WORKING PAPER

DEFLATING BANK TRANSACTION DATA FOR GDP NOWCASTING: WHETHER AND HOW TO USE INFLATION LAGS

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Deflating Bank Transaction Data for GDP Nowcasting: Whether and How to Use Inflation Lags*

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Abstract

Bank transaction data are increasingly used to nowcast real GDP growth due to their high frequency and broad coverage. A key challenge is the choice of an appropriate price deflator to transform nominal transaction values into real terms, as transaction values reflect invoiced amounts that are observed with a delay and based on prices quoted in earlier periods. This timing mismatch complicates the use of contemporaneous inflation measures. We find that using one-quarter lagged inflation, in particular, of the GDP deflator, and of an equally weighted estimate of the first lags of price indices, consistently outperforms the benchmark model that does not adjust for inflation and models using contemporaneous inflation, across different settings and periods.

At its best, the model using the one-quarter lag of the GDP deflator outperforms the benchmark in 68% of cases and achieves a maximum RMSFE reduction of 5.5%. The equally weighted prediction of models using the one-quarter lag of price indices, improves the benchmark in 54% of cases and attains a maximum RMSFE reduction of 3.78%. These findings suggest that relying on the most recent inflation data or nowcasting delayed figures like the GDP deflator may be unnecessary or even counterproductive, as lagged inflation data often offer more stable and informative signals for real-time analysis.

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1 Introduction

Economic growth and bank transactions are two sides of the same coin. However, while official indicators such as GDP are released with delays, bank transaction data is available nearly in real time. This makes them valuable for nowcasting, i.e. predicting current economic conditions before official statistics are published (Barlas et al., 2023; Felber & Beyeler, 2023; Galbraith & Tkacz, 2018). Corporate cash flow data, in particular, reflect the changing costs and revenues of firms and provide timely signals of growth. However, a downside is that these transaction values are nominal figures, and therefore need to be adjusted for inflation to accurately measure real economic activity. The importance of this nominal-to-real transformation lies in ensuring accuracy and is closely linked to the relevance of nowcasts themselves. Nowcasts are particularly valuable in turbulent times, when growth is uncertain, as investors, policymakers, and businesses require accurate and timely measures of economic activity to make informed decisions. Given that official figures are often delayed in such periods, a nowcast should not only be timely but also as accurate as possible.

While there are many price indices for inflation adjustment, none specifically track the evolving costs faced by firms. This gap partly results from bank clients not fully representing the broader economy. Additionally, and perhaps more importantly, there is a time lag between when an order is placed and when the actual payment is made. We hypothesize that the delay between order and payment justifies the use of lagged inflation measures to deflate corporate transaction data, as it better aligns the payment timing with the corresponding prices and quantities.

Although nowcasting research has developed substantially since its introduction for economic applications (Babii et al., 2021; Baffigi et al., 2002; Banbura et al., 2010; Barlas et al., 2023; Bok et al., 2018; Duarte et al., 2017; Giannone et al., 2008) and with this also nowcasting GDP with payments and transaction data (Aprigliano et al., 2019; Barlas et al., 2023; Chapman & Desai, 2023; Felber & Beyeler, 2023; Galbraith & Tkacz, 2018), relatively little attention has been paid to the role of inflation adjustment in order to obtain real growth measures. Often, researchers rely on the "best available" deflators without systematically assessing their suitability. For example, Barlas et al. (2023) use the domestic producer price index to deflate investment, while acknowledging the absence of a comprehensive set of deflators tailored to transaction-level data. Similarly, Aprigliano et al. (2019) note that constructing a suitable deflator for payment data would require a dedicated analysis and rely on the harmonized consumer price index as a proxy to account for price effects.

This study contributes to the literature by evaluating the effectiveness of using different price indices and their timing to convert nominal bank transaction data into real terms for nowcasting. We find that adjusting for inflation enhances nowcasting accuracy of bank transaction data in predicting real GDP growth. While the choice of price index matters, the time lag of the inflation measure turns out to be even more critical. Using inflation measured in the previous quarter, rather than the current one, yields significantly better predictive performance.

In particular, we find that deflating the corporate cost indicator with the first lag of the GDP deflator, or using an equally weighted prediction of models using the one-quarter lag of price indices, consistently outperforms the benchmark model that does not adjust for inflation and models that use contemporaneous inflation, across different settings and periods. At its best, the model using the one-quarter lag of the GDP deflator outperforms the benchmark in 68% of cases and achieves a maximum RMSFE reduction of 5.5%. The equally weighted prediction of models using the one-quarter lag of price indices, improves the benchmark in 54% of cases and attains a maximum RMSFE reduction of 3.78%. These findings have important implications for practitioners using transaction data to nowcast real GDP growth, suggesting that relying on the most recent inflation data or nowcasting delayed figures like the GDP deflator may be unnecessary or even counterproductive, as lagged inflation data often offer more stable and informative signals for real-time analysis.

While our study focuses on Belgium, the approach and insights are broadly applicable to other countries. The rationale of adjusting nominal data for inflation to obtain real values is universal, and the existence of a time gap between order and payment is a common feature of commercial transactions. However, conclusions regarding the length of this time lag may not be fully generalizable, as different countries have varying regulations on invoicing and payment periods. Within Europe, these findings may be more transferable, given the existence of a European directive that addresses payment terms.

The paper proceeds as follows. Section 2 discusses the timing of price and quantity setting that underlies later observed payments and explains why lagged inflation is appropriate for payment data. Section 3 presents the hypotheses. Sections 4 and 5 cover the data and methodology. Section 6 analyzes the out-of-sample results. Section 7 concludes.

2 Timeline of price and quantity determination prior to corporate payments

Throughout the paper, we use corporate spending on goods and services to nowcast GDP growth. This spending can be tracked through firms' bank transactions, which are available at high frequency and can therefore provide a valuable resource for nowcasting economic growth. In line with this idea, we construct a corporate cost indicator from firm-level bank transaction data in collaboration with one of the largest banks in Belgium. This indicator reflects firms' outflows related to the purchase of goods and services used in production, such as supplier payments, utilities, rent, and other operating expenses. The construction of this indicator is explained in detail in section 4.

The transactions included in the proposed cost indicator originate from business invoices that report a total nominal amount to be paid, which reflects both the price and quantity of goods or services. A naive approach to obtain the corresponding real value would be to divide by the contemporaneous price index. However, this overlooks the fact that the quantities and prices appearing on invoices are typically determined well before the invoice itself is issued.

Figure 1 illustrates this in a schematic way. Consider a company that receives an invoice at time t. The corresponding payment appears in the data only later, at time $t + k_0$. The price on which the invoice is based typically does not reflect market conditions at either t or $t + k_0$. Instead, it is usually determined earlier, when the supplier responds to the company's request for a quote at time $t - k_3$. The quoted price, $\hat{P}_{t-k_3}$, reflects both prevailing market conditions at $t - k_3$ (i.e. P_{t-k_3}) and the supplier's internal costs (Carricano, 2014; Morris & de Vincent-Humphreys, 2019). However, this quote is not binding. Firms often compare multiple quotes and negotiate before placing an order. As a result, the final order price, P_{t-k_2}, may differ from the initial quoted price $\hat{P}_{t-k_3}$, depending on bargaining power and market conditions. It is also possible that no prior quote is required. In this case, the buyer places an order directly at price P_{t-k_2}, for example, when the supplier uses catalog or list prices. Here too, prices reflect both external and internal factors. Firms take into account current market conditions and competitors' prices, as well as their own production costs, including raw materials, labor, and overhead (Carricano, 2014). Evidence from Morris and de Vincent-Humphreys (2019) shows that the relative importance of these factors varies along the supply chain: firms closer to final consumers rely more on market prices, while upstream firms place greater weight on costs and demand conditions.

Once the order is confirmed, delivery typically follows within an agreed period, the delivery time can vary depending on the agreed terms, product, industry, and is not directly observable. In contrast, the invoicing and payment time is more standardized due to legal requirements. For instance, by European Directive for intra-EU supplies and reverse-charge services, invoices must

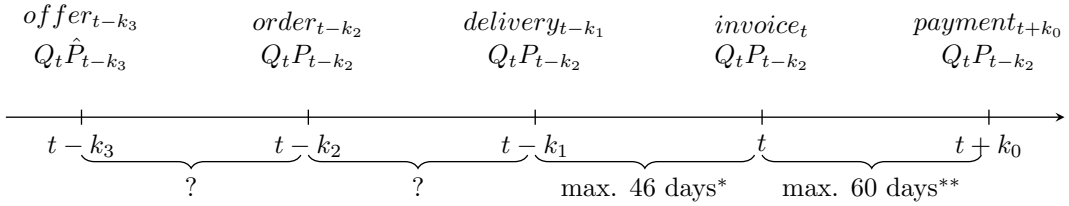

Figure 1: A typical transaction timeline - From offer to payment

Note: * Example assuming delivery occurs on the first day of a 31-day month (the law establishes invoices must be issued no later than the 15th of the month following delivery). ** Maximum 60 days unless otherwise specified by contract.

be issued no later than the 15th day of the month following delivery (European Union, 2010, Article 222). This implies a maximum lag of 46 days, assuming delivery occurs on the first day of a 31-day month.

The time between invoicing and payment is known as the payment term. Regulations on payment terms exist in many countries to prevent delayed payments in commercial transactions. For example, the European Union has a Late Payment Directive since 2000, updated in 2011, which caps payment terms in B2B commercial transactions at 30 and 60 days. The effective payment time can be influenced by various factors such as market power, supply chain characteristics, and industry context. Firms with greater market power, larger firms, and firms in industries with long operating cycles, such as manufacturing, are generally found to be slower to pay (Flynn & Li, 2023; Lieberman et al., 2025; Paul & Boden, 2011). Furthermore, evidence from periods of economic stress, such as the financial crisis, shows that suppliers often extended payment times to buyers due to disrupted access to credit (García-Appendini & Montoriol-Garriga, 2013; Love et al., 2007). However, Flynn and Li (2023) highlight that not every crisis has the same effect; they find that the COVID-19 pandemic did not lead to longer payment times or reduced compliance with payment terms for UK firms. They argue that this can be explained by the fact that the pandemic was not a credit crisis and by institutional pressures in the form of payment codes.

In summary, a significant delay can exist between the time the price is set (at the time of the order), the invoice date (used to compute GDP figures), and the payment date (captured in transaction data). This timing gap motivates the hypothesis: using a lagged price index may more accurately adjust corporate payment data for inflation to reflect real economic activity. We elaborate on this hypothesis further in the next section.

3 Hypotheses

To extract meaningful information on the real evolution of economic activity from nominal corporate payment data, it is necessary to distinguish changes in quantities from changes in prices. Corporate payment flows reflect firms' costs, which are jointly driven by price dynamics and underlying real activity. Following the Fisher rule, nominal growth rates can be transformed into real growth rates by adjusting for inflation using an appropriate price measure. However, the choice of inflation measure is not innocuous and may materially affect the signal extracted from the data. Because deriving real growth requires deflating nominal payments by a price index that reflects the prices of goods and services purchased by firms, this section develops two hypotheses concerning the optimal deflation strategy for corporate payment indicators in the context of nowcasting real economic growth. The first hypothesis concerns the choice of the price index used to adjust payment data for inflation, while the second addresses the timing of the adjustment, specifically the optimal lag structure of the price index.

It is natural to expect that production-side price indices constitute more appropriate measures for deflating corporate cash flow data than household-side price indices, as they more closely align with firms' cost structures. In particular, we posit that the producer price index (PPI) and the GDP deflator provide more informative deflators for corporate payment data than the consumer price index (CPI). The PPI captures price dynamics at the producer or seller level and therefore reflects the evolution of input costs within the production process, while the GDP deflator measures price changes across all final goods and services produced in the economy and thus provides a comprehensive indicator of domestic cost pressures.

Nevertheless, in the context of nowcasting, the practical usefulness of these indices is constrained by their publication frequency and release lags. Consumer-based indices, most notably the CPI, are typically released at higher frequencies and with shorter delays. Consequently, we also consider deflation strategies based on the CPI, which is widely used in practice to adjust nominal values, for example in inflation-indexed securities, rent indexation, and interest rate setting. This consideration motivates the following hypothesis.

Hypothesis 1 (Price index choice). Deflating corporate payment data using a production-side price index, such as the producer price index or the GDP deflator, yields a more accurate measure of real economic activity for nowcasting purposes than deflating the data using a consumer price index or leaving the data unadjusted.

The second hypothesis concerns the timing of the price adjustment applied to corporate payment data. It is motivated by the temporal separation between the moment at which prices are determined, typically at the time an order is placed, and the moment at which payment is executed and recorded in transaction data. As a result, the prices embedded in observed payments may reflect earlier price conditions rather than contemporaneous ones. In principle, the appropriate deflation should therefore rely on a lagged price index that corresponds to the average duration between order placement and payment settlement. Using a contemporaneous price index may introduce measurement error if current inflation dynamics differ from those prevailing at the time prices were set.

Hypothesis 2 (Timing of deflation). Deflating corporate payment data using a lagged price index provides a more accurate measure of real economic activity for nowcasting purposes than using a contemporaneous price index.

In practice, however, forming precise expectations about this lag is challenging. Delivery times are subject to uncertainty and may vary substantially across firms, sectors, and contractual arrangements. While invoice issuance and payment dates are more clearly defined due to legal and accounting requirements, the effective time elapsed between price setting and payment remains difficult to observe and may be heterogeneous. This uncertainty motivates an empirical assessment of the optimal timing of the price index used for deflation.

4 Data overview: real GDP, corporate payment data, and inflation indicators

To assess the value of adjusting corporate cash flow data for inflation in predicting real GDP growth, the study analyzes three data types: real GDP growth, corporate cash flow growth from bank transaction data, and inflation measures. We focus on Belgium, but the approach and insights are broadly applicable to other countries. The rationale of adjusting nominal data for inflation to obtain real values is universal, and the existence of a time gap between order and payment is a common feature of commercial transactions.

4.1 Corporate cost indicator vs. GDP growth and inflation

Central in our analysis is the quarterly **corporate cost indicator** quantifying the quarter-on-quarter growth in firms' outgoing cashflows based on their bank transaction data. We follow Boudt et al. (2026) in computing this growth indicator first at sector level followed by an aggregation to country level growth. The sectoral quarterly cost cash flow growth indicator, denoted $gCOST_{t,s}$, for sector s in quarter t, is described in detail in Appendix A. To obtain an aggregate indicator for the overall economy, we compute a weighted average of the sectoral quarterly growth rates. The weights reflect each sector's relative importance in the economy and are proxied by sectoral VAT shares $w_{t,s}$ obtained from the Belgian statistical agency Statbel. Using a weighted mean results in the final quarterly bank cost indicator for the overall economy:

$$gCOST_t = \sum_{s=1}^{S} w_{t-1,s}\, gCOST_{t,s}, \tag{1}$$

where $S = 21$ is the number of sectors and $w_{t-1,s}$ is the corresponding sector weight at the end of the previous quarter.

Figure 2 illustrates the relationship between the corporate cost indicator, real GDP growth and the inflation variables used in this analysis. The sample spans from 2008Q3 to 2023Q4, covering different economic periods, including the financial crisis, European debt crisis, COVID-19 crisis, and the energy crisis. The COVID-19 crisis stands out as a clear outlier in terms of real GDP growth, with a contraction far exceeding that observed during the global financial crisis. While GDP also declined during the financial crisis, the magnitude of the downturn was substantially smaller. By contrast, Belgium's GDP growth was only marginally affected during the European sovereign debt crisis.

The top row highlights a strong comovement between quarterly real GDP growth and the corporate cost indicator. This is especially evident during the financial crisis and the COVID-19 crisis, where the declines and recoveries are well captured. The corporate cost indicator, derived from bank transaction data, is noticeably more volatile than official GDP growth, suggesting a higher degree of noise, especially outside periods of economic stress. A key difference between the two series, however, is that GDP growth is measured in real terms, while the cost indicator is expressed in nominal terms. If inflation were constant over time, this difference would imply a stable wedge between the two series. In practice, inflation has varied substantially over the sample, as shown in the second and third rows of Figure 2, motivating a closer examination of inflation dynamics.

Regarding the evolution of the four price indicators, the energy crisis stands out: all four measures increased following the COVID-19 crisis, with most peaking during the energy crisis. Each series behaves differently due to its composition. For instance, the CPI increased more sharply than the GDP deflator or core inflation, as it reflects changes in the prices of imported goods, including energy. In contrast, the GDP deflator covers domestically produced goods (excluding imports), and core inflation excludes energy, making them less sensitive to energy price shocks. Notably, both indicators show a spike after the energy crisis, reflecting more fundamental inflation drivers such as wage increases following negotiations triggered by the energy price surge. The Producer Price Index (PPI) experienced the largest drop during the financial crisis, reflecting a sharp decline in demand for industrial goods and lower wholesale prices.

4.2 Frequency and publication lags

Table 1 provides an overview of the variables, together with their publication frequencies, lags, and the transformations applied to them. Timeliness and availability of variables are two im-

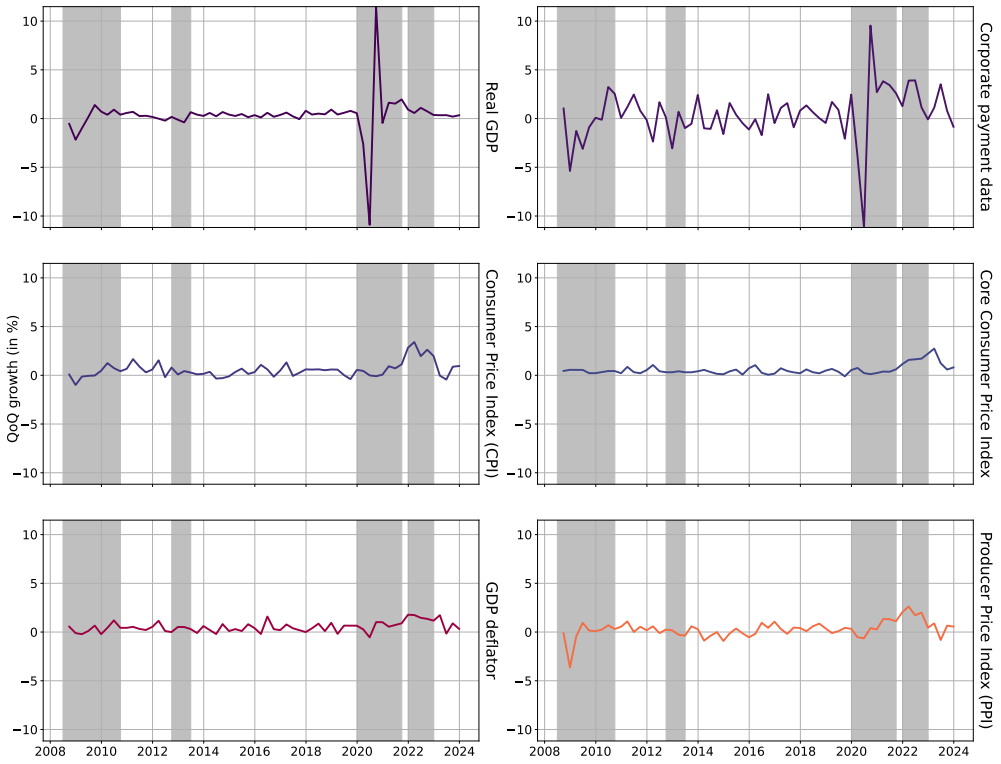

Figure 2: Quarter-on-quarter growth of macroeconomic indicators (2008Q3-2023Q4)

Note: Economic subperiods marked by the grey areas: (i) the financial crisis (2008Q3-2010Q3), (ii) the European debt crisis (2012Q4-2013Q2), (iii) the COVID-19 crisis (2020Q1-2021Q3), (iv) the energy crisis (2022Q1-2022Q4). The three first crisis periods are distinguished following the classical definition of a recession: 2 consecutive quarters of negative growth and include the quarters up until the GDP level is higher than the initial level before the crisis period. According to this definition, the surge in inflation due to energy prices does not qualify as a crisis period. However, we highlight this period because price inflation reached unprecedented levels, and various economic institutions, experts, and government sources also recognized the energy crisis, as evident from the financial stability reports of the NBB (National Bank of Belgium, 2023).

portant aspects to consider for nowcasting. The first **official GDP figure** is published at a quarterly frequency, with a delay of two months after the end of the quarter (National Accounts Institute, 2018). This makes it one of the least frequent and most delayed indicators in Table 1. In contrast, the growth estimate derived from corporate payment data based on bank transactions is the most frequent indicator, weekly available at the end of the week. Consequently, this high-frequency measure will be used to nowcast the official GDP figure.

Regarding **inflation measures**, consumer-based indices such as the CPI and core CPI are the most frequent and most timely, whereas producer price indices such as the PPI and GDP deflator are less frequent and more delayed. In Belgium, PPIs are published separately for the industrial sector, the construction sector, and certain subsectors of the services sector. For our research, we aggregate these sectoral PPIs into a single PPI figure, weighting them according to their contribution to GDP. Due to delays in the release of the services PPI, the aggregated PPI is only available three months after the end of the quarter.

We will perform nowcasts of the official GDP figure at the end of each quarter, which is two months earlier than the official publication. Although it is possible to conduct nowcasting at a higher frequency (e.g., at the end of the first or second month of the quarter), the aim of this study is to determine which price index is best suited to deflate the data. Earlier nowcasts tend to be noisier and would therefore not allow for fair comparability. Given this setup, all variables are converted into quarter-on-quarter (QoQ) growth rates to align with the target

Table 1: Overview of variables

Variable	Description	Frequency	Publication Lag (from period end)	Transformation
Real GDP growth data				
gGDP	Official real GDP growth.	Quarterly	2 months	QoQ growth
Bank transaction growth data				
gCOST	Quarterly GDP growth, derived from the cash-flow data according to the cost approach.	Weekly	End of week	QoQ growth
Price data				
gCPI	Growth of the CPI.	Monthly	End of month	QoQ growth
gCORE	Growth of the Core CPI.	Monthly	End of month	QoQ growth
gGDPDEF	Growth of the GDP deflator.	Quarterly	2 months	QoQ growth
gPPI	Growth of the Producer Price Indices (PPI) (weighted average of industrial, services, and construction PPIs, weighted by sectoral GDP shares).	Quarterly	3 months	QoQ growth
gPPI (industry)	Growth of the Producer Price Index in the industrial sector.	Monthly	1 month	QoQ growth
gPPI (services)	Growth of the Producer Price Index in the services sector.	Quarterly	3 months	QoQ growth
gPPI (construction)	Growth of the Producer Price Index in the construction sector.	Quarterly	2 months	QoQ growth

variable, quarterly GDP growth.

In this study, we assess the performance of GDP growth nowcasts based on the corporate cost series, deflated using price indices with different lags, including the contemporaneous index. Owing to publication delays, the contemporaneous GDP deflator and PPI are not available at the end of the quarter. Figure 3 indicates that, by the end of a quarter, only data from the previous quarter are available for these two indicators. Nevertheless, including contemporaneous deflators in the analysis enables us to assess whether using current price data would enhance nowcasting performance. If anything, this approach strengthens the evidence in favor of our hypothesis that a lagged price series is preferable.

4.3 Data revisions

In our study, there are two variables that are subject to data revisions, namely the GDP growth (target variable) and the GDP deflator (used for inflation adjustments in the explanatory part

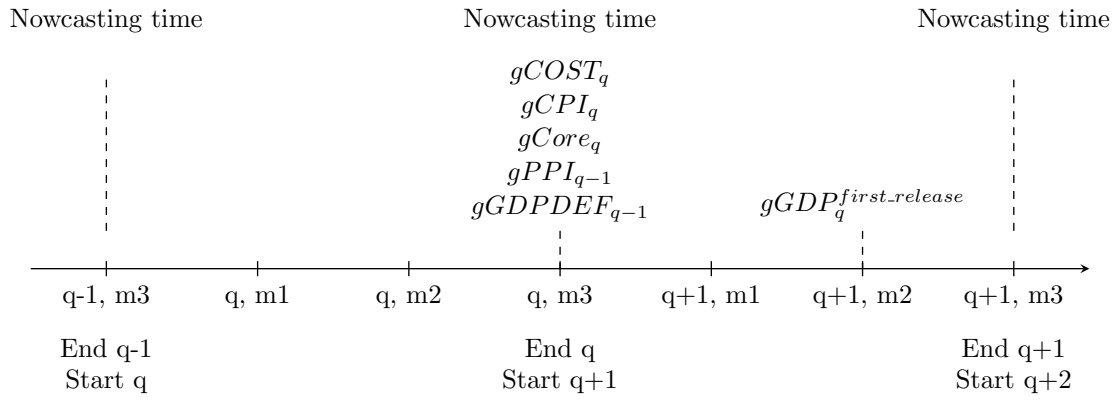

Figure 3: Available data at the time of nowcasting

of the models). Their revisions originate from revisions of the national accounts data (National Accounts Institute, 2022). The corporate cost indicator and all price indicators, except for the GDP deflator, are not subject to revisions. This also holds for the corporate cost indicator.

The difference between first releases and revisions raises an important question regarding the target of the nowcast or forecast, namely whether the target should be the first release or the revised data. Given the objective of simulating a realistic nowcasting scenario, we always construct and train the model using the data available at the time of the nowcast and evaluate comparing it to the most recent available real GDP growth data series (revised), assuming the revised data to be the most accurate. Specifically, this means that the explanatory variable gGDPDEF is always the first release, the target variable (gGDP, i.e., GDP growth) in the training sets corresponds to the latest available gGDP (revised data series) at the time of conducting the nowcast. In the test set, the dependent variable is the gGDP (revised data) available at the time of writing this paper. [1]

5 Methodology

5.1 Model specification

We aim to assess whether adjusting corporate cash flow data for inflation enhances its ability to explain real GDP growth. Equation (2) presents the benchmark model, in which real GDP growth is explained by the nominal cost-based indicator (without inflation adjustments). This specification serves as the reference point for evaluating models that incorporate inflation adjustments:

$$gGDP_t = \alpha + \beta_{benchmark}\, gCOST_t + \varepsilon_t. \tag{2}$$

As an alternative, we study the GDP growth nowcasting model that uses the Fisher rule to adjust the nominal cost series with one of the inflation indicators listed in Table 1:

$$gGDP_t = \alpha + \beta_{adjusted}\left(gCOST_t - gPRICE_{t-k}\right) + \varepsilon_t. \tag{3}$$

In this equation, $gPRICE_{t-k}$ represents the inflation variable at a lagged time period $t-k$, where $k \geq 0$ is the lag length. The lag length k can range from no lag $k = 0$ to $k = 3$, which implies 4 quarters, i.e., one year.

[1] Chain-linked quarter-on-quarter percentage change, reference year 2020, available as of 18/11/2025.

We expect $\beta_{benchmark} > 0$, indicating that corporate cash flow growth observed in bank transaction data has explanatory power for real GDP growth. The underlying intuition is that firms' expenditures on goods and services act as a leading indicator of economic activity, since such spending typically precedes increases in output. Furthermore, we expect that inflation-adjusted models (Equation (3)) exhibit higher explanatory power than the benchmark model (Equation (2)), as reflected by $R^2_{adjusted} > R^2_{benchmark}$ and $\beta_{adjusted} > \beta_{benchmark}$. Building on the arguments in Sections 2 and 3, we further expect models incorporating lagged inflation and those deflated using broader producer price measures, such as the PPI and the GDP deflator, to perform better.

Consistent with these expectations, in-sample regression results (Table 2) show that corporate cash flow growth observed in bank transaction data has explanatory power for real GDP growth ($\beta_{benchmark} = 0.62^{***}$ and $R^2_{benchmark} = 61\%$), while improvements in explanatory power $R^2_{adjusted} > R^2_{benchmark}$ as well as $\beta_{adjusted} > \beta_{benchmark}$, seem to depend on both the lag of inflation and the price index used. For most price indices, using a one-quarter lag of inflation to deflate the corporate cost measure provides a consistent improvement in explanatory power relative to the benchmark. The out-of-sample performance evaluation will provide further insights into the optimal choice of lag and price index.

Table 2: Regression results for benchmark model and inflation adjusted models (Total Period)

	Benchmark	Inflation adjusted cashflow			
	gCost	gCost - gCPI	gCost - gCORE	gCost - gGDPDEF	gCost - gPPI
Inflation lag (k=0)					
β	0.623***	0.637***	0.632***	0.644***	0.664***
	(0.200)	(0.206)	(0.196)	(0.213)	(0.232)
R^2	0.613	0.603	0.624	0.604	0.575
Inflation lag (k=1)					
β	0.623***	0.648***	0.632***	0.660***	0.662***
	(0.200)	(0.190)	(0.189)	(0.205)	(0.205)
R^2	0.613	0.637	0.635	0.628	0.624
Inflation lag (k=2)					
β	0.623***	0.636***	0.618***	0.630***	0.621***
	(0.200)	(0.195)	(0.203)	(0.183)	(0.189)
R^2	0.613	0.629	0.600	0.644	0.626
Inflation lag (k=3)					
β	0.623***	0.580***	0.603***	0.604***	0.615***
	(0.200)	(0.213)	(0.211)	(0.207)	(0.192)
R^2	0.613	0.563	0.581	0.576	0.614

Note: N=62. Heteroskedasticity and autocorrelation robust standard errors in parentheses.
*p<0.1; **p<0.05; ***p<0.01.

We evaluate the nowcasting performance of different models using both rolling and expanding window approaches. Models (2) and (3) are estimated via Ordinary Least Squares (OLS), initially on a training window of 12 quarters (3 years), the resulting estimates are then used to predict the subsequent quarter. After each prediction, the training window is updated by adding one additional quarter. The first training window in the dataset spans from 2008Q3 to 2011Q2. Following the rolling or expanding estimation procedure, we obtain 50 predictions, covering the period from 2011Q3 to 2023Q4.

In each window, a total of 17 models are estimated, and 21 predictions are generated for each

forecasted quarter, 17 direct predictions and 4 weighted predictions. The prediction set is based on 1 benchmark model (without inflation adjustment), 16 inflation-adjusted models based on 4 price indices and their respective lags ($k = 0, 1, 2, 3$), and 4 weighted predictions. The equally weighted predictions are the average of the inflation-adjusted predictions for each of the 4 lags.

5.2 Performance evaluation

The performance of the models is evaluated based on the root mean squared forecast error (RMSFE), following the practices in the literature (Cimadomo et al., 2021; Galbraith & Tkacz, 2018; Modugno, 2013). A lower RMSFE indicates higher forecast accuracy and better predictive ability of the model. The RMSFE of a certain model m is calculated as:

$$\text{RMSFE}_m = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(gGDP_t - \widehat{gGDP}_{m,t}\right)^2}, \tag{4}$$

where $gGDP_t$ are the official real GDP growth releases published by the NBB, and $\widehat{gGDP}_{m,t}$ are the estimated real GDP growth figures from model m.

To measure the improvement in forecast accuracy of a model m compared to the forecast of the benchmark model (which does not account for inflation), we calculate the RMSFE improvement:

$$\text{RMSFE}^{\text{improvement}}_{m,benchmark} = \frac{\text{RMSFE}_{benchmark} - \text{RMSFE}_m}{\text{RMSFE}_{benchmark}}. \tag{5}$$

The statistical significance of the RMSFE improvements is evaluated using a paired t-test, a Wilcoxon signed-rank test, and the Diebold and Mariano (1995) test statistic implemented with the heteroskedasticity and autocorrelation consistent (HAC) standard error estimator of Newey and West (1987) and corrected for small samples Harvey et al. (1997). Let $\Delta_t = \text{RMSFE}_{k,t} - \text{RMSFE}_{m,t}$ denote the difference in forecast errors between the benchmark model k and model m at time t. The paired t-test assesses whether the mean of these differences is significantly different from zero:

$$t = \frac{\overline{\Delta}}{s_\Delta/\sqrt{T}}, \tag{6}$$

where $\overline{\Delta}$ is the sample mean of the differences and s_Δ is the sample standard deviation. The Wilcoxon signed-rank test provides a non-parametric alternative that is robust to deviations from normality in the distribution of Δ_t. For the Diebold–Mariano (DM) test, the t-test statistic (Equation 5) is modified by using a heteroskedasticity- and autocorrelation-robust variance–covariance matrix and is further corrected for small samples following (Harvey et al., 1997).

In addition to the magnitude of RMSFE improvement, we also consider the frequency with which a model outperforms the benchmark in terms of lower RMSFE. We assess whether this frequency is significantly higher than would be expected by random guess using a binomial test, which provides a complementary measure of predictive performance, emphasizing models that consistently outperform the benchmark even when RMSFE improvements are modest.

6 Results

Figures 4 and 5 show the RMSFE improvements for the expanding and rolling window approaches, respectively. The results indicate that adjusting corporate cash flow data for inflation

using one-quarter lagged inflation yields the highest accuracy improvements for most price indices. Moreover, the one-quarter lag of the GDP deflator and the equally weighted prediction of models using one-quarter lagged inflation seem to outperform other models.

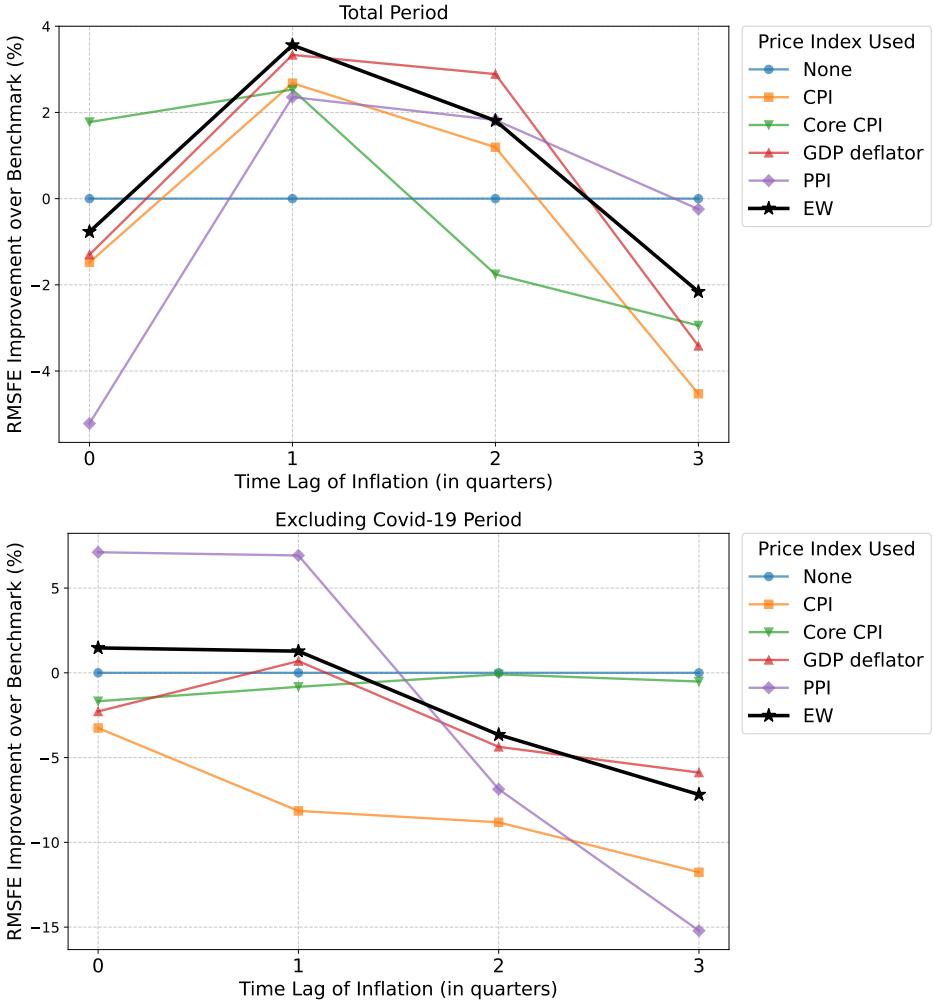

Figure 4: RMSFE improvement of adjusting corporate cash flow data for inflation for various price indices - Expanding window.

Note: RMSFE improvement of inflation-adjusted corporate cash flow models relative to the benchmark nominal model (Equation (2)). The benchmark model corresponds to the line labeled "price index used = None." Positive values indicate RMSFE improvements relative to the benchmark. Models are estimated using OLS on an expanding window with an initial training period of 12 quarters and predicting the subsequent quarter. The first training window in the dataset spans from 2008Q3 to 2011Q2. There are N=50 predictions for the total period covering 2011Q3 to 2023Q4, and N=43 predictions for the period excluding the COVID-19 crisis (2020Q1–2021Q3). Inflation-adjusted models (Equation (3)) use four different price indices and four different lags, $k = 0$–3 quarters. EW corresponds to the RMSFE of the equally weighted prediction across different price indices using the same lag.

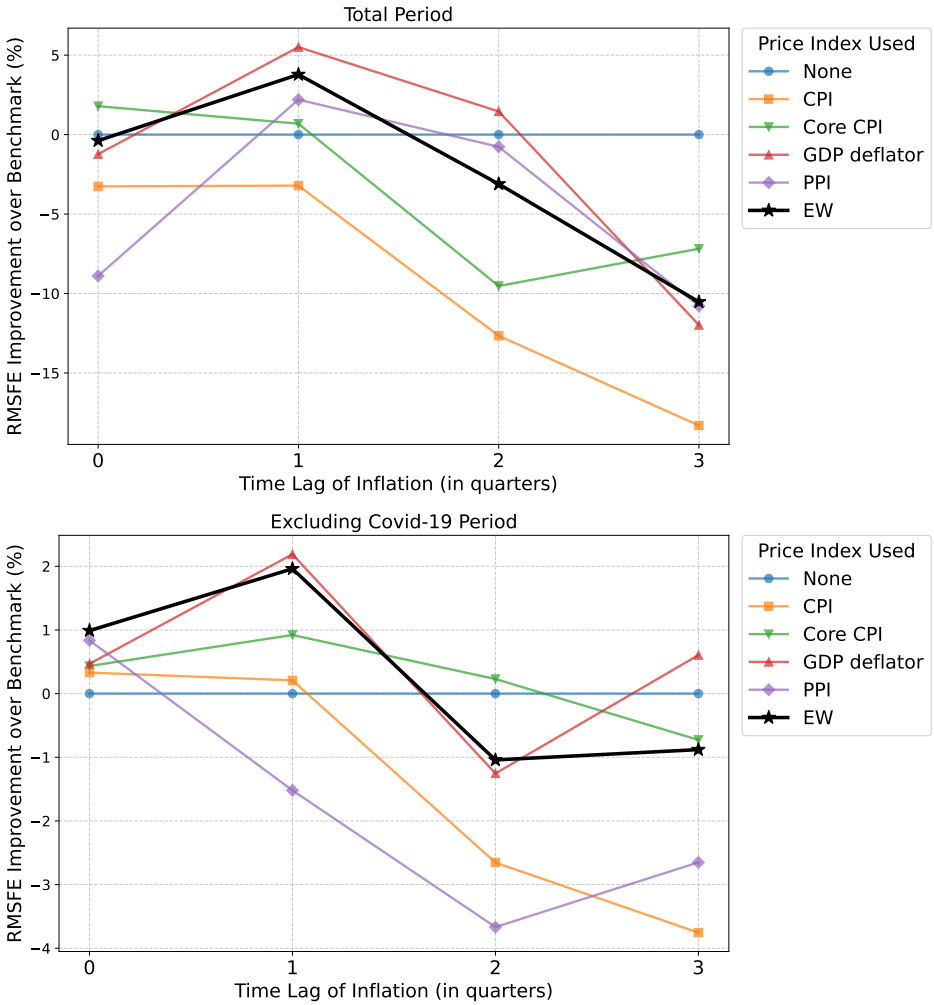

Figure 5: RMSFE improvement of adjusting corporate cash flow data for inflation for various price indices - Rolling window.

Note: RMSFE improvement of inflation-adjusted corporate cash flow models relative to the benchmark nominal model (Equation (2)). The benchmark model corresponds to the line labeled "price index used = None." Positive values indicate RMSFE improvements relative to the benchmark. Models are estimated using OLS on an rolling window with an initial training period of 12 quarters and predicting the subsequent quarter. The first training window in the dataset spans from 2008Q3 to 2011Q2. There are N=50 predictions for the total period covering 2011Q3 to 2023Q4, and N=43 predictions for the period excluding the COVID-19 crisis (2020Q1–2021Q3). Inflation-adjusted models (Equation (3)) use four different price indices and four different lags, $k = 0$–3 quarters. EW corresponds to the RMSFE of the equally weighted prediction across different price indices using the same lag.

When the COVID-19 period is excluded, the results are more mixed: not all first-lag specifications improve performance. Nevertheless, first-lag adjustments using the GDP deflator, as well as the equally weighted predictions of models using one-quarter lagged inflation, tend to yield consistent RMSFE gains, both in rolling window and expanding window estimations.

Interestingly, using contemporaneous inflation ($k = 0$) offers limited improvements with respect to the benchmark in most cases. Depending on the price index, it can even lead to a worsening of the RMSFE relative to the benchmark, or to smaller improvements compared to using their first-lag counterparts.

Table 3 presents the top five performing models in terms of RMSFE improvement, both in

magnitude and frequency, for the rolling and expanding windows, and for the full sample as well as for the period excluding the COVID-19 crisis. It can be noted that predictions based on the rolling window approach generally perform better, exhibiting lower RMSFE than those based on the expanding window approach. Second, while there is some variation among the top 5 depending on the window and sample, two models consistently outperform the benchmark in all cases: the first lag of the GDP deflator and the equally weighted estimate of models using the first lag of all price indices.

Table 3: Top 5 performing models in terms of RMSFE improvement magnitude and frequency.

Price index	**Lag (k)**	**Model RMSFE**	**Improvement (%)**	**Frequency of imp. (%)**
Total Period - Rolling window				
Benchmark		1.335		
GDP deflator	**1**	**1.280**	**5.510**$^{(-/*/-)}$	**68*****
EW	**1**	**1.303**	**3.780**	**54**
PPI	1	1.325	2.200	52
Core CPI	0	1.330	1.790	46
GDP deflator	2	1.335	1.460	38
Total Period - Expanding window:				
Benchmark		1.695		
EW	**1**	**1.634**	**3.560**	**58**
GDP deflator	**1**	**1.638**	**3.340**	**62***
GDP deflator	2	1.646	2.890	52
CPI	1	1.649	2.680	48
Core CPI	1	1.652	2.530	56
Non-COVID - Rolling window				
Benchmark		0.324		
GDP deflator	**1**	**0.317**	**2.190**$^{(*/**/*)}$	**72*****
EW	**1**	**0.317**	**1.960**$^{(*/-/*)}$	**56**
EW	0	0.320	0.990	47
Core CPI	1	0.321	0.920	53
PPI	0	0.321	0.840	51
Non-COVID - Expanding window				
Benchmark		0.403		
PPI	0	0.374	7.110	56
PPI	1	0.375	6.920	49
EW	0	0.397	1.470	58
EW	**1**	**0.398**	**1.280**	**56**
GDP deflator	**1**	**0.400**	**0.690**	**58**

Note: N_total=50, N_non_covid=43. Significance of RMSFE improvements: the first test statistic is a paired t-test; the second is a Wilcoxon signed-rank test; and the third is the Diebold and Mariano (1995) test statistic implemented with the heteroskedasticity and autocorrelation consistent (HAC) standard error estimator of Newey and West (1987) and corrected for small samples following Harvey et al. (1997).
Significance of frequency of improvements: binomial test to assess whether frequency is significantly higher than would be expected by a random guess.
*p<0.1; **p<0.05; ***p<0.01

When using the first lag of the GDP deflator for price adjustments, improvements relative to the benchmark occur significantly more frequently in 3 of the 4 settings. In the setting with

overall better performance (lower RMSFE), which is the rolling window approach, using the first lag of the GDP deflator results in significant improvements over the benchmark in 68% of cases during the total period and in 72% of cases when excluding the COVID crisis. Furthermore, the highest improvement is 5.5% (total period), and the lowest is 2.19% (non-COVID period). Note further that the equally weighted estimate of the models using the first lag of all price indices shows its highest improvement in the rolling window approach at 3.78% (total period) relative to the benchmark, and the lowest improvement is 1.96% (non-COVID period).

In conclusion, Table 3 shows that using the first lag of the GDP deflator yields improvements in more cases than the equally weighted model and can therefore be selected as the best-performing specification for adjusting the corporate cost indicator for inflation in terms of frequency. However, average out-of-sample performance alone may mask substantial time variation in predictive ability. To assess whether the observed gains are persistent over time rather than driven by a few isolated periods, we turn to a cumulative evaluation of squared forecast errors.

Following Goyal and Welch (2008) and Goyal et al. (2024), Figure 6 plots the net difference in the cumulative sum of squared errors (CSSE) between the benchmark model and the preferred models for inflation adjustment. The preferred models include (i) the model using the first lag of the GDP deflator to deflate the corporate cost indicator, and (ii) the equally weighted estimate of the first lags of all price indices:

$$\text{CSSE}_T = \sum_{t=1}^{T} \left[\left(gGDP_t - g\widehat{GDP}_{benchmark,t} \right)^2 - \left(gGDP_t - g\widehat{GDP}_{m,t} \right)^2 \right]. \tag{7}$$

Good out-of-sample performance is indicated by a sustained upward trend in the CSSE. This trend should be persistent across time, not driven by short-lived or exceptional episodes, and should remain positive in the most recent decades. A failure to meet these conditions may signal a decline in forecasting ability.

An upward slope indicates that the inflation-adjusted models outperform the benchmark model. When the CSSE is above zero, it reflects cumulative outperformance relative to the benchmark. Overall, both inflation-adjusted predictions show consistent outperformance, although some irregularities are observed, for example, the GDP deflator model shows a dip at the start of the COVID crisis, and both models experience some fluctuations in the second half of the energy crisis period.

While Table 3 indicates that the model incorporating the first lag of the GDP deflator outperforms the equally weighted model in a larger number of cases and might therefore appear to be the preferred specification, the equally weighted model proves superior when evaluated using CSSE. In particular, it achieves the highest cumulative outperformance relative to the benchmark. Overall, the figure provides strong evidence that adjusting the corporate cost indicator for inflation materially improves real GDP growth forecasts. These gains are evident during both stable and volatile periods. Although the improvements are modest in tranquil periods, they become pronounced and economically meaningful during episodes of high economic volatility and elevated inflation.

7 Conclusion

A growing body of research seeks to derive economic insights from bank transaction data (Baker, 2018; Galbraith & Tkacz, 2018). When the objective is to characterize real economic activity, such analyses are complicated by the timing gap between the price index corresponding to the time an order is placed and the time at which the payment is realized and thus recorded in the bank transaction.

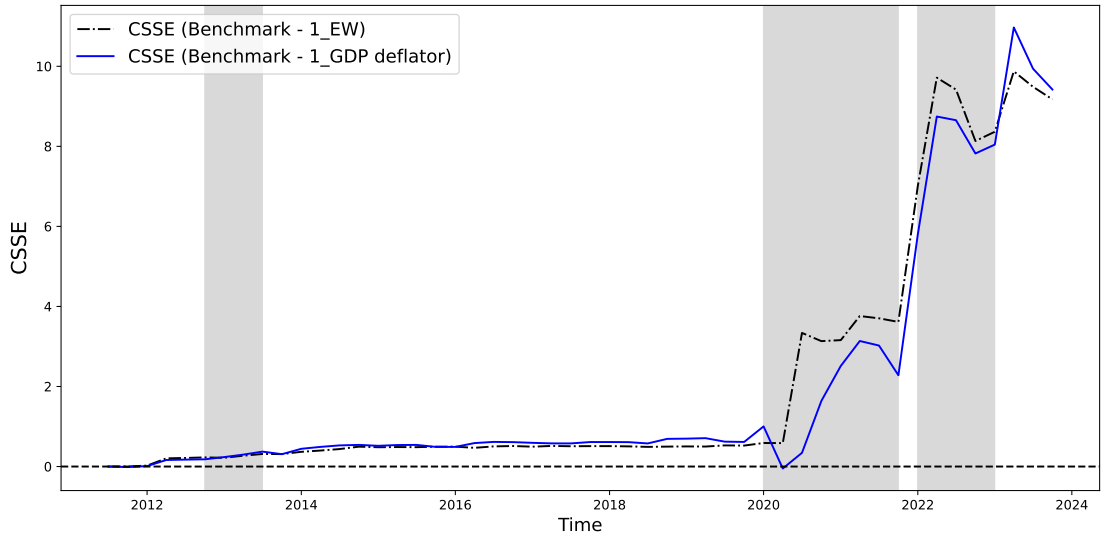

Figure 6: Cumulative Sum of Squared Errors (CSSE) of predictions. Comparison between: (i) predictions using the first lag of the GDP deflator to deflate the corporate cost indicator, and (ii) predictions using the equally weighted estimate of the first lags of price indices. Results are based on an expanding window estimation.

Note: Models are estimated using OLS on an expanding window with an initial training period of 12 quarters and predicting the subsequent quarter. The first training window in the dataset spans from 2008Q3 to 2011Q2. There are N=50 predictions for the total period covering 2011Q3 to 2023Q4. Economic subperiods are marked by the grey areas: (i) the financial crisis (2008Q3-2010Q3), (ii) the European debt crisis (2012Q4-2013Q2), (iii) the COVID-19 crisis (2020Q1-2021Q3), (iv) the energy crisis (2022Q1-2022Q4).

In this paper, we investigate this timing issue in the context of nowcasting real GDP growth, for which corporate cashflows observed in bank transaction data provide a timely source of information. Specifically, we examine whether adjusting these data for inflation improves their ability to nowcast real GDP growth, and how the choice of price index and the lag of the inflation measure influence this performance. We argue that the time lag of the inflation measure used to deflate the data is critical, as it reflects the gap between when prices are set (at the time of order) and when payments occur.

Our results show that using inflation from the previous quarter, rather than the current one, significantly improves predictive performance. In particular, deflating the corporate cost indicator with the first lag of the GDP deflator, or using an equally weighted estimate of the first lags of price indices, consistently outperforms the benchmark model that does not adjust for inflation and models using contemporaneous inflation, across different settings and periods. In the best-performing setting, the model using the GDP deflator outperforms the benchmark in 68% of cases and achieves a maximum RMSFE reduction of 5.5%. The equally weighted approach improves upon the benchmark in 54% of cases and attains a maximum RMSFE reduction of 3.78%.

These findings have important implications for nowcasting practices using transaction data. They suggest that relying on the most recent inflation data to deflate series, or attempting to nowcast lagged figures such as the GDP deflator, may be unnecessary or even counterproductive. Instead, using lagged inflation data often provides more informative signals for accurately capturing real economic activity. This improvement in accuracy is particularly relevant for investors, policymakers, and businesses, who require not only timely but also reliable estimates to make informed decisions, especially in periods of economic uncertainty.

Although our study has several strengths, such as the use of real-time data that account for first releases and revisions, in line with a real nowcasting exercise, and the consistency of

our results across both the full sample and the period excluding the COVID crisis, our data set remains relatively short in terms of observations. This is in part due to the low frequency of the target variable, namely, quarterly GDP growth. A larger dataset would provide greater statistical power and robustness to the results, while also enabling a more extensive analysis of performance across more crises and different states of the economy. Moreover, it would be valuable and a promising avenue for future research to evaluate the extent to which the findings also apply to practitioners working with invoice data, as a similar issue arises given that invoices themselves typically lag behind the actual order date.

Finally, extending this study to other countries would enhance its external validity. The approach and insights of our study are broadly applicable beyond Belgium. Adjusting nominal data for inflation to obtain real values is a universal principle, and the time gap between order and payment is a common feature of commercial transactions. However, findings regarding the length of this time lag may not be fully generalizable, as invoicing and payment regulations vary across countries. Within Europe, these findings are likely more transferable, given the European directive that standardizes payment terms.

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A Transforming corporate bank transaction data into sectoral cost growth indicators

Throughout the paper, we use the cost indicator developed by Boudt et al. (2026). The cost indicator reflects firms' outflows related to the purchase of goods and services used in production such as supplier payments, utilities, rent, and other operating expenses. While rising costs typically indicate expanding activity, inventory accumulation, or input price pressures, declining costs may signal weaker demand or cost-cutting behavior.

The starting point is a pseudonymized dataset of transactions from BNP Paribas Fortis with extensive corporate coverage, as the largest bank in Belgium. Each record contains anonymized identifiers for the sender and receiver, transaction amount, and execution date. All processing occurs on the bank's secure infrastructure, ensuring privacy and compliance with data governance standards. We restrict attention to active firms, defined as accounts exhibiting at least € 4500 in quarterly revenues during each of the preceding four quarters.

A.1 Step 1: Enriching the data with a cost label

We first enrich each transaction with a label indicating whether it is a corporate cost. Following Boudt et al. (2026), we identify costs as outgoing corporate cashflows that represent payments to suppliers and service providers, excluding (i) wage payments, and (ii) internal financial transfers such as movements between investment or loan accounts. Through this filtering, we isolate the cash movements most closely linked to firms costs.

The dataset covers the period 2008–2024 and comprises information on more than 600,000 firms. On average, approximately 300,000 firms are active in each quarterly sample, representing roughly one quarter of all VAT-registered firms in Belgium. In total, the dataset includes on the order of €3 trillion in outgoing transactions across more than 2 billion observations, of which approximately 73% are classified as cost-related cash flows. All figures are rounded.

A.2 Step 2: Aggregation of transaction-level costs to rolling-quarter cost cashflows

We then aggregate the daily outgoing transactions into daily cost cashflows. To mitigate the influence of outliers and rare accounting corrections, we apply transaction-level winsorization at the 99^{th} percentile.

To align high-frequency transaction data with quarterly economic concepts, we partition time into pseudo-weeks: each month is divided into four pseudo-weeks, where the first three weeks consist of seven days and a final one of variable length, between 7 and 10 days. Within each pseudo-week, we distinguish between working and non-working days and adjust cashflows to represent an average quarter with 63 working and 28.33 non-working days. Aggregating the daily cost cashflows per pseudo-week results in a weekly working-day standardized cash flow $CF_{s,i,w}$, for firm i in sector s for week w.

To align the indicator with GDP, we are interested in the quarterly frequency. For every week w, we sum the twelve preceding weekly cashflows, resulting in the weekly rolling-quarter cash flow $QCF_{s,i,w}$ for firm i in sector s in week w:

$$QCF_{s,i,w} = \sum_{j=0}^{11} CF_{s,i,w-j}, \tag{8}$$

This indicator smooths short-term volatility while preserving high-frequency responsiveness.

A.3 Step 3: Aggregation to sector level corporate cost growth indicators

Next, firms are grouped by NACE sector. Within each sector s, we compute outlier-resistant averages using the trimmed mean at the 99^{th} percentile of firm-level cashflows. Every quarter, we separate continuing firms from new clients, to avoid compositional distortions. Within-year seasonality is removed via multiplicative week-of-year seasonality factors, estimated from pre-pandemic years using a rolling multi-year window. This yields a seasonally adjusted sectoral cash flow indicator $\overline{QCF}_{s,w}$ for week w. Finally, the sectoral indicators are turned into quarterly growth rates as follows:

$$gCOST_{s,t} = \frac{\overline{QCF}_{s,w_t}}{\overline{QCF}_{s,w_t-12}} - 1, \tag{9}$$

where w_t denotes the last pseudo-week of quarter t.