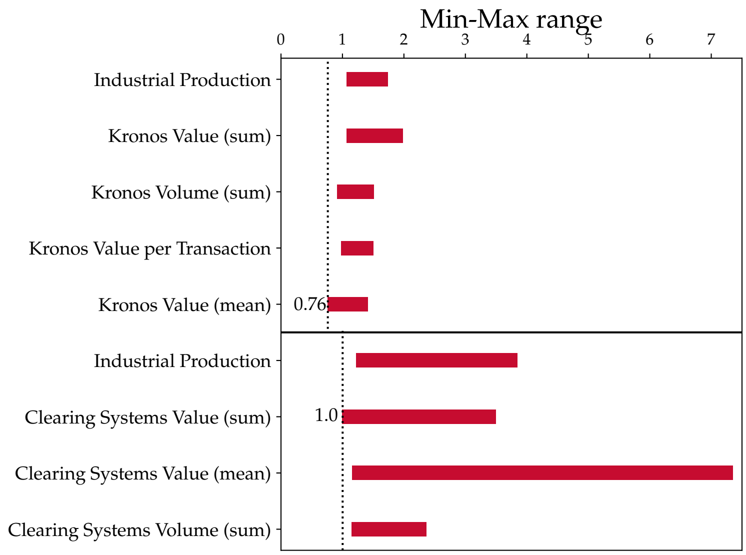
Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. Estimation for the top panel starts in 2008 and ends in 2015, with out-of-sample forecasting done using data from 2016 to 2019. Estimation for the bottom panel starts in 2014 and ends in 2017, with out-of-sample forecasting done using data from 2018 to 2019. Nowcasts are zero-quarter-ahead forecasts.

Figure 11: Root mean squared error for GDP forecasting



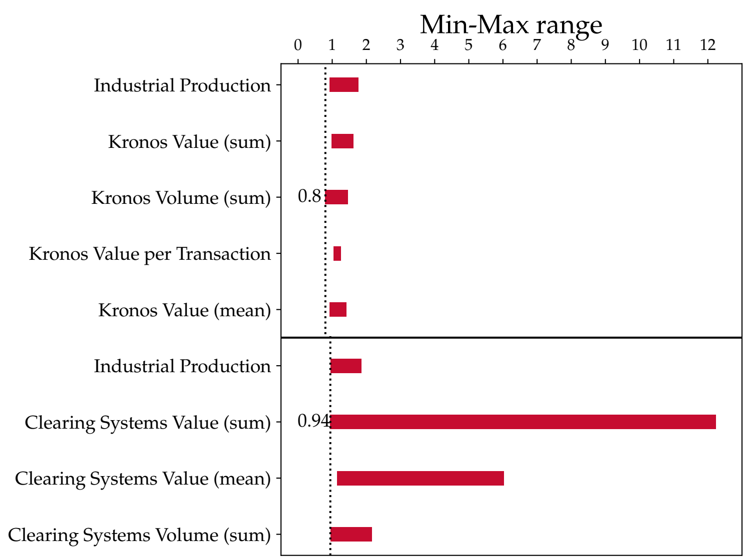
Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. Estimation for the top panel starts in 2008 and ends in 2015, with out-of-sample forecasting done using data from 2016 to 2019. Estimation for the bottom panel starts in 2014 and ends in 2017, with out-of-sample forecasting done using data from 2018 to 2019. The forecast horizon is equal to one quarter.

Figure 12: Root mean squared error for vintage GDP nowcasting



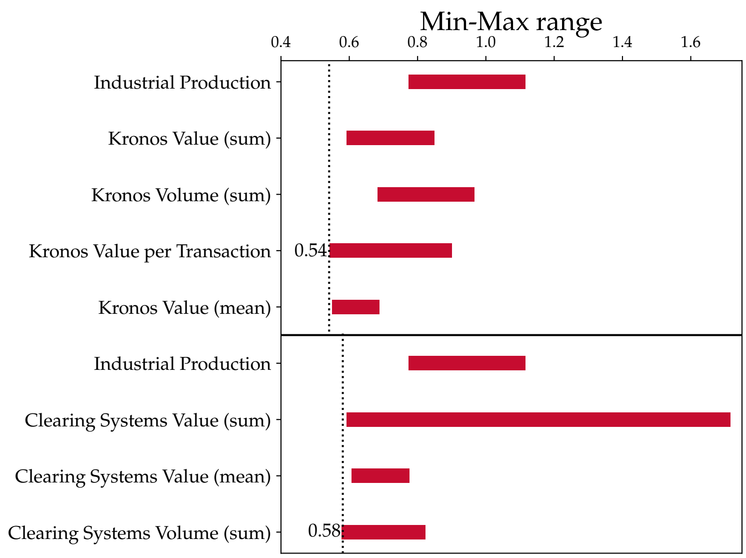
Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. The dependent variable used for estimation in this chart is vintage GDP growth. Nowcasts are zero-quarter-ahead forecasts.

Figure 13: Root mean squared error for vintage GDP forecasting



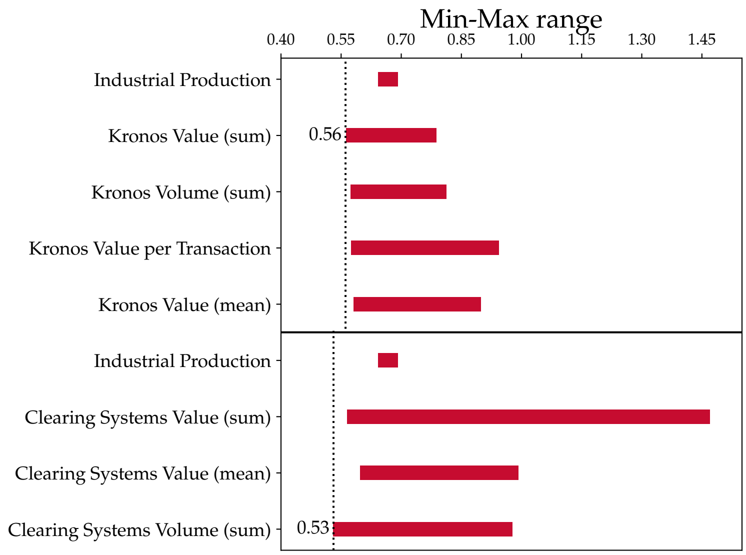
Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. The dependent variable used for estimation in this chart is vintage GDP growth. The forecast horizon is equal to one quarter.

Figure 14: Root mean squared error for GDP nowcasting



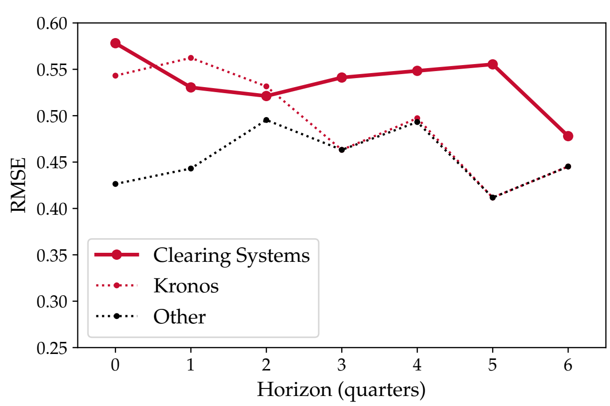
Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. Unlike figure 1, the period of estimation for both the Kronos and the Clearing Systems data is set to 2009-2015. We use the last three years of each sample (i.e., 2016-2019) to compute the models' RMSE. Nowcasts are zero-quarter-ahead forecasts.

Figure 15: Root mean squared error for GDP forecasting



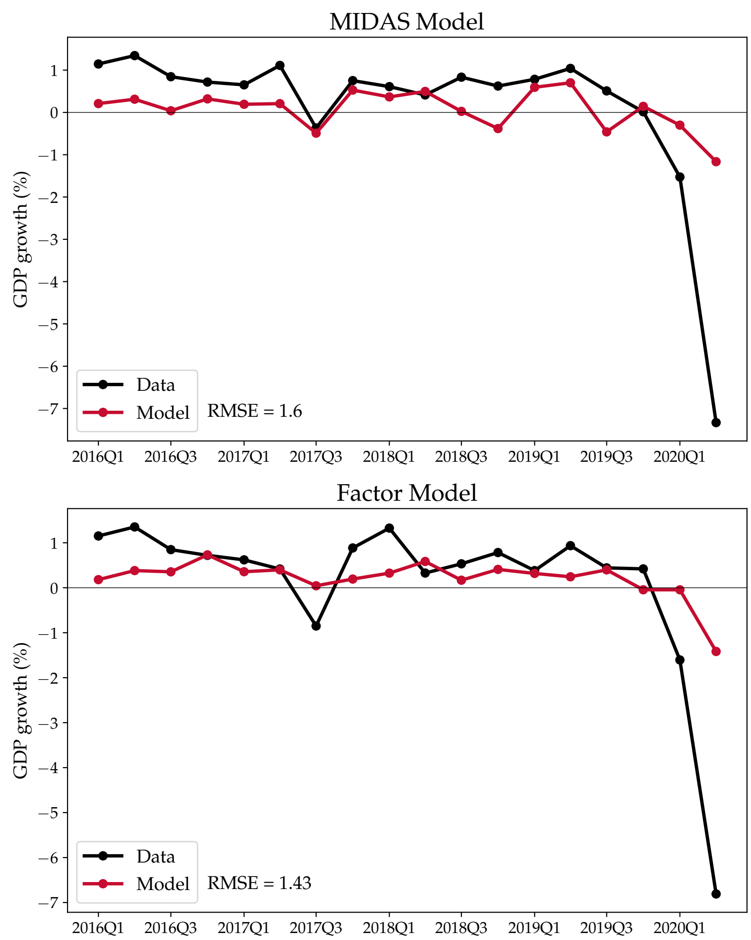
Notes: The x-axis reports the forecast RMSE for models where the independent variable is the series specified on the y-axis. The bars stand for the range between the minimum and maximum RMSE across models with different specifications for the polynomial weighting function $C(\cdot)$ in equation 1. Unlike figure 2, the period of estimation for both the Kronos and the Clearing Systems data is set to 2009-2015. We use the last three years of each sample (i.e., 2016-2019) to compute the models' RMSE. The forecast horizon is equal to one quarter.

Figure 16: GDP forecasts across different horizons



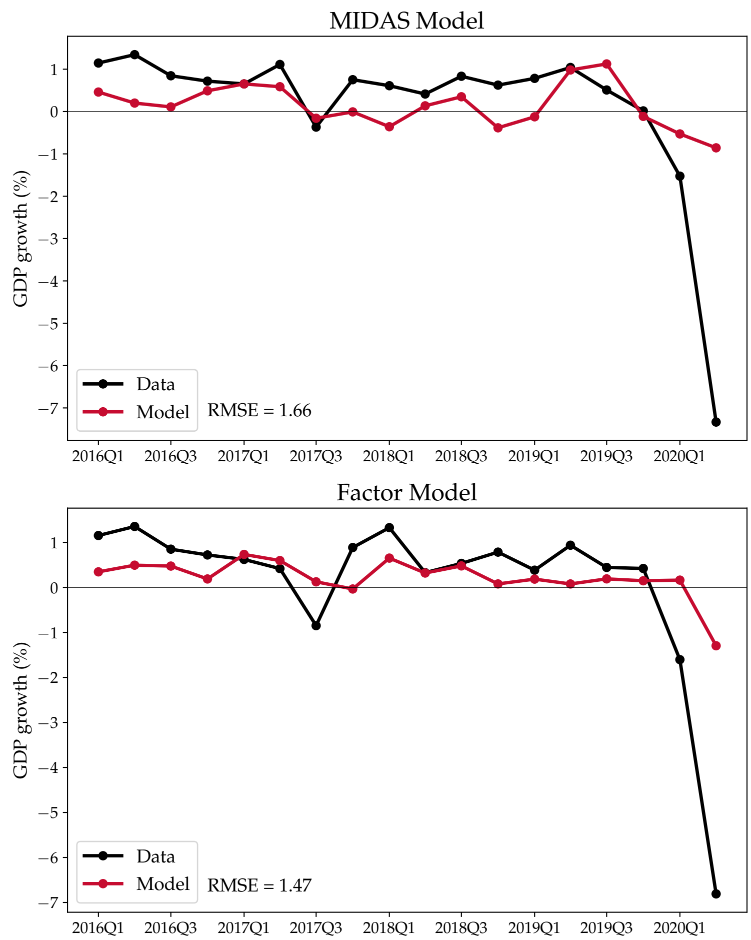
Notes: The numbers on the x-axis are quarters ahead used to create the forecasts. The period of estimation for all models is set to 2009-2015 in line with our Clearing Systems data. The black dotted line under the name "Other" stands for the lowest RMSE produced by single-variable MIDAS models from the set of high-frequency series in table 3 other than the Clearing Systems and Kronos data.

Figure 17: GDP nowcasts: MIDAS vs. factor model



Notes: The MIDAS model is based on our best nowcasting model combination as described in table 6. The factor model results are based on a simulation of the model in Grenestam and Schmith (2021). Nowcasts are zero-quarter-ahead forecasts.

Figure 18: GDP forecasts: MIDAS vs. factor model



Notes: The MIDAS model is based on our best forecasting model combination as described in table 6. The factor model results are based on a simulation of the model in Grenestam and Schmith (2021). The forecast horizon is equal to one quarter.

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