Economic Modelling 141 (2024) 106871

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

Disentangling demand and supply inflation shocks from electronic payments data[☆]

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ARTICLE INFO

JEL classification:
C1
C4
C5
E0
E3
E5

Keywords:
Emerging economy
COVID-19
Inflation
Supply and demand shocks
SVAR

ABSTRACT

We propose a novel way to track inflation dynamics by identifying supply and demand shocks at a highly disaggregated level using electronic payments data. We estimate SVAR models and group historical decompositions at the product level into categories of the CPI. Our approach differs from others by explicitly estimating the shocks and retrieving their time-series dynamics. This information is valuable for monetary policy design, as it allows us to assess: (i) the type of shock driving any inflation category, (ii) whether shocks are generalized or driven by large shocks to specific items, and (iii) how the shocks evolve over time. An application to Chile suggests three distinct phases of inflation dynamics since COVID-19. In 2020, negative supply and demand shocks nearly offset each other. In 2021, demand shocks were boosted by massive liquidity injections. In 2022, global supply shocks introduced additional pressures on top of already elevated inflation.

1. Introduction

The post-COVID surge in global inflation, fueled by disruptions in global supply chains, significant fiscal stimulus, and the war in Ukraine, surprised economists, policymakers, and investors alike (Reis, 2022). A growing body of research attributes this phenomenon to both supply and demand factors (e.g., Jordà et al., 2022). Understanding the relative contribution of these factors is crucial for monetary policy design. While monetary policy can influence demand, its effectiveness in achieving price stability hinges on supply-side factors outside its control.[1]

The pandemic-induced lockdowns presented significant challenges for forecasters and policymakers in accurately quantifying and assessing the current and future state of the economy. This situation ignited a renewed interest in identifying alternative indicators for real-time tracking of macroeconomic variables (Aastveit et al., 2020).

In this study, we explore the potential of leveraging price and quantity indices derived from electronic payments data to decompose

☆ We thank the editor, associate editor, and two anonymous reviewers. We are also grateful to seminar participants at the Central Bank of Chile, participants of the XXVIII Meeting of the Central Bank Researchers Network at CEMLA, and conference attendants at LACEA 2023 for their valuable comments and suggestions. The views expressed are those of the authors and do not necessarily represent the views of the Central Bank of Chile or its board members. All errors are our own. This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs of its competence. The CBC 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 CBC 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 the Chilean IRS. 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.

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[1] The idea that the response to inflation caused by supply shocks should be limited arises from the inherent tradeoff associated with these shocks. Supply shocks tend to push prices and employment in opposite directions, while monetary policy influences them in the same direction. Therefore, the central bank's response to higher prices due to an adverse supply shock should be restrained to avoid worsening the unwanted decline in employment (for an example in the context of energy price shocks, see Bodenstein et al., 2008).

https://doi.org/10.1016/j.econmod.2024.106871
Received 11 October 2023; Received in revised form 14 August 2024; Accepted 21 August 2024
Available online 28 August 2024

inflation into its supply- and demand-driven components. Highly disaggregated data from electronic payments offer several advantages: timeliness, lack of revisions, and strong correlations with economic activity due to their direct link to real-world transactions (Aprigliano et al., 2019). These characteristics position electronic payments data as a promising candidate not only for tracking traditional macroeconomic variables – with previous literature primarily focusing on GDP and consumption (details below) – but also for extracting information about the relative contributions of supply and demand forces shaping inflation dynamics.

To achieve this goal, we propose a novel, product-level approach that leverages monthly price and quantity indices constructed from electronic payments data, encompassing a significant share of the Chilean Consumer Price Index (CPI) basket. These indices serve as the foundation for estimating Bayesian Structural Vector Autoregressions (SVARs) for each product, employing a sign restrictions identification scheme (Rubio-Ramirez et al., 2010). This scheme leverages established economic theory, assuming that a demand shock induces price and quantity to move in the same direction (denoted as a positive shock shifting the demand curve to the right, and a negative shock to the left, with no movements in the supply curve), while a supply shock pushes them in opposite directions. Historical decomposition of inflation from the SVAR models at the product level can subsequently be used to compute any sub-aggregate, using the official CPI weights.

Our electronic payments data provides price and quantity indices spanning from February 2018 to November 2022. This timeframe encompasses the COVID-19 pandemic period and the subsequent surge in inflation. Notably, the Chilean economy experienced unique characteristics during this interval, making it a compelling case study for our approach. These idiosyncrasies include a series of shocks that began with social unrest in late 2019, followed by the COVID-19 outbreak in March 2020. Additionally, Chile witnessed a sequence of unprecedented economic events, including three distinct "one-time-only" withdrawals from pension funds authorized by Congress. These withdrawals, totaling US $50 billion (approximately 20% of GDP), occurred in July 2020, December 2020, and May 2021. Furthermore, significant fiscal transfers were implemented, with households receiving direct support measures reaching 15% of GDP in late 2020 and 2021, culminating in a cumulative total of 35% of GDP within a year and a half. This series of unprecedented shocks provides an ideal context to unravel the factors influencing inflation dynamics, illustrating how our decomposition sheds light on these shocks beyond those arising from the pandemic.

Our study yields two key findings. First, we demonstrate that our electronic payment data indices provide timely and reliable indicators for monitoring demand- and supply-driven inflation shocks in the Chilean context. Second, our estimates provide a coherent narrative explaining the evolution of inflation dynamics since the pandemic. To our knowledge, this is the pioneering attempt in the literature to disentangle the structural macroeconomic drivers of inflation using highly disaggregated data from electronic payment records. Our methodology showcases how readily available quantity and price indices can be leveraged to decompose inflation contributions from demand and supply shocks. While our analysis focuses on Chile, we aim to encourage other countries, especially those with accessible electronic payment data, to develop similar indices for inflation and its underlying drivers.

Our historical decompositions from the SVAR models reveal distinct inflation dynamics in Chile across three periods. The initial phase, coinciding with the pandemic's onset, was characterized by a combination of negative supply and demand shocks. Notably, these shocks were of similar magnitude in absolute value, leading to a near offsetting effect on inflation. In the second period (2021), the easing of restrictions and household liquidity injections fueled a surge in demand for goods. This demand shock intensified throughout the year, outpacing supply recovery and driving a significant acceleration in goods inflation. Finally, 2022 witnessed new pressures on top of already elevated inflation. The war in Ukraine and China's zero-COVID policy triggered a substantial rise in commodity prices and disruptions in global supply chains, leading to additional supply shocks. Interestingly, the narrative derived from our decomposition aligns with that of a large-scale structural DSGE model estimated by the Central Bank of Chile using macroeconomic aggregates. This alignment provides indirect validation for the effectiveness of our approach.

While providing a coherent macroeconomic narrative on inflation dynamics, our product-level decomposition offer valuable insights for monetary policy design. We explore four key applications that demonstrate the utility of our approach. First, our analysis can shed light on the inflationary impact of specific events. Consider the case study by Cavallo and Kryvtsov (2023), examining global supply bottlenecks during the pandemic and focusing on imported goods across seven countries. Our approach delves deeper, elucidating the specific shocks driving price behavior for these imported products. This granularity allows for a more nuanced understanding of how such events influence inflation across different product categories. Second, our decomposition framework aids in testing economic theories. For example, Cravino et al. (2020) propose a novel mechanism where monetary policy shocks can lead to distributional consequences by affecting prices differently across products and income levels. We argue that our framework can contribute to testing such theories by providing disaggregated data that isolates the effects of these shocks on specific product categories. Third, we discuss how our granularity can be useful for calibrating Heterogeneous Agent New Keynesian (HANK) models, as recently emphasized by Violante (2021), who underscores the significance of administrative data for this task. Finally, the granularity of our results could significantly assist central banks in refining their communications, facilitating more precise and impactful messaging. Indeed, Coibion et al. (2022), among others, demonstrate that when central banks communicate inflation drivers explicitly, households and businesses form more accurate expectations about future inflation and economic conditions. These applications not only highlight the potential utility of our analysis but also underscore the crucial role that disaggregated data plays in shaping monetary policy formulation.

Our findings demonstrate robustness across two key dimensions. First, there is a vast and long-standing literature discussing the informational losses vs. estimation uncertainty trade-off that arises when disaggregating macro variables for econometric modeling.[2] We show that estimating historical decomposition directly for EPD-based CPI categories, rather than aggregating the product-level decompositions, produces a similar narrative. Second, our results are robust to additionally identifying exchange rate shocks, which could be confounded with supply shocks.

The remainder of the paper is organized as follows. Section 2 provides a brief literature review. Section 3 describes our dataset. Section 4 describes the empirical methodology and Section 5 the main results. Section 6 reports robustness checks, and Section 7 concludes.

2. Related literature

Our work is related to four main strands of the literature. First, it aligns with research using payment transaction data for forecasting purposes. Studies conducted for Canada (Galbraith and Tkacz, 2018), Chile (Cobb, 2021), Denmark (Carlsen and Storgaard, 2010),

[2] See, for instance, Kohn (1982), Lütkepohl (1987), and Clark (2000), and for more recent developments, Giacomini and Granger (2004) and Hendry and Hubrich (2011). The more specific discussion on the costs and benefits of disaggregating inflation series has also attracted attention, e.g Bils and Klenow (2004), Lunnemann and Mathä (2004), Imbs et al. (2005), Clark (2006), Boivin et al. (2009), and Beck et al. (2016) for discussions on price stickiness, and Bermingham and D'Agostino (2014), Espasa and Mayo-Burgos (2013), and Carlomagno and Espasa (2021), for discussions on inflation forecasting.

Italy (Aprigliano et al., 2019), Ireland (Byrne et al., 2020), the Netherlands (Verbaan et al., 2017), Norway (Aastveit et al., 2020), Portugal (Esteves, 2009; Duarte et al., 2017), and the US (Barnett et al., 2016), indicate that payment transaction data is valuable for nowcasting and forecasting GDP and private consumption in the short term. Other research employs similar data to quantify the impact of the COVID-19 pandemic on consumption expenditure in various countries, including China (Chen et al., 2021), Denmark (Andersen et al., 2022), France (Bounie et al., 2023), the Netherlands (Pascal et al., 2020), Spain (Carvalho et al., 2020), and the US (Baker et al., 2020).

Our research focuses specifically on inflation decomposition at the product level, deviating from prior studies that primarily analyze economic activity. A key advantage of our approach lies in the utilization of electronic payments data. This data offers a unique advantage: detailed information on quantities sold for individual products. The combination of price and quantity indices constructed from this data allows us to estimate inflation decomposition not only at the product level but also for broader CPI categories. To the best of our knowledge, this study represents the first attempt in the literature to leverage such disaggregated price and quantity indices from electronic payments data to identify demand and supply shocks at the product level.

Second, our work relates to the emerging literature on the use of alternative high-frequency data to monitor inflation. The use of information from online prices obtained from retailers' web pages to track inflation, pioneered by Cavallo and Rigobon (2016), has gained a lot of momentum following the COVID-19 pandemic (see, e.g. Macias et al., 2023, and the references therein). Exploiting information from social media, Angelico et al. (2022) and Born et al. (2023) construct Twitter-based inflation indicators for Italy and Germany, respectively, demonstrating that they closely track CPI inflation and inflation expectations. Müller et al. (2022) employs media coverage of inflation to build newspaper-based inflation indices for Germany. Our work adds to this literature by showcasing the benefits of building indicators from alternative data sources, specifically focusing on electronic payments data and its application to inflation monitoring by estimating identified supply and demand shocks.

Third, our paper is connected to recent empirical contributions that employ disaggregated data to distinguish supply and demand drivers during the COVID-19 pandemic in macroeconomic variables. Examples of this research are varied. For the labor market, del Rio-Chanona et al. (2020) provide quantitative predictions of supply and demand shocks for the US economy at the level of individual occupations and industries. Brinca et al. (2021) measure labor demand and supply shocks at the sector level by estimating Bayesian SVAR models on monthly statistics of hours worked and real wages.

Regarding price dynamics, Schneider (2023) identify sector-specific supply and demand shocks to personal consumption expenditure (PCE) inflation in the US by imposing heterogeneity restrictions in a Factor Augmented VAR model using sectoral data on PCE inflation and consumption growth. Shapiro (2020, 2022) decomposes inflation in the US by running separate price and quantity reduced-form regressions on each of the categories that make up the PCE. Categories are then labeled as supply- or demand-driven based on the signs of residuals in the price and quantity regressions. These estimates are subsequently used to group categories into components of PCE inflation. In contrast to these papers, we employ a higher level of disaggregation as we employ product-level quantity and price indices from electronic payments data.

The approach of Shapiro (2022) is the most closely related to ours, as he also tries to identify supply and demand shocks from disaggregated prices and quantities. However, there are major methodological differences between his and our strategy. Shapiro (2022) employs a binary approach (Jump and Kohler, 2022) to label PCE categories as predominantly demand- or supply-driven, neglecting cases in which both factors may be contributing in the same or opposite direction at a certain point in time. In contrast, our approach relies on a SVAR models where supply and demand shocks are identified with sign restrictions (Rubio-Ramirez et al., 2010) at the product level. Under this setting, for a given period t, supply and demand shocks may coexist not only due to contemporaneous effects but also due to lagged dynamic effects.

These methodological differences translate into two key advantages for our approach. First, we can decompose any CPI item into its constituent supply and demand shocks at each point in time. This offers a more detailed understanding compared to Shapiro (2022) approach, which categorize items as solely supply-driven or demand-driven. Second, our framework allows us to directly measure how the magnitude of structural supply and demand shocks evolves over time. Shapiro's procedure, by contrast, focuses on classification and cannot estimate these dynamic changes in shock size.

Finally, this paper is also related to a large strand of the literature that employs SVAR strategies to identify macroeconomic shocks (see e.g., Blanchard and Quah, 1993; Dungey and Fry, 2009; Leu, 2011; Cover and Mallick, 2012; Jiang and Kim, 2013; Chatziantoniou et al., 2013; Mertens and Ravn, 2014; Arias et al., 2019). Our approach departs from this literature by leveraging the rich detail of electronic payments data. This granularity allows us to pinpoint instances where macroeconomic shocks stem from a few specific sectors, rather than generalized effects rippling across the entire economy. As we argued above, this fine-grained analysis can also prove valuable in assessing the inflationary impacts of specific events, testing established macroeconomic theories, refining model calibrations, and ultimately, enhancing central bank communication.

3. Data

3.1. Electronic payments data

In this section, we present the electronic payments data (henceforth, EPD) employed in our analysis and show their usefulness in tracking inflation in Chile. We employ monthly price and quantity indices constructed from Chilean administrative records from the VAT registry maintained by the Internal Revenue Service and processed by the Central Bank of Chile. The dataset is anonymized but still confidential and is available from February 2018.[3] From this data, one can retrieve information about what goods and services are sold, in what quantities, and at what prices.

It should be noted that a single product may have different varieties, and what we actually obtain is information at the variety level, rather than the product level. This information is then aggregated to obtain the products included in the CPI basket. The product level represents the highest level of disaggregation for the CPI regularly published by the National Institute of Statistics (the Chilean Statistical Office).

Table 1 summarizes the coverage of the EPD for different categories of the official Chilean CPI. The base 2018-CPI basket consists of 303 products grouped into 12 broad categories. The EPD covers 10 categories and the product coverage is somewhat heterogeneous: it covers well food and beverages, alcoholic beverages, furnishing, and restaurants, but they are less successful in capturing clothing and footwear, housing, health, transport, recreation, and miscellaneous. Furthermore, the EPD does not cover the categories of communication and education.

Similarly, Table 2 summarizes the coverage of EPD for some selected CPI aggregates. Of particular interest, are the *core* aggregates, including the Central Bank's preferred measure of core inflation, also known as *non-volatile inflation*.[4] We notice that coverage is pretty good for core

[3] The use of electronic invoices started in 2003, but it became mandatory for all firms in 2014. Starting from February 2018, the price and quantity indices from electronic payments data cover a significant share of the Chilean CPI, as shown in Table 1. For further details about the dataset and its construction, see Acevedo et al. (2023).

[4] For details of the *non-volatile* inflation measure, see Carlomagno et al. (2023).

Table 1
Official CPI categories and Electronic Payments Data (EPD) coverage.

	CPI category	Weights (%)	Products	Covered products	Covered weights (%)
1	Food and beverages	19.3	76	70	92
2	Alcoholic beverages	4.8	8	8	100
3	Clothing and footwear	3.5	28	12	43
4	Housing	14.8	16	5	31
5	Furnishings	6.5	36	28	78
6	Health	7.8	22	7	32
7	Transport	13.1	24	8	33
8	Communication	5.5	6	0	0
9	Recreation	6.6	37	12	32
10	Education	6.6	11	0	0
11	Restaurants	6.4	7	6	86
12	Miscellaneous	5.2	32	17	53
	TOTAL	100	303	177	48

Note: The CPI weight is the share of expenditure in a given category over total expenditures as reported by the National Institute of Statistics.

Table 2
Official CPI categories and Electronic payments Data (EPD) coverage.

	CPI aggregate	Weights (%)	Products	Covered products	Covered weights (%)
1	CPI total	100	303	173	57
2	CPI core	65.15	161	81	49
3	CPI core goods	26.72	135	112	83
4	CPI core goods excl. food	17.53	95	74	78
5	CPI core services	38.42	69	7	10
6	CPI non-core food	10.11	36	32	89

Note: The CPI weight is the share of expenditure in a given category over total expenditures as reported by the National Institute of Statistics.

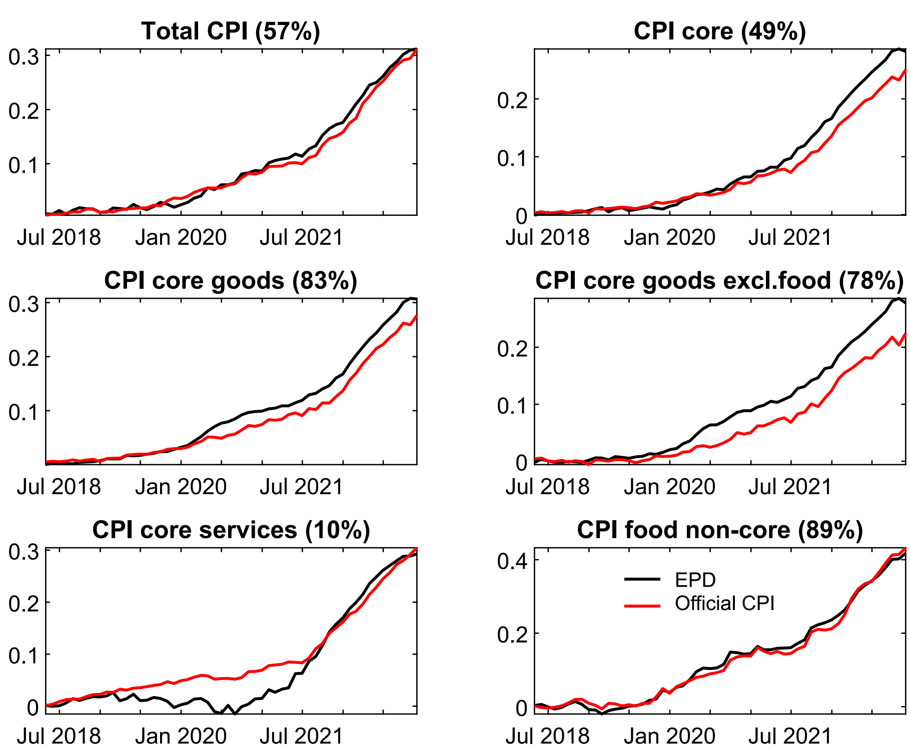

Fig. 1. Electronic payments data and official CPI for different aggregates in levels. Notes: Aggregates are constructed from price indices at the product level covered by our electronic payments data (EPD) and re-weighted using original CPI weights. Values in parentheses indicate the share of products covered by EPD within the respective category.

goods (83%), core goods excluding food (78%), and non-core food (89%), but not so for core services (10%). In Fig. 1 we plot the profile of several CPI aggregates in levels and observe that index levels based on EPD data resemble those constructed using CPI indices.

3.2. A simple validation exercise

To establish alignment between our EPD and official CPI data, we conduct a straightforward validation exercise. We first construct

Table 3
Nowcast of ΔCPI_t using Electronic payments Data (EPD).

	(1)	(2)	(3)	(4)	(5)	(6)
β_1	0.55***	0.61***	0.78***	0.57***	0.35***	1.00***
	(0.11)	(0.11)	(0.12)	(0.20)	(0.09)	(0.11)
Reject $H_0 : \beta_1 = 1$	***	***			***	
Observations	56	56	56	56	56	56
R^2	0.36	0.37	0.45	0.21	0.33	0.73
Adj. R^2	0.35	0.36	0.44	0.20	0.32	0.73

Note: Estimates from the nowcast regression specified in Eq. (1). Sample estimation from February 2018 to November 2022. Newey–West standard errors with one lag reported in parentheses with *, **, and *** corresponding to 10%, 5%, and 1% significance, respectively. Columns 1 to 6 represent aggregates 1 to 6 of Table 2.

aggregate indices that mirror the product coverage of the EPD, utilizing the official weights of the CPI basket as outlined in Table 2. Then, we estimate the following individual regressions:

$$\Delta CPI_{it} = \beta_{0i} + \beta_{1i}\Delta CPI_{it}^{EPD} + u_{it}, \tag{1}$$

where ΔCPI_{it} and ΔCPI_{it}^{EPD} denote the monthly log changes in the CPI and the EPD-based CPI at month t, respectively, and the sub-indices i, denote the aggregate, with $i = 1, \dots, 6$ ordered as in Table 2.

The validation strategy consists of testing the null hypotheses of $\beta_{1i} = 0$, and $\beta_{1i} = 1$. Results are summarized in Table 3. With regards to the first hypothesis, we find that for all of the aggregates considered, the estimated coefficients on ΔCPI_i^{EPD} are statistically significant at the 1% level. The second hypothesis ($\beta_{1i} = 1$) is rejected only for overall CPI (column 1), CPI core (column 2) and CPI core services (column 5). This is expected given that CPI core services are poorly measured by electronic payments data, which also biases overall CPI and CPI core. As a result, EPD-based aggregates pass the acid test for core goods, but not so for aggregates including services.

In summary, our electronic payments indices effectively track CPI categories with high coverage, exhibiting strong correlations ranging from 0.7 to 1. In subsequent sections, we present a more rigorous analysis using structural identification of shocks to further validate the reliability of our data.

4. Empirical framework

In this section, we describe how we decompose inflation into demand and supply shocks at the product level. We use a Bayesian Vector Autoregression (BVAR) to model the joint dynamics of monthly log changes in the price ($\Delta p_{i,t}$) and quantity ($\Delta q_{i,t}$) indices for each product i in the CPI basket covered by our electronic payments data. Our estimates can then be grouped into different categories of CPI inflation using official CPI weights.

4.1. Reduced-form VAR

Consider a structural vector autoregression (SVAR) model:

$$A_0 y_t = c^* + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \epsilon_t, \qquad t = 1, \dots, T, \tag{2}$$

where $y_t = [\Delta p_t, \Delta q_t]'$ is a 2×1 vector of observed variables (for ease of notation we have omitted the index i for each product), p is the lag order, A_j are fixed 2×2 coefficient matrices for $0 \leq j \leq p$, with A_0 invertible, c^* is a 2×1 fixed vector of constants, and ϵ_t are the structural shocks with zero mean and covariance matrix I_2. The reduced-form VAR model obtained from (2) can be written as:

$$y_t = c + B_1 y_{t-1} + \cdots + B_p y_{t-p} + u_t, \qquad t = 1, \dots, T, \tag{3}$$

where $B_j = A_0^{-1} A_j$, $c = A_0^{-1} c^*$ and $u_t = A_0^{-1}\epsilon_t$ are the reduced-form residuals with covariance matrix $E(u_t u_t') = \Omega = (A_0' A_0)^{-1}$.

We set $p = 1$ and rely on Bayesian techniques to estimate the model. Given that we consider growth rates in price and quantities indices for each product in our VAR models, we specify the prior belief that these variables follow an AR(1) process.[5] Details of the Bayesian estimation are outlined in Appendix.

Table 4
Sign restrictions imposed on impact responses.

Shocks/Variables	Δp_t	Δq_t
Demand shock	+	+
Supply shock	+	−

4.2. Identification strategy

We identify as many structural shocks as variables. Structural shocks can be computed from reduced-form residuals as:

$$\epsilon_t = A_0 u_t, \tag{4}$$

where A_0 is the matrix of contemporaneous dependencies of prices and quantities. We follow the microeconomic literature and assume that demand (supply) shocks move prices and quantities in the same (opposite) direction. More specifically, we define a positive (negative) demand shock as one that implies a shift of the demand curve of product i to the right (left). Thus, with a fixed upward-sloping supply curve, a demand shock moves equilibrium prices and quantities in the same direction. Similarly, a positive (negative) supply shock moves the supply curve to the right (left) which, given a fixed downward-slopping demand curve, moves equilibrium prices and quantities in the opposite direction.

In our SVAR models, the structural shocks are identified by imposing traditional sign restrictions on the impulse response functions (IRFs), following the approach by Rubio-Ramirez et al. (2010). In particular, we require that the impact of demand and supply shocks satisfy the sign restrictions given in Table 4. For each product i covered by our data, we generate 1000 draws satisfying the sign restrictions and select the median target (MT) solution (Fry and Pagan, 2005, 2011). After obtaining the MT solution for each product, computing all objects of interest, such as historical decompositions and forecast error variance decompositions, is straightforward. These objects can be grouped into specific CPI categories using official CPI weights, as described in the preceding section. We delegate the details of the sign restrictions identification and the model selection via the MT solution to Appendix.

5. Estimation results

In this section, we showcase our main findings by presenting historical decomposition exercises.

5.1. Three phases for Chilean inflation since the pandemic

In Fig. 2, we present the historical decompositions for the main EPD-based CPI aggregates, covering the period from March 2020 until November 2022. We find that inflation dynamics since the start of the pandemic can be characterized by three periods. The first period corresponds to the onset of the pandemic when the economic shutdown caused a supply shock pushing inflation upwards. Simultaneously, restrictions to mobility and precautionary savings generated a drop in

[5] Given our short sample data, we employ Bayesian methods for estimation. These methods do not rely on asymptotic theory. Instead, they require a specification of distribution priors about the parameters being studied, which helps stabilize estimates, especially in small samples (see, e.g., Greenberg, 2014, pg. 22, 41). In our estimation, we have selected a short number of lags; however, the results are robust to different lag selections—details are available upon request.

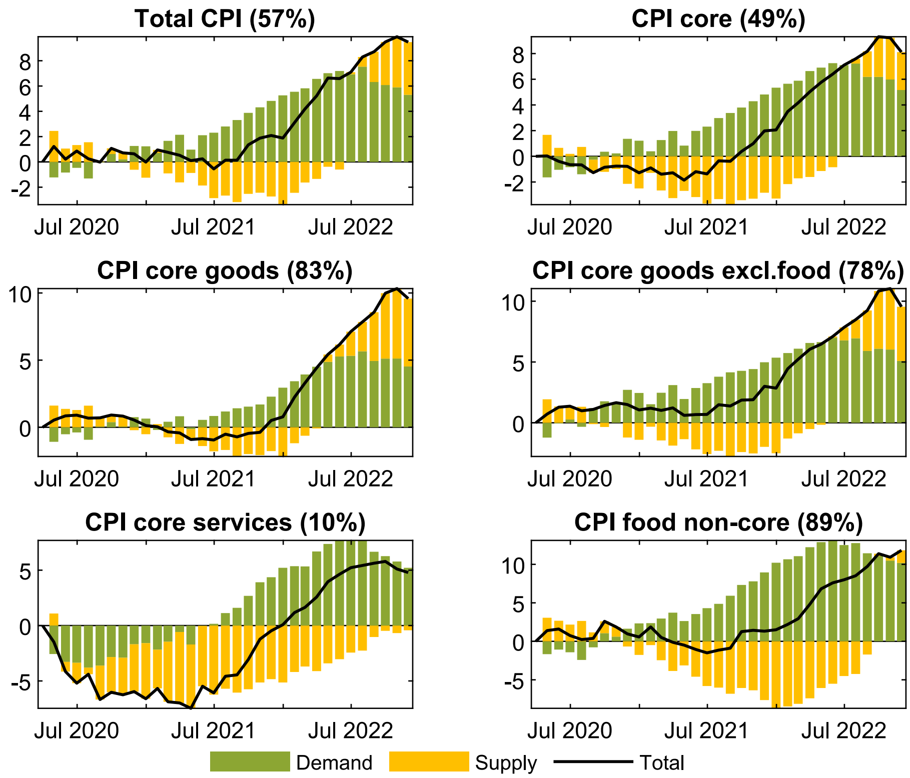

Fig. 2. Historical decomposition (HD) of main EPD-based CPI aggregates. Notes: The HD is computed from SVAR models estimated at the product level using Chilean electronic payments data (EPD) and then aggregated using official CPI weights. The HD is expressed as deviations from zero. We index March 2020 = 0 and cumulate onwards. Values in parentheses show the percentage of the total aggregate covered by EPD.

demand, pulling inflation in the opposite direction. These two shocks nearly cancelled each other out, which helps to explain why prices hardly moved at the beginning of the pandemic.

During the second period, in 2021, supply began to normalize as companies adapted to restrictions, and supply chains came back online. Simultaneously, the lifting of stay-at-home restrictions, coupled with the massive liquidity injections to households described in the introduction, triggered a surge in demand for goods (Cobb, 2021). This demand shock continued to intensify throughout the year, surpassing the pace of supply recovery and propelling a significant acceleration of goods' inflation.

Finally, at the beginning of 2022, amidst strong demand, the Russian invasion of Ukraine and China's zero-COVID policy led to a substantial increase in commodity prices and disruptions in global supply chains. Consequently, additional supply shocks occurred on top of the already elevated inflation levels due to strong demand. As the year progressed, demand pressures began to subside, aligning with the conclusion of liquidity injections and the implementation of restrictive monetary policy. At the same time, supply pressures exhibited signs of stabilization, driven by a decrease in international raw material prices and a reduction in global supply chain disruptions.

These results are consistent with those obtained with the structural DSGE model estimated by the Central Bank of Chile based on macroeconomic aggregates.[6] This serves as an external validation of our strategy. From a policy perspective, our approach offers a crucial advantage: policymakers can track sectors leading the macro shock. Are all sectors affected similarly? Are there sectors experiencing a different type of shock than the aggregated one? Answering these questions can inform diverse policy designs, and our approach is well-equipped to provide these insights. We delve into this point by providing specific examples in Section 5.3.

[6] We refer the reader to the official Central Bank's narrative and results in Figure II.8 of the Monetary Policy Report of September 2022 here.

5.2. How important are supply and demand shocks in explaining CPI volatility?

Fig. 3 presents the one-step-ahead forecast error variance decomposition (FEVD) for several Electronic Payments Data (EPD)-based CPI aggregates. Our analysis reveals that, on average, supply and demand shocks contribute roughly 60% and 40% respectively to the variance of inflation. This finding suggests that both types of shocks hold similar weight in driving short-term inflation fluctuations across various categories. This is an important insight for central banks, as they typically require different policy responses to address supply-driven versus demand-driven inflation.

5.3. Insights from product-level decompositions

While this study aims to propose and showcase how price and quantity indices from EPD can be leveraged to understand the supply and demand drivers of inflation, we also discuss four applications where our product-level decomposition can provide additional insights. They include evaluating the inflationary consequences of specific events, testing macroeconomic theories, improving model calibrations and enhancing central bank communication.

Assessing the inflationary impact of specific events. We take the case study of Cavallo and Kryvtsov (2023) as an example. They investigate the inflationary effects resulting from global supply bottlenecks during the pandemic, focusing on the behavior of imported products in seven countries—the US, Canada, China, France, Germany, Japan, and Spain. Using a comprehensive micro dataset on product availability and stockouts, they show that imported products experienced prolonged stockouts and higher inflation rates compared to domestically produced goods. While they offer plausible explanations for how supply and demand shocks influence their findings, they point out the following: *"Disentangling supply and demand forces [...] is outside the scope of this*

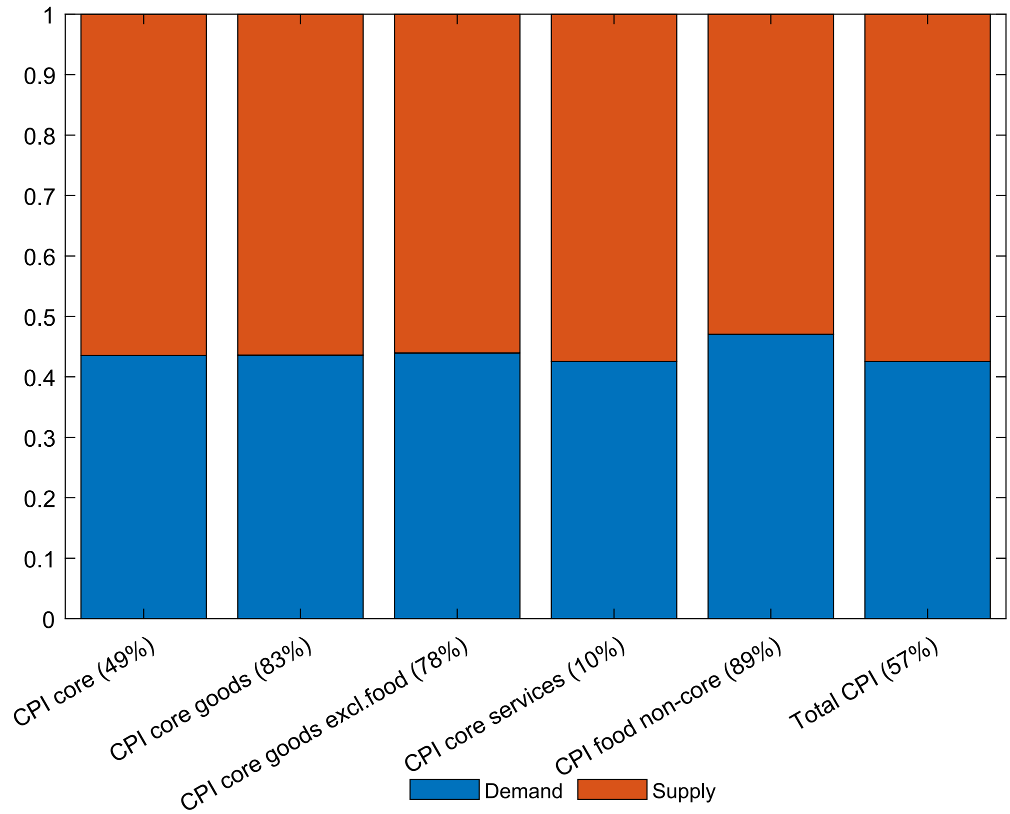

Fig. 3. Forecast Error Variance Decomposition (FEVD) of main EPD-based CPI aggregates. Notes: The FEVD is computed from SVAR models estimated at the product level using Chilean electronic payments data (EPD) and then aggregated using official CPI weights. Each bar presents the estimated contribution of each structural shock to the one-step-ahead FEVD, expressed as a percentage of the total FEVD. Values in parentheses show the percentage of the total aggregate covered by EPD.

paper, but [...] this would be a fruitful task for future research efforts". Our methodology is well-suited to tackle such an endeavour, as one can identify and group imported products and disentangle the supply and demand components within these products.

Testing theories - Distributional effects of monetary policy. Cravino et al. (2020) proposes a novel mechanism through which monetary policy shocks have distributional consequences. Their argument is as follows: if the impact of monetary policy shocks on prices vary among products (Boivin et al., 2009), and consumption baskets differ across the income distribution (see, e.g. Almås, 2012), these shocks will have diverse effects on the prices encountered by households of different incomes. Our decomposition can further help discern whether these differences are due to supply or demand factors influencing product prices and whether monetary policy shocks amplify/dampen those effects.

Calibrating heterogeneous agent models. The seminal work by Kaplan et al. (2018) on HANK models emphasizes the value of granular data for calibrating these models. Violante (2021) further emphasizes the critical need for precise and detailed data to empirically assess the mechanisms by which monetary policy influences consumption within HANK models. He specifically highlights the potential of *administrative data* in this context. Given its administrative origin, such data notably reduces the risk of measurement error – a prevalent issue in survey data – while offering granular and high-frequency information. Our indices derived from electronic payment data exemplify this type of administrative data, suggesting their significant applicability in enhancing the calibration of HANK models.

Central bank communication. The availability of a granular decomposition can significantly enhance the efficacy of central bank communication. This can allow policymakers to tailor their messages with greater precision. For example, when inflationary pressures are primarily due to supply shocks in certain sectors, central banks can specifically communicate these details, thereby setting appropriate expectations among households and businesses. This approach is underscored by Coibion et al. (2022), among others, who highlight the importance of such specificity in central bank communication.

6. Robustness checks

In this section, we discuss and provide some robustness checks. Given that core services inflation is not well captured by electronic payments data, we focus on *core goods inflation excluding food*. First, we show that our results obtained using disaggregated data resemble those obtained using more aggregated data. Second, we also show that our results remain robust when accounting for exchange rate shocks, which could be confounded with supply shocks.

6.1. Aggregated vs. Disaggregated identification

Given that core services inflation is not well captured by electronic payments data, we focus on *core goods inflation excluding food*. As mentioned in the introduction, there exists a substantial body of literature that delves into the trade-off between informational losses and estimation uncertainty when disaggregating macro variables for econometric modeling. While this debate is ongoing and is far from settled, during the pandemic, the price response to shocks was uneven across products, supporting the idea of using more granular data. We re-estimate the decomposition for the EPD-based CPI *core goods excluding food* by applying our strategy directly to this aggregate instead of adding up the product's decomposition. The historical decomposition is included in Fig. 4, closely resembling the original ones (compare Fig. 4 with the plot in the second column and first row of Fig. 2).

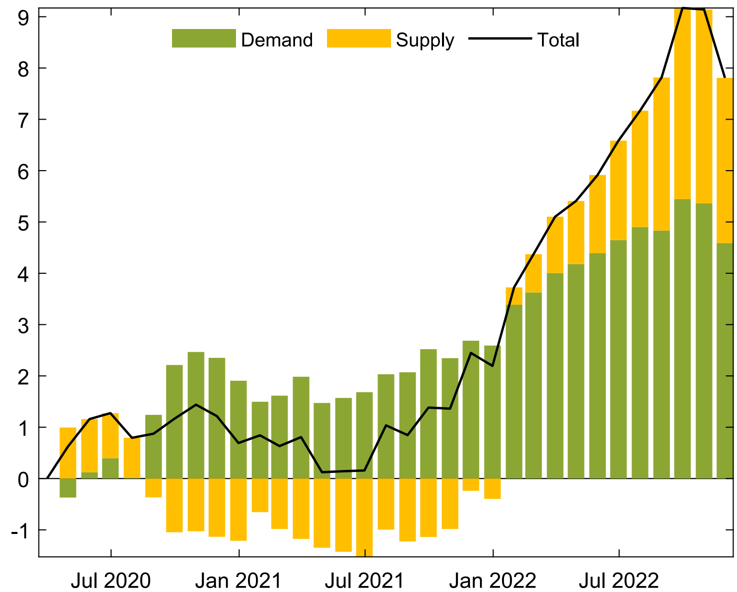

Fig. 4. Historical decomposition (HD) of the EPD-based CPI goods without volatiles excluding food. Notes: The HD is computed from a SVAR model using the aggregated EPD-based CPI category directly. The HD is expressed as deviations from zero. We index March 2020 = 0 and cumulate onwards.

Table 5
Sign restrictions imposed on impact responses.

Shocks/Variables	Δp_t	Δq_t	Δe_t
Demand shock	+	+	
Supply shock	+	−	0
FX shock	+	−	+

We are inclined to favor estimates using disaggregated data over aggregated data for three reasons. First, similar conclusions are obtained when using aggregated data. Second, from a policymaker standpoint, it can be more useful to monitor more disaggregated information on the shocks driving price dynamics at the product level as discussed in Section 5.3. Finally, the results obtained using disaggregated data also resemble those obtained using structural DSGE models for the Chilean economy, validating the narrative obtained by our strategy.

6.2. Alternative identification strategy incorporating exchange rate shocks

Our previous decomposition of inflation may encompass both pure supply shocks (e.g., those related to productive capacity) and exchange rate fluctuations. To disentangle these effects, we extend the SVAR model for each product by including exchange rate variations (Δe_t) in our identification strategy. This expanded model allows us to distinguish pure supply shocks from exchange rate shocks. The details of this identification strategy are presented in Table 5.

Similarly to the previous identification, demand shocks move prices and quantities in the same direction, irrespective of the movements in the exchange rate. On the other hand, if there is a *pure* supply shock at the product level, this should not affect the exchange rate. Therefore, we set the response of the exchange rate to zero.[7] Finally, an exchange rate shock, such as a depreciation, should resemble a supply shock, increasing the cost of goods *across the board*.

Results for this exercise are summarized in Fig. 5, focusing on core goods excluding food, which are more likely to be subject to these types of shocks. Compared to the plot in Fig. 2 we do not find significant differences. Demand shocks have been more dominant in goods inflation, whereas exchange rate shocks explain part of the supply pressures during 2021. At the margin, the decomposition suggests that these effects turned positive, yet not dominant, which coincides with the large depreciation of the Chilean exchange rate since June 2022.

7. Conclusions

This paper represents an initial attempt to showcase the significant value of highly disaggregated administrative data in disentangling the macro structural drivers of inflation. By estimating Bayesian Structural Vector Regressions on price and quantity indices derived from electronic payments data for Chile, we proposed a simple approach to help monitor and understand the inflation dynamics. As opposed to other approaches in the literature we explicitly estimate demand and supply shocks and can retrieve their time-series dynamics. Post COVID-19, our estimates suggest that economic shutdowns caused a generalized supply shock that pushed inflation up, while mobility restrictions and precautionary savings dropped demand, nearly canceling each other out. In 2021, eased restrictions and massive liquidity injections surged demand, accelerating inflation. In early 2022, the Russian invasion of Ukraine and China's zero-COVID policy raised commodity prices and disrupted supply, further increasing inflation.

Two limitations exist with our approach. First, while it offers valuable insights for the Chilean case, its applicability is currently limited due to the unique data requirements. Second, the length of our time series may raise concerns about large estimation uncertainty leading to volatile results or small samples' biases. The paper addresses this concern through robustness checks and comparisons with alternative approaches, demonstrating reassuring results.

We believe there are several interesting avenues for future research. In particular, we discussed some applications where our detailed product-level decomposition can yield a better understanding of inflation dynamics beyond just a macroeconomic viewpoint. This includes assessing the inflationary effects of specific events, testing macroeconomic theories and refining model calibrations. Additionally, the granular decomposition can significantly bolster central bank communication. Such insights not only shed light on the complex dynamics of inflation but also highlight the crucial role that detailed data plays in shaping monetary policy design.

[7] We follow the approach by Arias et al. (2018) to impose zero restrictions on IRFs.

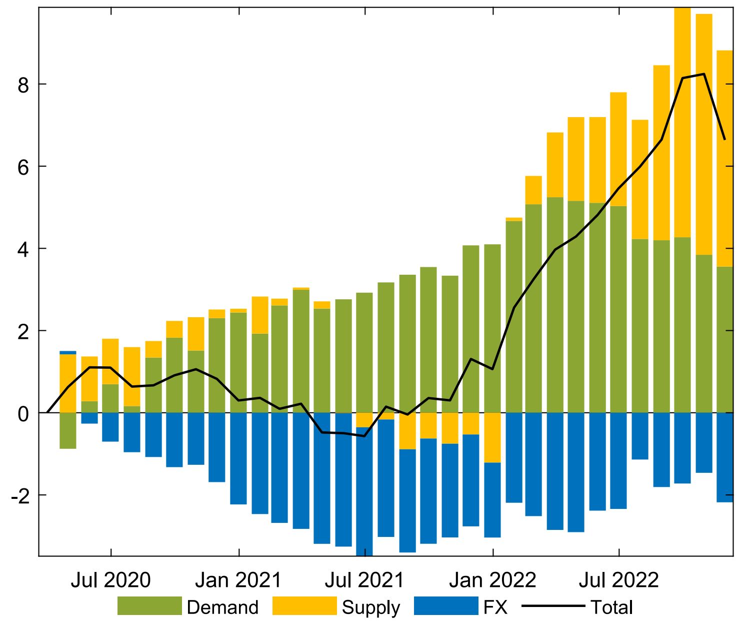

Fig. 5. Historical decomposition including FX shocks of CPI goods without volatiles excluding food. Notes: The HD is computed from SVAR models estimated at the product level using Chilean electronic payments data (EPD) and then aggregated using official CPI weights. The HD is expressed as deviations from zero. We index March 2020 = 0 and cumulate onwards.

Declaration of competing interest

No conflict of interest to declare

Data availability

The data that has been used is confidential.

Appendix. SVAR estimation details

A.1. Bayesian estimation

The reduced-form VAR model in the main text in Eq. (3) can be expressed in a more convenient form for Bayesian simulation of reduced-form parameters as:

$$y_t = X_t'\beta + u_t, \tag{A.1}$$

where

$$X_t' = I_n \otimes [1, y_{t-1}', \dots, y_{t-p}'] \ (n \ \times (pn^2 + n)),$$
$$\beta = vec([c \ \ B_1 ... B_p]') \ ((pn^2 + n) \ \times 1), \tag{A.2}$$

with $n = 2$. We sample coefficients and the error covariance matrix from an independent normal-inverse-Wishart prior. Under this prior reduced-form coefficients and the error covariance matrix are independent:

$$\beta \sim N(\underline{\beta}, \underline{V}_\beta), \qquad \Omega \sim IW(\underline{M}, \underline{\gamma}), \tag{A.3}$$

and the conditional posterior distributions $p(\beta|y,\Omega)$ and $p(\Omega|y,\beta)$ have the following form:

$$\beta|y,\Omega \sim N(\overline{\beta}, \overline{V}_\beta), \quad \Omega|y,\beta \sim IW(\overline{M}, \overline{\gamma}), \tag{A.4}$$

where

$$\overline{V}_\beta = \left(\underline{V}_\beta^{-1} + \sum_{t=1}^{T} X_t \Omega_{-1} X_t' \right)^{-1}, \quad \overline{\beta} = \overline{V}_\beta \left(\underline{V}_\beta^{-1} \underline{\beta} + \sum_{t=1}^{T} X_t \Omega^{-1} y_t \right), \tag{A.5}$$

and

$$\overline{\gamma} = T + \underline{\gamma}, \quad \overline{M} = \underline{M} + \sum_{t=1}^{T} (y_t - X_t'\beta)(y_t - X_t'\beta)'. \tag{A.6}$$

A sample from the posterior of the reduced form parameters and the residual covariance matrix is drawn by using a Gibbs sampler (see, e.g., Koop and Korobilis, 2010). Given that we consider growth rates in price and quantities indices for each product in our VAR model, we specify the prior belief that these variables follow an AR(1) process.

A.2. Identification strategy

Traditional sign restrictions algorithm. In our SVAR models, structural shocks are identified by imposing traditional sign restrictions on the impulse response following the approach by Rubio-Ramirez et al. (2010). In short, for each posterior draw of the reduced-form parameters we first generate a uniformly distributed orthogonal matrix Q, then, we multiply the Cholesky-based impact matrix A_0 by the orthogonal matrix Q and construct the resulting IRFs. If the impulse responses satisfy the sign restrictions, the posterior draw is accepted, otherwise, we repeat the procedure with a new posterior draw of reduced-form parameters. For each product, we generate and save 1000 valid solutions (or draws) for our analysis.

Median target solution. To avoid model multiplicity, we follow the approach of Fry and Pagan (2005, 2011) and select the median target (MT) solution, such that contemporaneous responses to structural shocks are the closest to the median response. That is, for each $Q_i \in \mathbb{R}$, we denote the vector of contemporaneous responses as $\theta_i = vec(A_0(Q_i))$. We then standardize each solution, θ_i, by subtracting the element-wise median and dividing by the standard deviation, both measured over the set of models that satisfy identification restrictions:

$$\theta^{MT} = \min_i \left[\frac{\theta_i - median(\theta_i)}{std(\theta_i)} \right]' \left[\frac{\theta_i - median(\theta_i)}{std(\theta_i)} \right]. \tag{A.7}$$

A.3. Historical decomposition

We represent the log change of each product price-quantity pair y_t as a sum of initial conditions y_0 and subsequent shocks:

$$y_t = \beta^{t-1} y_0 + \sum_{k=0}^{t-2} \beta^k A_0 \epsilon_{t-k} \quad for \quad t > 1. \tag{A.8}$$

For each product, we define π_t^i as the contributions of the ith shock to its price variation (the first element vector y_t), for $i \in [S(supply), D(demand)]$. Thus:

$$\pi_t^S = \sum_{k=0}^{t-2} \beta^k J_1 A_0 \epsilon_{t-k}, \tag{A.9}$$

$$\pi_t^D = \sum_{k=0}^{t-2} \beta^k J_2 A_0 \epsilon_{t-k}, \tag{A.10}$$

where J_i is a 2×2 square matrix with (i,i)th element equal to one and zeros elsewhere. Then,

$$y_t = \pi_t^S + \pi_t^D. \tag{A.11}$$

Thus, each product price change can be decomposed as the sum of the demand and supply shocks contributions. Then, the decomposition of any aggregate of interest can be obtained by adding up the contributions of the corresponding products, using official weights.

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