DOCUMENTOS DE TRABAJO

Nowcasting Economic Activity with Microdata

Diego Vivanco Vargas
Camilo Levenier Barría
Lissette Briones Molina

N° 1059 Diciembre 2025
BANCO CENTRAL DE CHILE

banco central Chile

Documentos de Trabajo del Banco Central de Chile
Working Papers of the Central Bank of Chile
Agustinas 1180, Santiago, Chile
Teléfono: (56-2) 3882475; Fax: (56-2) 38822311

Documento de Trabajo N° 1059

Working Paper N° 1059

Nowcasting Economic Activity with Microdata*

Diego Vivanco Vargas, Camilo Levenier Barría, and Lissette Briones Molina†
Central Bank of Chile

Resumen
Pending

Abstract
High-frequency microdata can significantly enhance the accuracy of nowcasting models for economic activity. This study evaluates the performance of using microdata to nowcast the monthly Chilean activity. We compare models with granular data from electronic invoicing and digital payment systems with conventional univariate and multivariate time series models and leading indicators. For the nowcasts with microdata, we employ SARIMAX specifications and a bottom-up aggregation methodology, complemented with satellite models for specific economic sectors. Our empirical results show a substantial reduction of approximately 34% in root mean square errors (RMSE) for nowcasts of the annual growth of IMACEC (monthly economic activity indicator in Chile) over a 36-month out-of-sample evaluation period. These findings underscore the value of microdata for improving real-time estimates of economic activity, encouraging its integration into nowcasting frameworks.

* The views expressed are those of the author and do not necessarily reflect the views of the Central Bank of Chile or its board members. Any errors are the sole responsibility of the authors. This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (BCCh) in economic and financial affairs of its competence. The BCCh has access to anonymized information from various public and private entities, by virtue of collaboration agreements signed with these institutions. To secure the privacy of workers and firms, the BCCh mandates that the development, extraction and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. All the analysis was implemented by the authors and did not involve nor compromise Transbank, Chilean IRS or Getnet. The information contained in the databases of the Chilean IRS is of a tax nature originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service. We are grateful to Lucas Bertinatto, Markus Kirchner and an anonymous referee for their valuable comments

†E-mails: dvivanco@bcentral.cl, clevenier@bcentral.cl, lbriones@bcentral.cl, respectively.

1. Introduction

Real-time macroeconomic analysis is useful for monetary policy, forecasts and other purposes. While GDP is the most reliable indicator of economic activity, there is a considerable lag in its publication. In Chile, the monthly indicator of economic activity (IMACEC) is released with a one-month delay and partially anticipates quarterly growth. This opens a window for timely insights into current economic conditions, especially in the face of negative shocks or turning points that are not predictable with past information, since their nature is different (e.g., the Covid-19 pandemic), or their persistence is unknown. Nowcasting enhances this advantage by using high-frequency indicators to provide current-period estimates of GDP growth, enabling policymakers and forecasters to make informed decisions based on the most current economic data.

Before the Covid-19 pandemic, the short-term forecasting process for economic activity at the Central Bank of Chile (BCCh) used the latest available information —typically IMACEC— and applied time series models to forecast future periods. Approaches range from SARIMA and VAR models to mixed frequency specifications (bridge models and MIDAS) using exogenous variables, such as expectations of consumers and firms, financial indicators, foreign trade data, and energy production, among others (Cobb and Peña, 2020)[6].

Nevertheless, the pandemic underscored the importance of having more frequent access to estimates of whether the economy is growing or experiencing a recession. Based on this, the BCCh has significantly increased the use of microdata from tax records for nowcasting, some of which are nearly real-time. Among these, electronic invoices and receipts are particularly relevant, as they contain monthly sales between firms and weekly sales to consumers. Digital payment systems are also important for activities more related to private consumption (retail trade and some services). These should exhibit a closer relationship with GDP compared to other indicators, offering substantial coverage of domestic activity.

There is limited literature on the use of high-frequency microdata based on electronic tax records in nowcasting. Globally, the usual approach is focused on the use of transactions passing through payments systems, which provide information on the values and volumes of debit and credit card transactions. Galbraith and Tkacz (2018) use electronic payments data for nowcasting Canadian GDP, finding statistical evidence that payments system data can reduce the nowcast error for both GDP and retail sales growth. Cobb (2021) employs aggregates on electronic payments to nowcast Chilean household consumption, showing that this data could have better anticipated the negative shock of the Covid-19 pandemic, although it would perform similarly in “normal” times (similar conclusion are obtained in Jardet and Meunier, 2022).

Another strategy proposed by Bok et al. (2017) involves integrating traditional macroeconomic indicators and big data techniques within a dynamic factor model[7] (DFM). They apply this extended framework for the US economy, noting increased accuracy as more economic information becomes available. Alternatively, Loermann and Maas (2019) combine high-frequency data and artificial neural networks, which outperform DFMs.

More recently, the Bank of England (2025) introduces a MIDAS approach, used by the staff to nowcast UK GDP and other variables. Specifically, they use a mix of restricted and unrestricted MIDAS regressions and two forecast combination steps to exploit hard and soft data.

[6] An extensive review of forecasting techniques for GDP is covered by Ghysels and Marcellino (2018) and Foroni and Marcellino (2014). SARIMA: Seasonal Autoregressive Integrated Moving Average. VAR: Vector autoregression. MIDAS: Mixed-Data Sampling.

[7] The availability of new data sources has accelerated the development and application of various econometric techniques. Dimension reduction of a wide cross-section of time series, for instance, is one of the frequently used techniques. This concept served as the foundation for the nowcasting dynamic factor model (DFM) created by Giannone et al. (2008).

In this paper, we assess the performance of nowcasting the annual growth of the monthly economic activity indicator (IMACEC), in other words projecting each time at the horizon t=0, using microdata, including electronic tax documents[8], electronic payments, and foreign trade data, which collectively covers approximately 80% of economic activity. These nowcasts corresponds to the actual out-of-sample projections made in each period with the available information at each time, where qualitative information was also introduced as expert judgment for outlier events, as work stoppages announced in the press. Given data availability, the out-of-sample evaluation period spans from June 2022 to May 2025. We will contrast these results with a set of macroeconomic time series models projections for the same period.

The process involves obtaining a bottom-up nowcast and subsequently aggregating these estimates based on the chain-weighted mechanism of Chile's National Accounts (Guerrero et al., 2012), methodology that provides a more accurate measurement of real economic growth than constant prices estimation –especially over longer periods– using the prices of the previous year as weights. The comparison spans 36 months using IMACEC first publication, also known as unrevised data or vintages, for forecasting error calculation.

Our findings demonstrate that the microdata-based approach, even when it's introduced in a simple model, significantly outperforms traditional models for the aggregated IMACEC and non-mining IMACEC, reducing the root mean squared error by nearly 34%, and proves to have a higher predictive capacity at the 1% level of significance using the Diebold Mariano test. When we compare the performance of each of the 16 available sectors of IMACEC, there is heterogeneity in the results. In half of the sectors the nowcast with microdata improves precision of the forecast at a statistically significant level, and in the rest of it doesn't. This highlights that the administrative records used have an advantage in a specific set of economic activities, while in others it does not provide additional information than traditional models.

The document is organized as follows. Section 2 details the data utilized and the main stylized facts from the database. Section 3 describes the methodology. Section 4 presents the absolute and relative evaluation methods and results. Section 5 concludes.

2. The data

2.1. IMACEC

The most relevant monthly indicator of economic activity in Chile is the IMACEC. This indicator is an estimate that summarizes the state of the economy. Its annual growth rate approximates the evolution of GDP. It involves several supply indicators such as mining and industrial production, electricity generation and foreign trade. In terms of microdata, it is highly intensive in the use of administrative records from the value-added tax form (VAT) from Chilean IRS (Servicio de Impuestos Internos, SII, in Spanish), which allows for the approximation of monthly sales at firm level, including domestic sales and exports. This data is available for BCCh a few days before the IMACEC release.

It is published monthly with a thirty-day lag, making it the first release of GDP data. Subsequently, it is revised quarterly with the publication of GDP[9], which incorporates new information that was not

[8] Since 2023, the BCCh has regularly published monthly nominal data based on electronic tax documents such as invoices and receipts. These can be downloaded from the experimental statistics website.
[9] IMACEC is revised in each GDP release, which is quarterly and annually. In the latter, the revisions include new sources and data, but also different compilations methods. For more information, see Banco Central de Chile (2022).

available at the time of the IMACEC's release. The public release of IMACEC involves 6 sectors, while the quarterly data expands to 16 economic activities.

Complementary, electronic tax documents (including invoices and receipts) are accessible two weeks prior to the VAT form. The early availability of this data, along with its strong correlation to IMACEC at sector level, renders it valuable for nowcasting. The next section covers the description of the data.

2.2. Electronic tax documents

The microdata used in this work corresponds to electronic tax documents (ETD) from the SII. We use two different datasets: (1) electronic invoices (EI) and (2) electronic receipts (ER), which are described below:

- **Electronic invoices**: The first source of information employed is the firm invoices (affected and exempts[10]) dataset with firm level data used for tax purposes on monthly sales revenue and expenditure on intermediate and capital goods. Chilean firms must submit their electronic form by law; therefore, the dataset covers the universe of formal firms and is available since 2017 for both large, small, and medium companies (SMEs).

Since its implementation, EI has provided more timely access to monthly sales and purchases data. Moreover, it enables the identification of transaction counterparties (whom to whom)—specifically, the "issuer" (seller) and the "receiver" (buyer). This level of detail contrasts with the aggregated data typically available in monthly tax returns, such as the VAT form. As a result, EI has facilitated research into the relationships between sellers and buyers, including studies on production networks, investment dynamics, and geographic distribution (see, e.g., Arkolakis et al., 2025; Huneeus et al., 2022; Miranda-Pinto et al., 2023; Koike-Mori and Martner, 2024). Currently, transactions involving electronic invoices account for approximately 68% of total sales reported in the VAT form.

- **Electronic receipts**: The dataset provides daily information at firm level on the universe of domestic purchases in the retail trade sector, regardless of the payment method and sales channel. For this work, we employ the indicator compiled by the experimental statistics department of the BCCh based on a sample of selected companies.

To select the sample, the experimental statistic department use the business registry of National Accounts, which is primarily based on the economic activity reported by taxpayers on the VAT form. The criteria used to select the sample of companies were defined according to two main objectives: (1) have a stable time series and (2) provide a period that would allow for relevant year-on-year comparisons for the analysis.[11]

2.3. Electronic payments data

Electronic tax documents of the retail trade sector are complemented with electronic payments data (EP) since 2017, which includes monthly payments (debit or credit) from two major transaction intermediation companies, Transbank and Getnet, which account for roughly 70% of the market share[12]. For confidentiality reasons, companies do not provide the raw data to the BCCh. Hence, time

[10] An exempt or VAT-exempt invoice is a tax document that records a transaction between taxpayers for operations exempt from or not subject to VAT. Conversely, a VAT-affected invoice incorporates the corresponding tax into the purchase price, which must be reported on the monthly tax return by both the seller (debit) and the buyer (credit).

[11] For more information, see Banco Central de Chile (2022).

[12] Cobb (2021) only uses data from Transbank. In this work, we also have access to Getnet, allowing to increase the market share considered in the analysis.

series are aggregated with a breakdown of self-reported economic sector. Then, this classification is linked to the business registry of National Accounts.

2.4. Deflation and weighting

To deflate nominal values, we follow a similar approach to that used in the compilation of Imacec, that is, using price indices collected from the Statistical Office and the BCCh[13]. This includes the consumer price index (CPI), producer price index (PPI), labor cost index[14] (LCI), international trade price index (IIP) and nominal exchange rate[15].

Lastly, value-added shares of GDP sectors of the previous year are used to weigh sales at constant prices. This step is relevant since the IMACEC accounts for the difference between production and intermediate consumption. Therefore, adding sales directly could lead to an aggregation bias. As an example, the contribution of wholesale and retail trade to GDP is defined by margins at industry level, which may differ significantly from sales in activities highly intensive in imported inputs[16].

2.5. Data analysis on electronic tax documents

Figure 1 shows the evolution of EI from January 2017 to July 2025 —including seasonal adjusted levels, year over year evolution and moving quarter over quarter evolution, highlighting several shocks. At the beginning of 2020, the Covid-19 pandemic severely impacted the Chilean economy due to mandatory lockdowns implemented to contain the spread of the virus. Indeed, the activity decreases around 10% month-to-month in April, reaching its lowest value in June of 2020. Subsequently, activity accelerated beyond its trend between 2021 and 2022, driven by fiscal stimulus and extraordinary withdrawals from pension funds, both policies implemented during the pandemic. Since 2024, the annual growth rate of the economy according to EI has reached, on average, 1.8%.

Figure 2 displays the same set of metrics as previously discussed but focused on the non-mining IMACEC. A preliminary analysis reveals that EI effectively acted as a leading indicator during the Covid-19 crisis, anticipating both the sharp contraction in economic activity and the subsequent recovery. This predictive capacity highlights the value of EI data for real-time monitoring and nowcasting of macroeconomic trends. Since 2024, the relatively stable behaviour of EI-based indicators aligns with a pattern of moderate economic growth, with non-mining IMACEC annual growth rate fluctuating around 2.5%. This consistency further supports the use of EI as a complementary tool for tracking short-term economic dynamics, particularly in contexts where traditional indicators may be subject to reporting lags or aggregation limitations.

[13] We do not use the prices reported in ETD because i) it is not evident how to aggregate them due to the heterogeneity of the goods producing industries and ii) the difficulty of obtaining a relevant price for the service sectors from tax records.

[14] Due to a lack of specific price indexes for service sector, labor costs per hour are used based on the assumption that time spent provision is a proxy for the volume of services provided. Hourly rates, in this respect, represent a straight mechanism and a natural starting point for the deflation of services-producing industries.

[15] The nominal exchange rate is used mainly for the wholesale trade sector of machinery and equipment, since it is a reasonable proxy for the national account deflator.

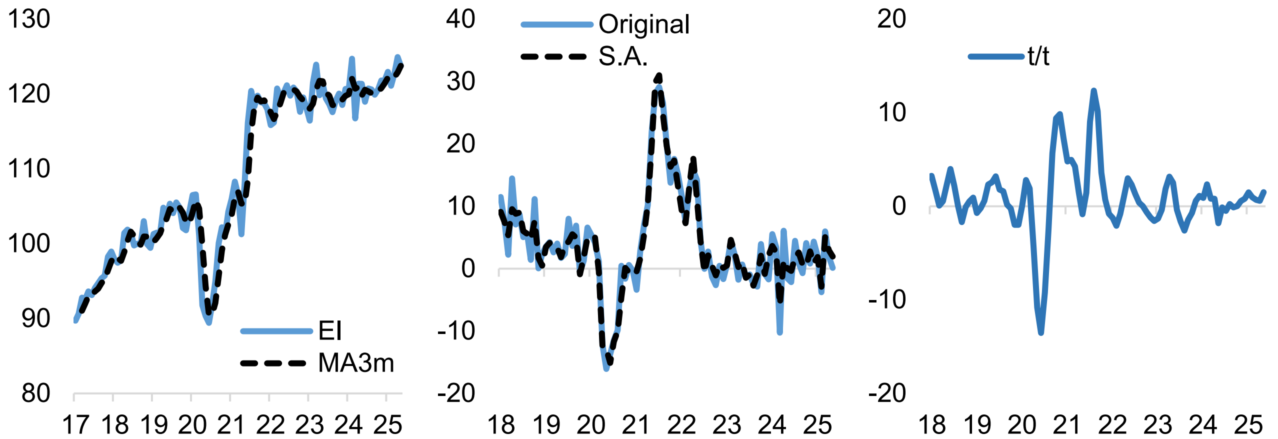
[16] Since IMACEC is a measure of volumes based mainly of deflated sales from VAT form, we proxy their evolution using deflated values from EI and EP data. This gives a better result than using aggregate nominal values as regressors and subsequently deflating them because it allows taking advantage of the granularity of the multiple sectors that exist in the IMACEC estimate.

Figure 1: Electronic invoices (EI)

(a) Index 2018 = 100
(monthly frequency, constant prices, seasonally adjusted)

(b) YoY evolution
(monthly series, %)

(c) Moving QoQ evolution
(%, seasonally adjusted)



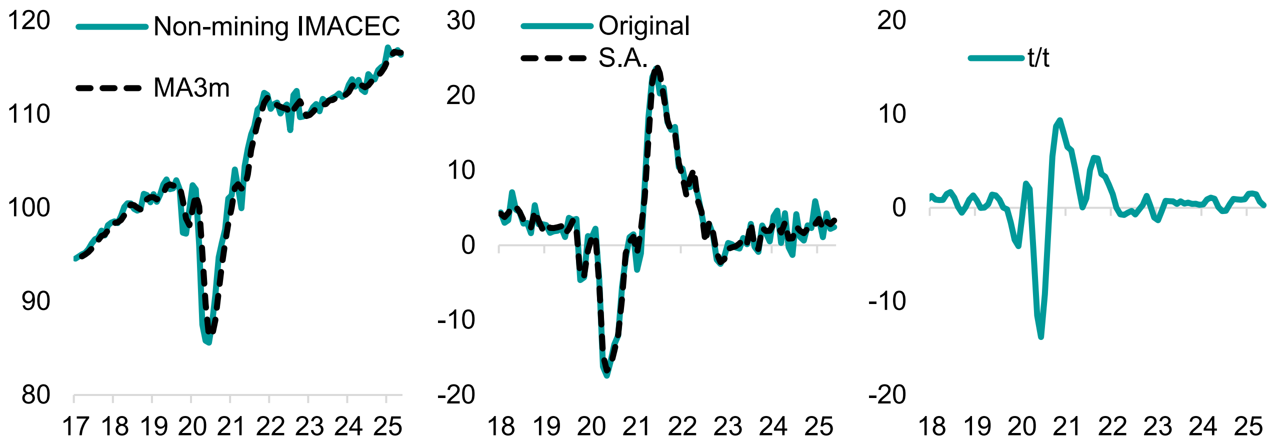
Note: Moving QoQ corresponds to the moving average of 3 months. QoQ: quarter-to-quarter evolution. Source: Own elaboration based on SII.

Figure 2: Non-mining IMACEC

(a) Index 2018 = 100
(monthly frequency, constant prices, seasonally adjusted)

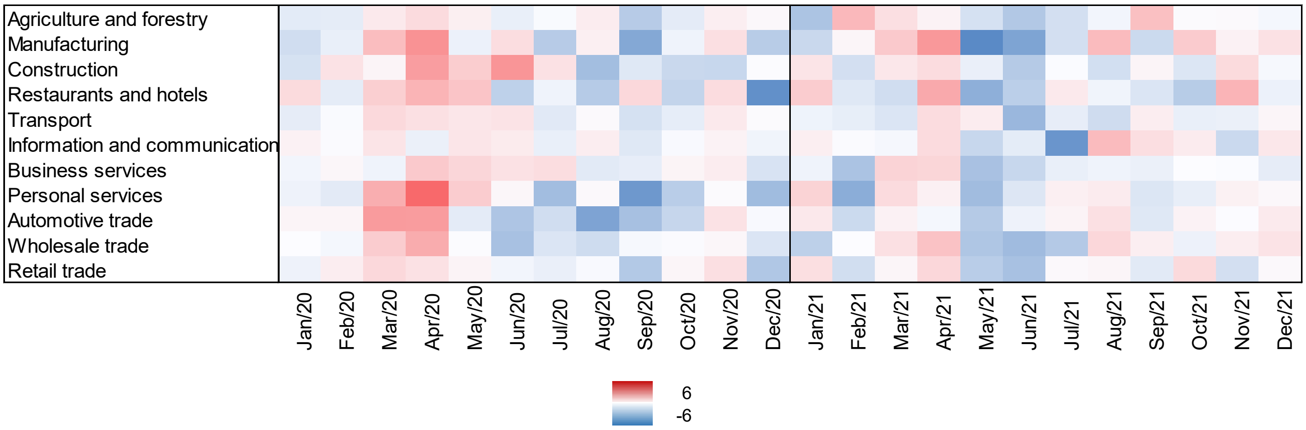
(b) YoY evolution
(monthly series, %)

(c) Moving QoQ evolution
(%, seasonally adjusted)



Complementarily, Figure 3 exhibits a standardized heatmap of the seasonally adjusted evolution of the different economic sectors. This allows us to analyze the sectorial heterogeneity of the economy along with turning points that affect the nowcasting of IMACEC. For example, during April of 2020, the whole economy contracted, and the initial recovery was driven mostly by goods-producing industries, whereas the trade and services sectors remained lagging. Later, several lockdowns implemented during the pandemic were anticipated by electronic invoice data, as well as the boost from demand-side due to stimulus measures.

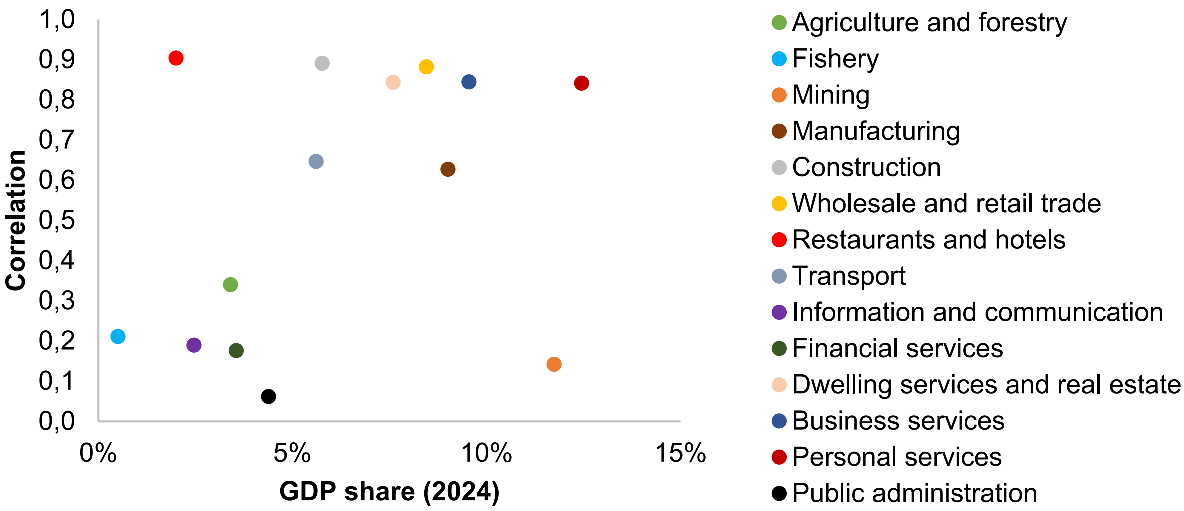
Figure 3: Heatmap – electronic invoices (monthly seasonally adjusted series, standardized)



Note: Mean and standard deviation are estimated for 2017-2019 period. Source: Own elaboration based on SII.

Lastly, Figure 4 presents the correlation between the annual growth rates of various IMACEC sectors and their respective electronic invoice data[17]. The results show that several sectors —such as construction, wholesale and retail trade, transport, business and personal services, and manufacturing— exhibit a high degree of correlation. These sectors also represent a substantial proportion of the total activity reflected in the IMACEC, indicating that microdata captures significant aspects of overall economic fluctuations. This underscores the potential of electronic invoice data as a proxy for broad economic dynamics in real time.

Figure 4: Correlation between annual growth rate of IMACEC and electronic invoices



Source: Own elaboration based on BCCh and SII.

Overall, the analysis of microdata and the correlation with IMACEC concludes that this real-time information allows for a close follow-up of monthly activity in terms of level and especially for annual growth.

[17] To further assess this relationship within a time series framework, Figure A.1 in the appendix shows the annual growth rate of selected sectors within a time series framework alongside their corresponding electronic invoice microdata. Furthermore, Figure A.2 provides aggregate indicators of retail trade based on electronic receipts and electronic payments, used in the nowcasting of trade sector.

2.6. Other leading indicators

ETD and EP do not cover all IMACEC sectors; therefore, more “traditional” indicators —which are available even before tax records— also play a significant role. For example, real exports and electricity production are useful for nowcasting the agricultural and mining sectors, along with some manufacturing subsectors such as foods and pulp which are primarily export oriented. In addition, the monthly automobile sales reported by the National Automotive Association (ANAC, in Spanish) complements the electronic invoices for estimating automotive trade. Lastly, the estimation of taxes on products uses data on foreign trade (FT), mainly fuel imports and retail trade indicators, as proxies of custom tariff and households’ consumption taxes, respectively.

Considering all the available information, Table 1 summarizes the regressors used to nowcast each economic sector.

Table 1: Available data for each economic sector

Economic sector	**EI**	**ER**	**EP**	**ANAC**	**FT**	**Energy**
Agriculture and forestry					■	
Fishery						
Mining					■	■
Manufacturing	■				■	
Electricity, gas and water (EGW)						
Construction	■					
Wholesale and retail trade	■	■	■	■		
Restaurants and hotels	■		■			
Transport	■		■			
Information and communication	■					
Financial services						
Business services	■					
Dwelling services and real estate	■					
Personal services	■		■			
Public administration						
Taxes on products	■	■	■		■	

Note: For sectors without a regressor or satellite specification (financial services and public administration), a SARIMA model is used. Source: Own elaboration.

3. Methodology

3.1. SARIMAX

Seasonal Autoregressive Integrated Moving Average (SARIMA) models are widely used in the context of time series forecasting[18]. Due to their simplicity and robust performance in a variety of situations, SARIMA models have been the subject of much research.

A useful extension for our goals is to add exogenous information (e.g. electronic tax documents) that affects the variable for nowcasting to gain accuracy (SARIMAX model). Formally:

[18] A detailed description can be found in most texts applied to time series analysis (e.g., Box and Jenkins, 1976).

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)\left(1-\sum_{i=1}^{P}\Phi_i L^i\right)\nabla^d\nabla^D(\mathrm{y}_t-\alpha\mathrm{x}_t-\beta D-\gamma C)=\left(1-\sum_{i=1}^{q}\theta_i L^i\right)\left(1-\sum_{i=1}^{Q}\Theta_i L^i\right)\mu_t \quad (1)$$

Where:

- y_t: log level of sectoral IMACEC
- x_t: vector of exogenous variables (possibly including lags, linear trends and constant)
- D: outliers' vector
- C: calendar vector
- L^i: lag operator of order i
- ∇^d: non-seasonal differentiation
- ∇^D: seasonal differentiation
- μ_t: white noise

The SARIMA specification $(p,d,q)(P,D,Q)$ is determined for each time series using optimality criteria[19]. The parameters $\{\phi_i,\Phi_i,\theta_i,\Theta_i,\alpha,\beta,\gamma\}$ are obtained by maximum likelihood.

All sectors in Table 1 with a marked box include a regressor in the estimation. The rest is modeled using only a SARIMA specification.

3.2. Satellite models

Because of the nature of some industries, tax records are not a proper proxy for either measurement or nowcasting purposes. This is typically the case of goods producing industries such as agriculture and forestry, fishery, mining, manufacturing, and electricity, gas, water and waste management (EGW).

While some can be reasonably estimated by including leading indicators (e.g., agriculture, manufacturing and mining), others impose a challenge since their dynamics are more dependent on supply shocks that are not directly predictable or because their composition affects the correlation between production and value added. This is the case of fishery and EGW, where we develop satellite models that focus on their specific characteristics. For the former, we employ information on average sea surface temperatures, due to the existence of a regularity between the volume of biomass and the level of extraction[20]. This data is modelled using different methods such as Ridge, LASSO, and elastic net. For EGW, we use a linear model based on electricity production data[21] from different technologies to proxy the value added of the generation[22].

[19] While our baseline specification for forecasting year-over-year Imacec growth is a SARIMAX model with seasonal differencing only, it should be noted that, depending on the sample and variable transformations, information criteria (AIC/BIC) may select a double-differenced model. In such cases, forecasts are obtained for the doubly differenced series and must subsequently be reintegrated to express the results in the standard year-over-year growth format.

[20] Data obtained from the Hydrographic and Oceanographic Service of the Chilean Navy (SHOA, in Spanish).

[21] The daily data is obtained from the National Electrical Coordinator (Coordinador Eléctrico Nacional, CEN, in Spanish) and processed internally to classify each power plant to a wide set of technologies and sources.

[22] Since GDP measures the value added of economic activities —that is, the value of total production after costs have been discounted— significant changes in the composition of the electricity generation mix can affect GDP without impacting production. For more details, see Vivanco et. al (2023).

3.3. The role of judgement

Despite the accuracy gained from tax records and electronic payments data, nowcasting models are subject to some concerns and limitations. In the short-run analysis, it is common to deal with uncertainty about the most appropriate specification, the stability of the relationship between variables, and unforeseen future events. Thus, incorporating new aspects may not be technically feasible, as it might be too time-consuming, which could affect the opportunity to make informed decisions based on the most current economic data, and could also lead to over-fitting the data in other periods without shocks.

The role of judgement, in this sense, must be present at some point and complement the nowcast of models, helping them to overcome their limitations by incorporating elements of the data that the models cannot correctly interpret. Judgement is included through quantitative elements not considered in the nowcasting model, and quantitative and qualitative information obtained from BCCh or other institutions.

For example, in front of a supply shock where goods-producing firms cease operations but continue to sell from declining inventories, microdata or leading indicators might not display a drop in sales; however, production would decline, affecting negatively economic activity. This is the case when mining firms announce a stoppage within a given timeframe. To quantify this impact, we use the weight of the affected firms in production and subtract this value from the model's point estimation[23]. Another situation is where the education sector[24] announces a strike, affecting the provision of the service. In that case, using the education registrations affected by the strike and assuming a proportional distribution of classes within a month, it is possible to proxy the impact in the nowcast. Overall, while nowcasting models serve as a strong starting point, judgment plays a role in complementing the models' predictions by integrating elements that they cannot fully account for.

Therefore, we will concentrate on assessing the out-of-sample projections of IMACEC, using the models described above, incorporating microdata along traditional leading indicators and a smaller component of judgment. This expert judgment corresponds to the actual projection made in each period with the available information at the time. For simplicity, henceforth we will refer to this nowcast as 'Microdata'.

3.4. Baseline models

The univariate and multivariate time series models reported in Cobb and Peña (2020) and BCCh (2020) serve as the primary benchmark models, which will be referred to as traditional models or 'TM' in the next section. These include SARIMA models, Bayesian VAR, dynamic factor models, and bottom-up Bayesian time-varying parameters. Some also incorporate leading indicators such as foreign trade, copper prices, expectations, and financial indicators.

The nowcasting process involves 25 specifications for each sector, which are then aggregated into a point forecast weighted by the pseudo out-of-sample root mean square error over (RMSE) the past

[23] Using Cochilco data, is it possible to obtain a monthly breakdown of copper production by firm. Then, assuming production as a value-added indicator —like IMACEC— and the weight of copper within mining sector, it is relatively straightforward to estimate the shock.

[24] One of the main shocks during pandemic was the drop of service sector, particularly education, due to the duration of the lockdowns.

12 months[25]. Finally, using the chain-linking method, we aggregate the sectors at the IMACEC and non-mining IMACEC level.

These models are estimated in a completely out-of-sample matter, considering the information available at each time and the unrevised series of data for the same period of evaluation as our new models.

4. Results

4.1. Absolute evaluation: RMSE against traditional models

A usual approach to evaluate the performance corresponds to the root mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(y_t - \widehat{y_t})}{T}} \tag{2}$$

For each month $t = 1$ until T.

Where:

- y_t is the vintage IMACEC
- $\widehat{y_t}$ the nowcast
- $T = 36$ is the sample period

Also, y_t and $\widehat{y_t}$ are the annual growth rate. Table 2 shows the sectorial RMSE in each nowcast for 36 months of out-of-sample evaluation:

[25] Experience has shown that good in-sample fit of a forecasting model does not necessarily imply good out-of-sample performance. The method of pseudo out-of-sample forecast evaluation aims to address this by generating h-period ahead forecast standing in time t for date $t + h$. But it's still using the data available at the final time, different than an out-of-sample forecast which uses the IMACEC vintages and the unrevised exogenous variables at each t period.

Table 2: RMSE for each economic sector, Jun.22-May.25

Economic sector	(% 2024)	TM	Microdata	Satellite
Agriculture and forestry	3.4	8.01	5.25	
Fishery[a]	0.5	16.96	16.98	18.77
Mining	11.7	3.67	3.73	
Manufacturing industry	9.0	2.53	2.53	
EGW	3.6	5.45	4.69	4.22
Construction	5.8	1.46	1.76	
Wholesale and retail trade	8.5	2.88	1.90	
Restaurants and hotels	2.0	3.28	3.33	
Transport	5.6	2.67	1.78	
Information and communication	2.5	2.42	1.78	
Financial services	3.6	1.11	1.25	
Dwelling services and real estate	7.6	0.65	0.75	
Business services	9.5	2.07	1.67	
Personal services	12.4	4.90	1.90	
Public administration	4.4	1.09	1.18	
Taxes on products	9.9	2.05	1.68	
IMACEC	**100.0**	1.31	0.87	
Non-mining IMACEC	**88.3**	1.30	0.77	

Note: [a] Fishery's satellite model includes only the last 26 months. In red the smallest RMSE by row.

In red, we highlight the smallest RMSE for each economic activity across all nowcasting exercises. A key finding is that our proposal results in a significant reduction in nowcasting error; the RMSE decreases from 1.31 to 0.87, representing a 34% decline (41% for non-mining IMACEC).

This improvement is largely attributed to key sectors with a high share of the IMACEC, which show considerable gains when microdata is added. Particularly, wholesale and retail trade, transport, business services and personal services exhibit the most significant reductions in their RMSE.

In some instances, the traditional models still outperform those using microdata. For example, the construction sector was expected to show better performance, since the electronic invoices represent an important share of VAT form. However, ETD exhibits high volatility due to the inherent characteristics of the billing process of these firms, where significant sales are concentrated in certain periods while production spans several months.

4.2. Relative evaluation: Diebold Mariano test

In this section we will test the statistical difference between the nowcast using microdata and traditional models through Diebold-Mariano test (1995). For this, we will consider the traditional measure of square mean error and the comparison using the quadratic loss function:

$$f_{t|t-h} \equiv L\left(\hat{e}^2_{t|t-h}\right) - L\left(\tilde{e}^2_{t|t-h}\right) \equiv \hat{e}^2_{t|t-h} - \tilde{e}^2_{t|t-h} \tag{3}$$

We want to test predictive precision, where the null hypothesis will be $\mathbb{E}(\Delta L_t) = 0$, and the alternative: $\mathbb{E}(\Delta L_t) \neq 0$. Then, the Diebold Mariano test is given by:

$$DM_{12} = \sqrt{P}\frac{P^{-1}\sum_{t=1}^{P}\Delta L_t}{\hat{\sigma}_{12}} \tag{4}$$

Where $\hat{\sigma}_{12}$ is the consistent estimator of the square root of the long-term variance of the numerator (HAC estimator, Newey and West, 1987).

The null hypothesis states that both models have equal predictive precision, where we use a one-tailed test in which the first model is evaluated against the second. So, if it's rejected, we can confirm that the first model –in this case the nowcast with microdata– has a higher predictive capacity. If it's not rejected it implies that there is no significant difference among both models.

Then, we test if $\beta_0 = 0$ in the regression:

$$f_{t|t-h} = \beta_0 + v_t \tag{5}$$

Table 3 shows the p-values resulting from this test.

Table 3: Diebold-Mariano test, Jun.22-May.25 (p-values)

Economic sector	**TM**	**Satellite**
Agriculture and forestry	0.04	
Fishery	0.09	0.32
Mining	0.52	
Manufacturing industry	0.39	
EGW	0.07	0.90
Construction	0.70	
Wholesale and retail trade	0.01	
Restaurants and hotels	0.50	
Transport	0.02	
Information and communication	0.03	
Financial services	0.98	
Dwelling services and real estate	0.84	
Business services	0.08	
Personal services	0.04	
Public administration	0.62	
Taxes on products	0.18	
IMACEC	0.01	
Non-mining IMACEC	0.01	

Note: In red the p-values that are below 10%. The null hypothesis states that both models have equal predictive precision. We use a one-tailed test in which the first model is evaluated against the second, so if it is rejected, we can determine that the first model has higher predictive capacity.

We observe that for aggregated IMACEC and non-mining IMACEC the nowcast with microdata has a higher predictive capacity statistically significant at 1%. At the sectoral level, results vary. For half of them the difference in precision is significant at 10%. Again, as in results of the RMSE we observe that microdata has an advantage in some sectors, but in others (e.g., mining, financial and dwelling services) they don't provide an improvement from traditional models.

In the case of EGW we find that the nowcast with microdata is significantly better than the results from traditional models but does not improve precision with respect to the satellite model that includes electricity generation variables. Therefore, the information provided by this information continues to be better.

4.3 Bias analysis

An additional and desirable property is that nowcasts exhibit random and unbiased errors, meaning they should not consistently deviate in the same direction. Figure 5 illustrates the nowcast errors, which represent the difference between the vintage IMACEC and its prediction.

A starting point for assessing bias is to estimate the sample average of the difference and expect it to be close to zero. For TM, the averages are -0.19 for the IMACEC and -0.22 for the non-mining IMACEC. With respect to nowcast using microdata, the results are 0.19 and 0.21, respectively. Hence, both results are similar but in different directions.

Subsequently, we employ the approach established by West and McCracken (1998), which has been widely used for forecast evaluation (Rossi and Sekhposyan, 2016; Binder and Sekkel, 2023), to estimate an impartiality test.

Formally, the error ($\varepsilon_{t+h|t}$) in h periods ahead will be written as:

$$\varepsilon_{t+h|t} = z_t\beta + u_{t+h} \tag{6}$$

For the out of sample period $t = \{1, \dots, T\}$, where $z_t = 1$, the null hypothesis is as follows:

$$\beta = \beta_0 = 0 \tag{7}$$

If the null is rejected, it indicates that the forecast is biased. To test this, we implement the Wald test using a HAC-consistent estimator for variance, following the Newey and West (1994) rule for selecting the appropriate lag.

As a robustness check, we also apply the Ljung-Box test to assess autocorrelation for lag selection.

Table 4: Bias tests, Jun.22-May.25

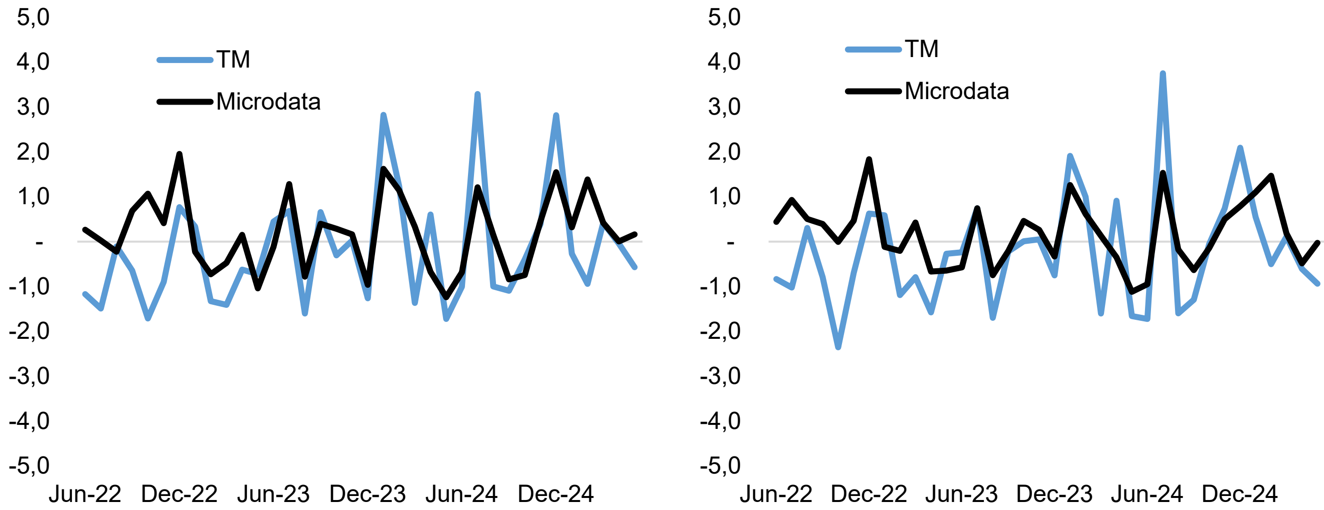
	Average bias (annual percentage change, %)		**Impartiality test** (p-values)	
Aggregation	**TM**	**Microdata**	**TM**	**Microdata**
IMACEC	-0.19	0.19	0.29	0.59
Non-mining IMACEC	-0.22	0.21	0.21	0.41

As Table 4 shows, there is no significant evidence of bias in either of the tested estimations.

Finally, Figure 5 shows the evolution of the errors from June 2022 to May 2025. As shown, the nowcast using microdata consistently exhibits lower variance in its nowcast errors. This improvement is not due to differences in sample or timing, but rather to the richer informational content provided by granular, real-time transactional data. Hence, microdata allows the model to detect early signals of economic activity more effectively, resulting in more stable and accurate predictions.

Figure 5: Errors **-** Difference of vintage IMACEC and nowcast (annual growth rate)

(a) IMACEC **(b) Non-mining IMACEC**



Source: Own elaboration.

5. Concluding remarks

This paper presents a fully out-of-sample evaluation to test whether the integration of microdata into the nowcasting process can enhance the performance of a set of traditional time series models. The evaluation period spans from June 2022 to May 2025.

Our results show that incorporating micro-level data has significantly improved the accuracy of nowcasting models for Chilean economic activity, both for the aggregated IMACEC and the non-mining IMACEC. The bottom-up aggregation strategy, which combines sector-specific microdata with SARIMAX models, allows for better capture of sectoral heterogeneity and enhances the timeliness and reliability of the estimates.

Empirical evidence reveals substantial reductions in RMSE, particularly in sectors with high contributions to IMACEC, alongside statistically significant gains in predictive performance as measured by the Diebold-Mariano test. Importantly, both traditional and microdata-based nowcasts remain unbiased.

At the sectoral level, microdata integration improves model performance in approximately half of the economic sectors, demonstrating its value as a complementary source of information. These findings underscore the importance of a mixed strategy for effectively nowcasting Chilean economic activity and suggest room for further refinement.

Despite these improvements, challenges remain in modeling supply shocks and structural breaks, which are less predictable using high-frequency microdata from tax records. Future research should explore, for example, the integration of real-time data streams and machine learning techniques tailored to specific sectors to further enhance nowcasting capabilities.

References

Arkolakis, C., Huneeus, F. and Miyauchi, Y. (2025). “Production Network Formation, Trade and Welfare”, National Bureau of Economic Research, Working Paper 30954.

Banco Central de Chile (2020). “Uso de modelos macroeconómicos en el Banco Central de Chile 2020”. ISBN: 956-7421-16-1.

Banco Central de Chile (2022). “Cuentas nacionales de Chile. Métodos y fuentes de información”.

Bank of England (2025). “Nowcasting GDP at the Bank of England: A Staggered-Combination MIDAS approach”. Macro Technical Paper No.2.

Binder, C. and Sekkel, R. (2023). “Central Bank Forecasting: A Survey”. Journal of Economic Surveys, 38:342–364. https://doi.org/10.1111/joes.12554

Bok, B., Caratelli, D., Giannone, D., Sbordone, A. and Tambalotti, A. (2017). “Macroeconomic Nowcasting and Forecasting with Big Data”. Staff Reports, N° 830, November 2017.

Box, G. and Jenkins, A. (1976). “Time Series Analysis: Forecasting and Control”. 2nd Edition, Holden-Day, S. Francisco.

Cobb, M. (2021). “Nowcasting Chilean household consumption with electronic payment data”, Documentos de Trabajo N° 871, Banco Central de Chile, April 2020.

Cobb, M. and Peña, J. (2020). “Proyecciones de corto plazo para el PIB trimestral: Desempeño de una serie de modelos estándar”, Documentos de Trabajo N° 931, Banco Central de Chile, November 2021.

Foroni, C. and Marcellino, M. (2014). “A comparison of mixed frequency approaches for nowcasting Euro area macroeconomic aggregates”, International Journal of Forecasting, 30, (3), 554-568.

Diebold, F. X. and Mariano, R. S. (1995). “Comparing predictive accuracy”. Journal of Business and Economic Statistics, 13(3), 253–263.

Galbraith, J. W. and Tkacz, G. (2018). “Nowcasting with payments system data”. International Journal of Forecasting, 34, pp. 366-376.

Ghysels, E. and Marcellino, M. (2018). “Applied economic forecasting using time series methods”. New York, NY: Oxford University Press.

Giannone, D., Reichlin, L. and Small, D. (2008). "Nowcasting: The real-time informational content of macroeconomic data". Journal of Monetary Economics, Elsevier, vol. 55(4), pages 665-676, May.

Guerrero, S., Luengo, R., Pozo, P. and Rébora, S. (2012). “Nuevas series de Cuentas Nacionales encadenadas: Métodos y fuentes de estimación”, Estudios Económicos Estadísticos N° 90, Banco Central de Chile, marzo 2012.

Huneeus, F., Kroft, K. and Lim, K. (2022). “Earnings Inequality in Production Networks”. National Bureau of Economic Research, Working Paper 28424.

Jardet, C. and Meunier, B. (2022). “Nowcasting world GDP growth with high-frequency data”. Journal of Forecasting, vol. 41, N° 6, pp. 1181-1200.

Koike-Mori, Y. and Martner, A. (2024). “Aggregating Distortions in Networks with Multi-Product Firms”, Documentos de Trabajo N° 1022, Banco Central de Chile, August 2024.

Loermann, J. and Maas, B. (2019). “Nowcasting US GPD with artificial neural networks”, Munich Personal RePEc Archive N° 95459.

Miranda-Pinto, J., Silva, A. and Young, E. (2023). “Business Cycle Asymmetry and Input-Output Structure: The Role of Firm-to-Firm Networks”, Journal of Monetary Economics, vol. 137, 1-20.

Newey, W. K. and West, K. D. (1987). “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix”. Econometrica, 55(3):703-708.

Newey, W. K. and West, K. D. (1994). “Automatic Lag Selection in Covariance Matrix Estimation”. The Review of Economic Studies, 61(4):631-653.

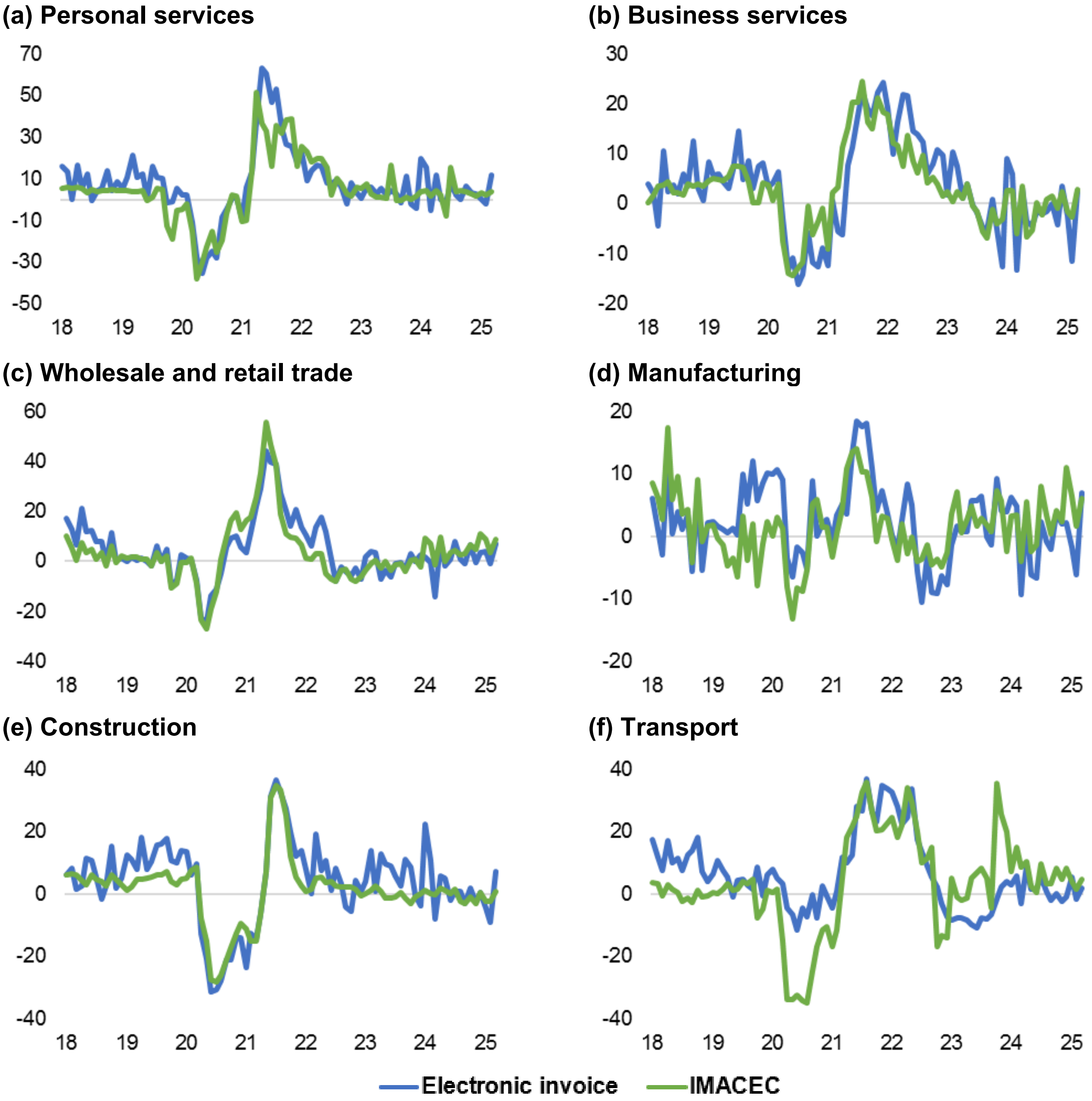
Rossi, B. and Sekhposyan, T. (2016). “Forecast Rationality Tests in the Presence of Instabilities, with Applications to Federal Reserve and Survey Forecasts”. Journal of Applied Econometrics, 31(3):507-532.

Vivanco, D., Guzmán, F. and Briones, L. (2023). “Rol reciente de la generación eléctrica en la actividad y sus perspectivas”. Blog, Central Bank of Chile.

West, K. and McCracken, M. (1998). “Regression-Based Tests of Predictive Ability”. International Economic Review, 39(4):817-40.

Appendix

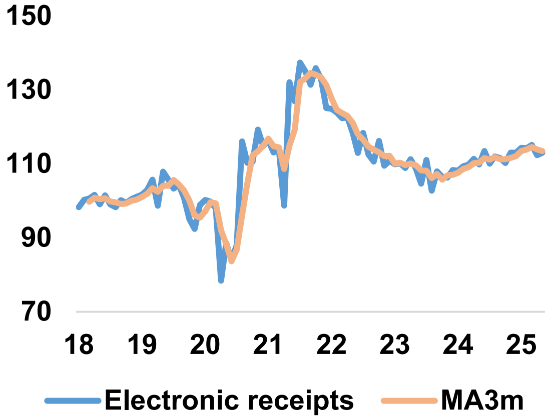
Figure A.1: IMACEC vs electronic invoices, YoY (%)



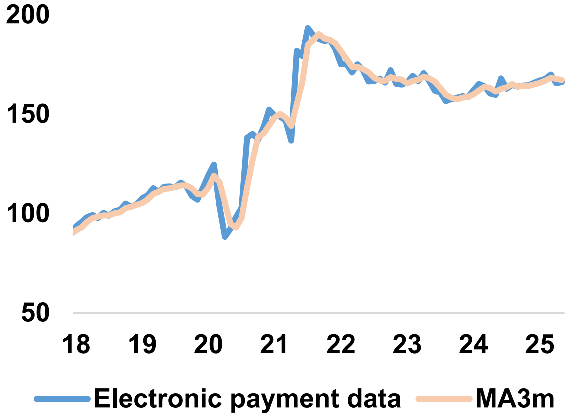
Source: Own elaboration based on BCCh and SII.

Figure A.2: Electronic receipts and electronic payments data

(a) Electronic receipts
(index 2018 = 100, s.a.)



(b) Electronic payments data
(index 2018 = 100, s.a.)



Note: MA3m corresponds to the moving average of 3 months. Source: Own elaboration based on BCCh, SII, TBK and Getnet.

Documentos de Trabajo **Banco Central de Chile** NÚMEROS ANTERIORES La serie de Documentos de Trabajo en versión PDF puede obtenerse gratis en la dirección electrónica: www.bcentral.cl/esp/estpub/estudios/dtbc. Existe la posibilidad de solicitar una copia impresa con un costo de Ch$500 si es dentro de Chile y US$12 si es fuera de Chile. Las solicitudes se pueden hacer por fax: +56 2 26702231 o a través del correo electrónico: bcch@bcentral.cl.	**Working Papers** **Central Bank of Chile** PAST ISSUES Working Papers in PDF format can be downloaded free of charge from: www.bcentral.cl/eng/stdpub/studies/workingpaper. Printed versions can be ordered individually for US$12 per copy (for order inside Chile the charge is Ch$500.) Orders can be placed by fax: +56 2 26702231 or by email: bcch@bcentral.cl.

DTBC – 1059
Nowcasting Economic Activity with Microdata
Diego Vivanco Vargas, Camilo Levenier Barría,
Lissette Briones Molina

DTBC – 1058
Artificial Intelligence Models for Nowcasting Economic Activity
Jennifer Peña, Katherine Jara, Fernando Sierra

DTBC – 1057
Clasificación de Riesgo de Crédito Bancario, Ventas y Estados Financieros en Base a Información Tributaria de Firmas en Chile
Ivette Fernández D., Jorge Fernández B.,
Francisco Vásquez L.

DTBC – 1056
Exogenous Influences on Long-term Inflation Expectation Deviations: Evidence from Chile
Carlos A. Medel

DTBC – 907*
Earnings Inequality in Production Networks
Federico Huneeus, Kory Kroft, Kevin Lim

DTBC – 1055
Markup Distribution and Aggregate Dynamics
Mario Giarda, Will Jianyu Lu, Antonio Martner

DTBC – 1054
Decoding Central Banks' Practices: A Closer Look at Inflation Expectations Surveys
Valentina Cortés Ayala, Karlla Muñoz Cáceres, Daniel Pérez Klein

DTBC – 1053
An Assessment of the Effects of Monetary Policy Communication in Chile
Mario González-Frugone, Ignacio Rojas

DTBC – 1052
This Time is Global: Synchronisation in Economic Policy Uncertainty Indices
Carlos Medel

DTBC – 1051
Beyond Costs: The Dominant Role of Strategic Complementarities in Pricing
Elias Albagli, Francesco Grigoli, Emiliano Luttini, Dagoberto Quevedo, Marco Rojas

DTBC – 1050
The Anatomy of Aggregate Productivity
Federico Huneeus, Yasutaka Koike-Mori, Antonio Martner

DTBC – 1049
The Aggregate Welfare Effects of Nonlinear Prices in Supply Chains
Luca Lorenzini, Antonio Martner

DTBC – 1026*
The Incidence of Distortions
David Atkin, Baptiste Bernadac, Dave Donaldson, Tishara Garg, Federico Huneeus

banco central Chile

DOCUMENTOS DE TRABAJO Diciembre 2025