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Optimal temporal distribution of supply multipliers for final demand forecasting: Argentina 2004-2023.

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Summary:

I. Introduction

Introduction

- Primary goals:

  - **Forecast quarterly final demand components** (private consumption, investment, exports) from a time series of sectoral value-added, using Ghosh's supply driven interpretation of the input-output framework.

  - Give a **forward looking (optimal) temporal distribution** to the total supply multiplier for each final demand component. In particular, **one that does not alter their total magnitude**.

  - In doing so, **improve the accurancy** and fitting of the models for short term forecast.

Introduction

- Secondary goals:
  - Revisit the **supply driven input-output model**, and the controversy over its plausibility and assumptions. Expand the horizon of its uses.
  - Reinforce the articulation between **input-output** and econometrics, particularly **time series analysis**, for projection purposes.
  - Reclaim some ground for input-output analysis for short therm forecast.

Introduction

- **Medium and long term forecasting was one of the primary use cases for input-output tables**, at the birth of the discipline (Cornfield *et al* 1947, Leontief 1949, Barnett 1951, Arrow 1951). A projection of final demands allowed to forecast gross production, and other key derived metrics (employment, imports, etc.).

- At that time, the comparison of input-output projections against other simpler methods (like multiple regression) showed that input-output **was not the best performer**, but it was a promising technique that insures consistency among the projections.

- The empirical contrast of input-output forecast was thought to be, at the same time, an empirical contrast of the **hypothesis of constant linear production coefficients** (Leontief 1949, Adams and Stewart 1956, Rey and Tilanus 1963, Matuszewski, Pitts, and Sawyer 1963).

Introduction

- Sometimes, trend or factor corrections **on the coefficients** where envised as a solution to poor accuracy (like in a RAS adjustment). Perfect match of the forecast with observed values.

- But, from the mid 1970's and onwards, with the **consolidation of the Box-Jenkins methodology**, time series analysis (e.g. ARIMA, VAR and VEC models) has become the most widely used tool for short and medium term forecast.

- In macroeconomic, regional science and environmental input-output, instead of thinking in terms of competing techniques, **econometrics and input-output analysis walked a path of articulation and integration**.

- This articulation first appear in Keynesian macro-econometric models (Ghosh, Ghose, and Chakraborty 2011, S. J. Rey 2000, Beaumont 1990), and later in CGE models.

Introduction

- The most **traditional interpretation of the Leontief inverse (*L*) is a static one**. Causes and effects occur simultaneously. No time lags in multiplier effects.

- In the 1980s, significant efforts were made to incorporate the fact that **production and distribution take time.**

- In general, past attempts to introduce a time dimension to input-output models required **an explicit decomposition (time distribution), or modification, of the coefficient matrix (*A*)** (Romanoff and Levine, 1986; Mules 1983; Avelino 2017).

- The supply driven interpretation has been **subject of a long controversy**, limiting its use to price models, multiplier analysis or impact evaluation of catastrophic events. **Ghosh's model is plausible if transient supply-induced variations in labor productivity are assumed**.

II. Information sources and methodology

Information sources and methodology

- The **Monthly Estimator of Economic Activity (EMAE)** is a leading indicator of sectoral value added. It is elaborated and published by the National Institute of Statistics and Censuses (INDEC) of Argentina. It comprises a total of fifteen (15) sectors.

- Constant value added (quantities) in index numbers with base 2004 = 100. **Converted from index numbers to constant prices** (millions of AR$), using base year value added from national accounts.

- Final demand, by component, is also published by INDEC, as part of the quarterly national accounts. Provided at 2004 constant market prices, with a seasonal adjustment. Components available are: **household consumption (hc), public consumption (pc), gross fixed capital formation (inv) and exports (ex)**.

Information sources and methodology

- **Both consumption and investment comprise national and imported production**. INDEC provides a national and imported series of “machinery and equipment” and “transport equipment”, but without a seasonal adjustment. This imported component was deseasonalized, and subtracted from the total investment series.

- **All time series used are seasonally adjusted**. The ones that were not provided in this way, they were adjusted using an exponential smoothing state space model, inside the forecast package (Hyndman and Khandakar 2008).

- An **industry-by-industry input-output matrix, with fixed product sales structure (type “D”)** (European Commission and Eurostat 2008, 297), **was constructed using 2018 SUT**. The matrix is expressed at basic prices. Later, it was aggregated to match the sectors of the EMAE series.

Information sources and methodology

- All calculation and graphics were done using the R language and environment for statistical computing (R Core Team 2024).

- Estimated total output was calculated from sectoral value added, **using Ghosh's inverse** (*G*):

$$v'_t \cdot G = \tilde{x}'_t \; for \; t = 1, 2, \ldots . n$$

- Total final demand components (*f*) where estimated using the participation of each industry in each final demand component from the 2018 input-output matrix (as a diagonal matrix *P*).

Information sources and methodology

- **Final demand is expressed at market prices**. So, to ensure consistency in the estimates, taxes (less subsidies) over products must be added (*q*). Export tariffs where independently estimated. Value added tax could not be included.

$$\text{for } t = 1, 2, \ldots n \begin{cases} \tilde{x}_t' \cdot \hat{P}^{hc,pc,in} \cdot (u + q^{hc,pc,in}) & = \tilde{\boldsymbol{f}}_{\boldsymbol{t}}^{\boldsymbol{hc,pc,in}} \\ \tilde{x}_t' \cdot \hat{P}^{ex} \cdot (u + q^{ex}) & = \tilde{\boldsymbol{f}}_{\boldsymbol{t}}^{\boldsymbol{ex}} \end{cases}$$

- The last step was to **aggregate the estimates from monthly to quarterly time series**.

III. Results

Results

- The first thing that we want to analyze is **how unbalanced was growth during the period 2004-2023**.

- Sectoral growth has not been equal during the period under consideration. This is specially true for two very important departments of argentine economy: “Agriculture, hunting and forestry” and “Mining and quarrying”.

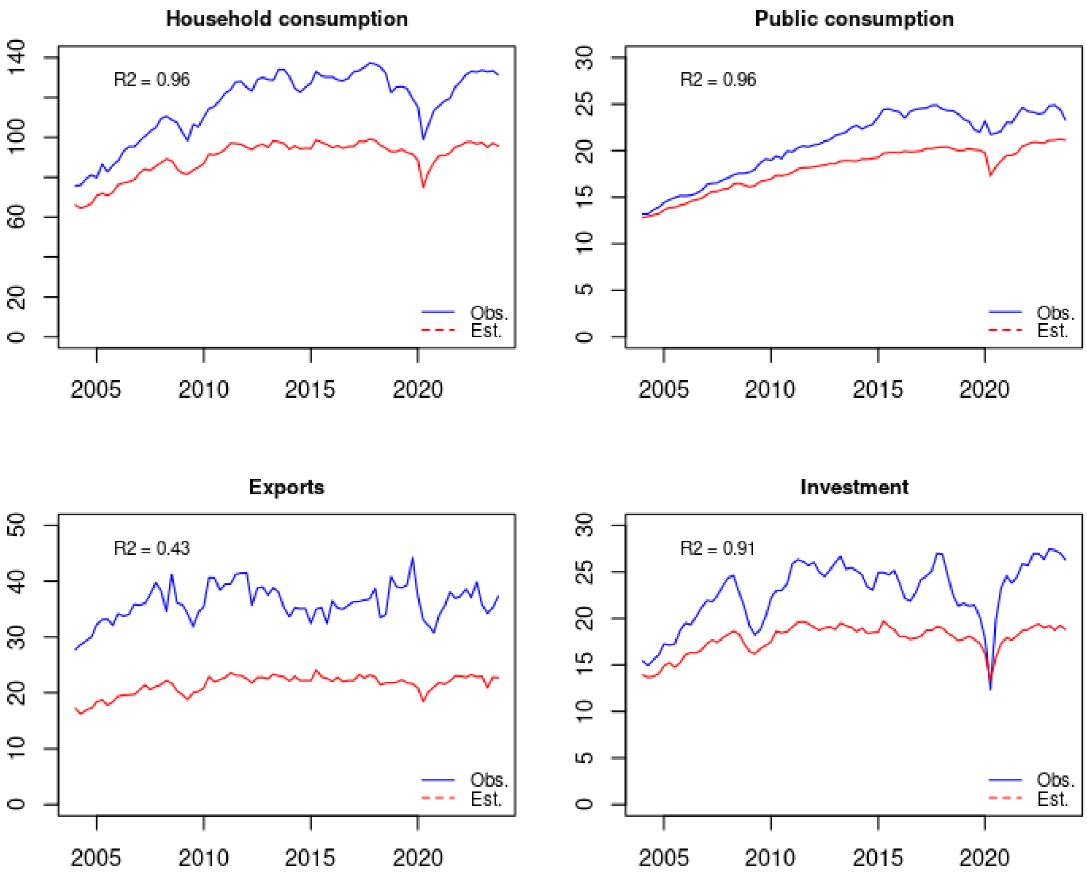
Cross-ratio of total sectoral growth (annual or triennial average). Argentina 2004-2023.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
A	1	1.53	1.02	1.24	1.43	1.46	1.53	1.45	1.73	1.56	1.48	1.59	1.64	1.79	1.25
B	0.65	1	0.67	0.81	0.93	0.95	1	0.94	1.13	1.02	0.96	1.04	1.07	1.16	0.81
C	0.98	1.5	1	1.21	1.39	1.43	1.49	1.42	1.7	1.52	1.44	1.56	1.6	1.75	1.22
D	0.81	1.24	0.83	1	1.15	1.18	1.23	1.17	1.4	1.26	1.19	1.28	1.32	1.44	1.01
E	0.7	1.08	0.72	0.87	1	1.02	1.07	1.02	1.22	1.09	1.04	1.12	1.15	1.25	0.88
F	0.69	1.05	0.7	0.85	0.98	1	1.05	0.99	1.19	1.07	1.01	1.09	1.12	1.22	0.86
G	0.66	1	0.67	0.81	0.93	0.96	1	0.95	1.14	1.02	0.97	1.04	1.07	1.17	0.82
H	0.69	1.06	0.71	0.85	0.98	1.01	1.05	1	1.2	1.08	1.02	1.1	1.13	1.23	0.86
I	0.58	0.88	0.59	0.71	0.82	0.84	0.88	0.83	1	0.9	0.85	0.92	0.94	1.03	0.72
J	0.64	0.99	0.66	0.79	0.92	0.94	0.98	0.93	1.11	1	0.95	1.02	1.05	1.15	0.8
K	0.68	1.04	0.69	0.84	0.97	0.99	1.03	0.98	1.17	1.05	1	1.08	1.11	1.21	0.85
L	0.63	0.96	0.64	0.78	0.9	0.92	0.96	0.91	1.09	0.98	0.93	1	1.03	1.12	0.79
M	0.61	0.94	0.62	0.76	0.87	0.89	0.93	0.88	1.06	0.95	0.9	0.97	1	1.09	0.76
N	0.56	0.86	0.57	0.69	0.8	0.82	0.85	0.81	0.97	0.87	0.83	0.89	0.92	1	0.7
O	0.8	1.23	0.82	0.99	1.14	1.17	1.22	1.16	1.39	1.25	1.18	1.27	1.31	1.43	1

Results

- Next, let's explore the correlation between our crude estimates, with no temporal adjustment, and the original final demands series.

- At a first glance, **there seems to be some correlation between the observed values and the estimates**. But correlation tends to be rather high when time series are expressed in levels.



Final demand components, Argentina 2004-2023. Observed vs. estimate. Billions of AR$ 2004.

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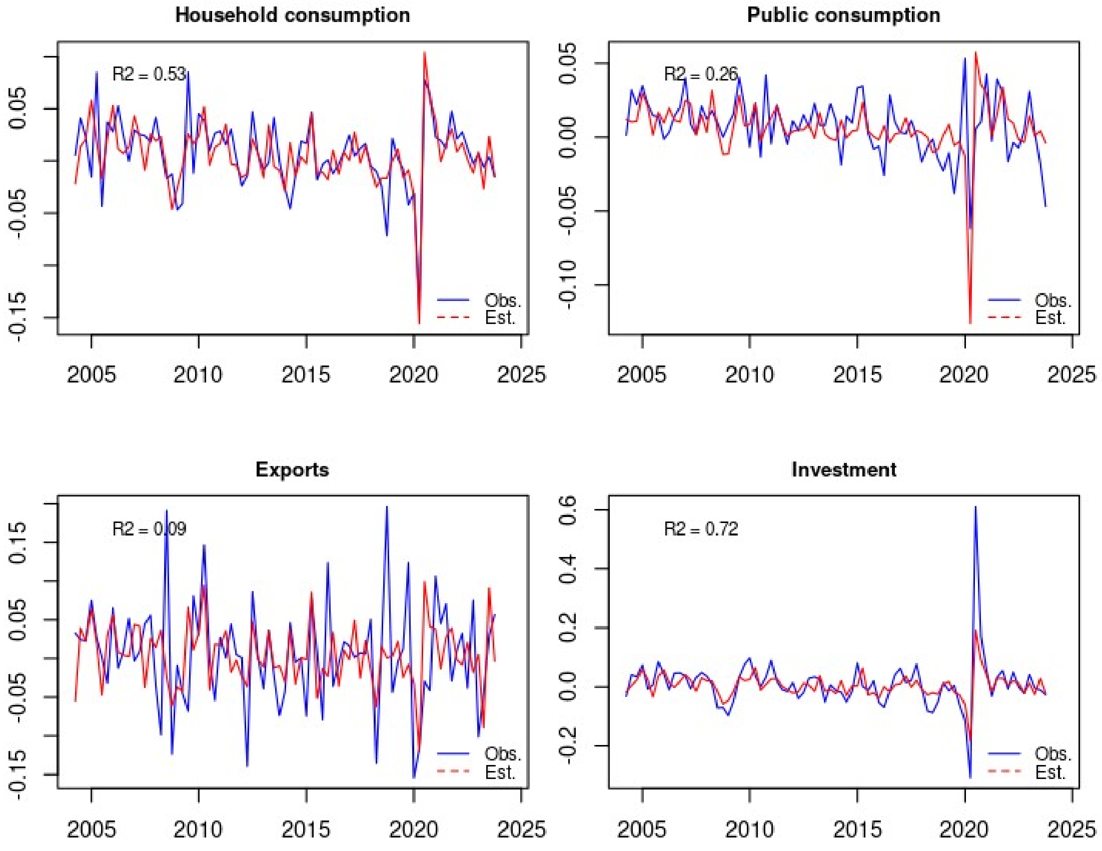
Results

- A greater deal of reliability in short term predictions will be achieved by transforming our time series into variations.

- Now the landscape has changed. **The accuracy of the prediction of exports just falls apart**. One possible explanation is that a time lag exist between the creation of value added and when the commodity its sold (in this case, exported).



Final demand components, Argentina 2004-2023. Observed vs. estimate. Variations against last period.

Results

- The first approximation to the temporal dimension is fitting **a finite distributed lag model (DLM)**, to each observed final demand component. **To capture the time window of a full year, we need three more additional quarters**, i.e. three lags. Therefore, the initial specification of the models is:

$$\text{for } i = hc, pc, ex, in:$$

$$f_t^i = \beta_0 \cdot f_t^i + \beta_1 \cdot f_{t-1}^i + \beta_2 \cdot f_{t-2}^i + \beta_3 \cdot f_{t-3}^i + e_t^i$$

- The result of the fitted models can be seen next.

Results

	Dependent variable:
	hc
$\tilde{hc}_{t-0}$	0.826***
	p = 0.000
$\tilde{hc}_{t-1}$	0.251***
	p = 0.004
$\tilde{hc}_{t-2}$	0.029
	p = 0.731
$\tilde{hc}_{t-3}$	0.101
	p = 0.235
R^2	0.608
Adjusted R^2	0.586

	Dependent variable:
	pc
$\tilde{pc}_{t-0}$	0.569***
	p = 0.00000
$\tilde{pc}_{t-1}$	0.142
	p = 0.155
$\tilde{pc}_{t-2}$	0.154
	p = 0.123
$\tilde{pc}_{t-3}$	0.003
	p = 0.973
R^2	0.363
Adjusted R^2	0.328

	Dependent variable:
	ex
$\tilde{ex}_{t-0}$	0.668***
	p = 0.0004
$\tilde{ex}_{t-1}$	0.548***
	p = 0.004
$\tilde{ex}_{t-2}$	0.060
	p = 0.744
$\tilde{ex}_{t-3}$	0.376**
	p = 0.049
R^2	0.236
Adjusted R^2	0.194

	Dependent variable:
	in
$\tilde{in}_{t-0}$	1.914***
	p = 0.000
$\tilde{in}_{t-1}$	-0.345**
	p = 0.011
$\tilde{in}_{t-2}$	-0.023
	p = 0.860
$\tilde{in}_{t-3}$	0.054
	p = 0.685
R^2	0.752
Adjusted R^2	0.738

Results

- **All estimated components of final demand show some sort of lagged effect**, that affects present values.

- **Almost all beta coefficients are positive** (except for the first lag in investment); and almost all of them are not close to zero (except for the third lag in public consumption).

- Furthermore, only a subset of them is statistically significant, i.e. we can trust that they aren't different from the estimate value.

- **The fitting of the models generally improves**, especially in the case of exports.

Results

- Let's take a look at **the total sum of the coefficients**, the "long term multiplier" of distributed lags (Gujarati and Porter 2010, 619):

hc	pc	ex	in
1.206	0.869	1.652	1.600

- The total sum of the estimated betas **does not add up to unity**. If we allow the total sum of the betas to diverge from unity, **we are not performing a temporal distribution of a certain input-output multiplier**. We backtracking over the assumptions of the input-output model.

Results

- It is essential to secure total non-negativity of all betas, and also the total sum must add up to unity. To do so, we must find a framework similar to regression, that allow us to **introduce the desired restrictions over the coefficients**.

- It is well known in statistics and linear algebra that **least squares is just a subclass of convex optimization** (Boyd and Vandenberghe 2004, 1–4, 136–44). Particularly, it is a **quadratic program** (QP) (Boyd and Vandenberghe 2004, 152–54).

- In this context, **the squared difference between observed and estimated values (the stochastic error) becomes the *objective* function** (*g*). The vector of betas (*b*) for the time lags becomes our *optimization variable*.

Results

- **The restrictions that we want to incorporate are *constraints functions***, with their corresponding bounds. Rephrasing the model specification, and incorporating the desired constraints:

$$\text{for } \ \text{i} \ = \text{hc, pc, ex, in:}$$

$$\min g(b_i) = \|\tilde{F}_i \cdot b_i - f_i\|_2^2 = b_i' \cdot \tilde{F}_i' \cdot \tilde{F}_i \cdot b_i - 2 \cdot f_i' \cdot \tilde{F}_i' \cdot b_i + f_i' \cdot f_i$$

$$\text{subject to:} \begin{cases} u' \cdot b_i - 1 & = 0 \text{ : \textit{unit sum}} \\ I \cdot (-b_i) & \leq 0 \text{ : \textit{non-negative}} \end{cases}$$

- **We need to find a vector *b**, that is feasible and optimal**. The R package quadprog (Turlach, Weingessel, and Moler 2019) was chosen for solving the problem.

Results

- The optimal temporal distribution of supply multipliers obtained is:

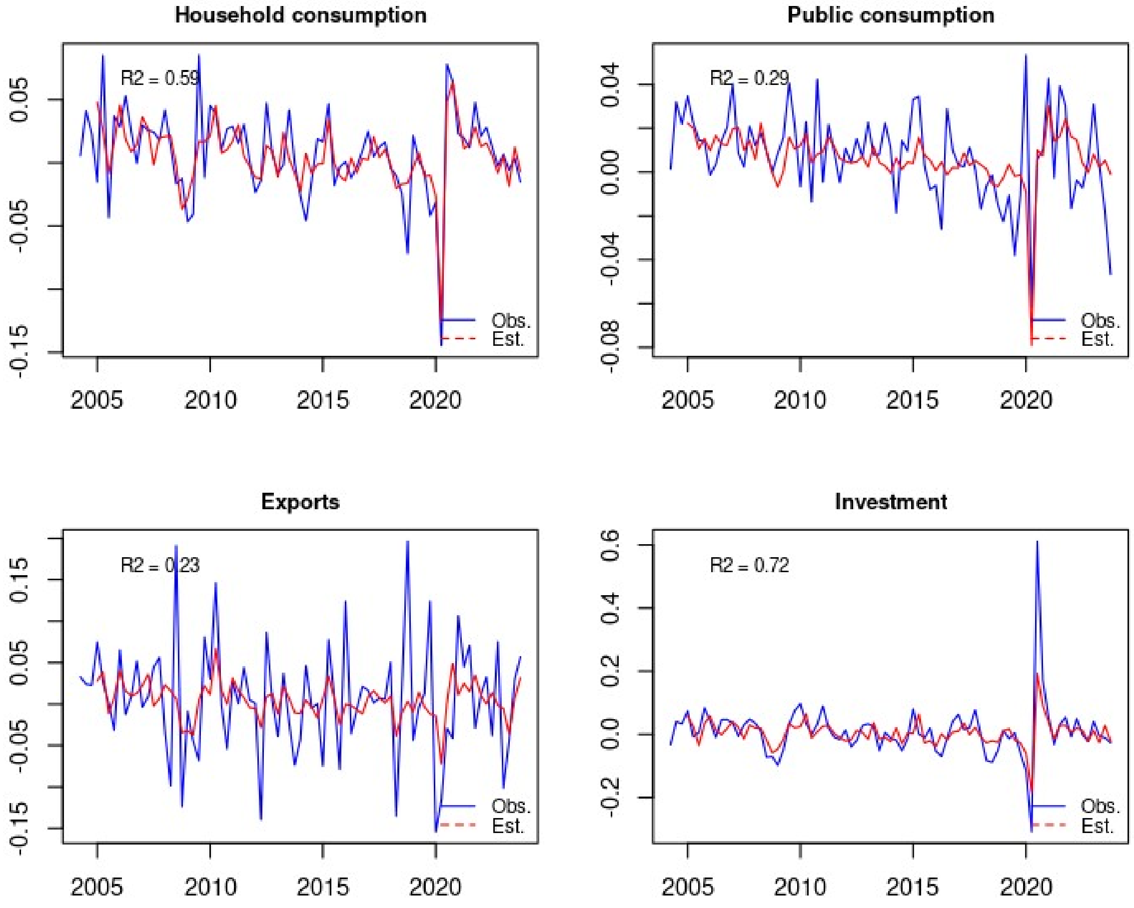
	hc	pc	ex	in
t	0.765	0.603	0.466	1
t-1	0.197	0.174	0.357	0
t-2	0	0.186	0	0
t-3	0.038	0.037	0.177	0

- The evidence seems to suggest that a **temporal lag exists between the creation of value added and its realization in the market**. That is especially true for the case of exports, where **more than half of the effect of the multiplier does not impact in the same period**.

Results

- Taking the optimal temporal lags (OTL) and using them for re-estimating the final demand components, yield the following forecast.

- They are similar to the results of the DLM. **However, OTL are more congruent with the framework of input-output analysis**.



Final demand components, Argentina 2004-2023. Observed vs. estimate with OTL. Variations against last period..

IV. Conclusion

Conclusion

- Given the aggregation of the matrix used (only fifteen sectors), we believe that **the fit of the models is adequate**. A greater dissagregation could improve the predictive power.

- The variance of final demand explained by the supply multipliers can be fully **attributed to the availability of more inputs** (the creation of more product of value).

- At the same time, this means that **we must look somewhere else for explanations of the variance that we cannot account for**.

- **Technological change, economies of scale, and other factors can indeed change the matrix of inter-industry transactions in 20 years**. A possibility could have been to quarterly balance the matrices, with some biproportional technique. But, that could stand in the way of capturing the phenomenon of temporal lags, that we just presented.

Conclusion

- The proposed framework for estimating optimal temporal lags **could be extrapolated to the more common demand driven model**, provided that the information is available.
- The estimated structure of temporal lags is not only useful for short term forecasting. **It could be easily incorporated to add a temporal dimension to impact evaluation and other exercises**.
- In a sense, input-output can play a role that is somehow analogous to what principal component does in short term forecast, **but with a straight forward economic interpretation**.

Thank you very much!!

VI. Annex

a) The temporal dimension in input-output analysis

The temporal dimension in input-output analysis

- The most **traditional interpretation of the Leontief inverse (*L*) is a static one**. No time lags in multiplier effects.

- The temporal dimension of input-output models was first thought in conjunction with the problem of **introducing fixed assets and inventories** to the model (Miller and Blair 2009, 639–45).

- With a capital stock matrix by unit of output (*B*), future (or present) final demand has impact in present (or future) output.

- But, “(…) this intertemporal influence is not a result of the fact that production takes time, it is entirely the result of the capital goods (…)” (Miller and Blair 2009, 651).

The temporal dimension in input-output analysis

- In the decade of 1980, other approaches where elaborated with the aim of incorporating production and distribution lags.
- Romanoff and Levine (1981) developed **sequential inter-industry models** (SIMs). **Production delays are represented with the power series approximation of the Leontief inverse** (*L*). Each power of *A* is a uniform and synchronized industry interval (*t*).
- Next, they specify **two polar forms of inventory management and information flow**, that will give birth to two different models: anticipatory and responsive (Romanoff and Levine 1981, p. 183).

Anticipatory:

$$X_t = A \cdot X_{t+1} + Y_t$$

Responsive:

$$X_t = A \cdot X_{t-1} + Y_t$$

The temporal dimension in input-output analysis

- This allows them to explain **present total output, in terms of weighted past, or future, final demands**.

$$X_t = \sum_{r=0}^{\infty} A^r \cdot Y_{t+r} \qquad X_t = \sum_{r=0}^{\infty} A^r \cdot Y_{t-r}$$

- Furthermore, **with a mix of anticipatory and responsive industries, present output depends upon both of them**. In principle, there is no limit to the extent of the effects. Infinitely into the past and the future.

- Mules (1983) takes a similar path, with a temporal decomposition of the power series approximation of *L*. But, he **inhibit some of the coefficients of *A* from working in some periods**. Given a finite time window, total effects will be strictly lower than the Leontief inverse.

The temporal dimension in input-output analysis

- Later on, Romanoff and Levine (1986) refined the SIM model, to accommodate it for **non-uniform industry intervals, i.e., *a changing A matrix***. Here, a time distribution for each of the production coefficients is assumed (“time phased input coefficients”).

- SIM models are quite demanding in terms of information. He et al (2022) calculated the best fitted technical coefficients with linear regression with a set of simulated total output and final demands.

- More recently, Avelino (2017) made **a *seasonal* decomposition of annual inter-industrial transactions into intra-year quarterly tables**. This novel approach tries to recover part of the information that is lost in the annual aggregation of output of industries with a different product mix composition (e.g. agricultural activities).

- Our approach to the temporal dimension **will not try to (explicitly) decompose the *A* matrix**, or change any production coefficient. **It will be foward looking** in the sense that future consumption will depend on present production.

b) The supply interpretation of the input-output framework

The supply interpretation of the input-output framework

- The supply driven version of the input-output model has been a **subject of long debate between input-output scholars**.

- When it was first presented by A. Ghosh (1958), the author assimilated the allocation system to "(…) a planned economy under centralised control with scarce material resources and productive capacity with ample supply of available labour." (A. Ghosh 1958, p. 59).

- The allocation of intermediate inputs occurs following a matrix quota (H). So, given a vector (v) of "(..) net national income generated (…)" (A. Ghosh 1958, 61), total outlays can be uniquely determined.

$$v' \cdot (I - H)^{-1} = x'$$
$$v' \cdot G = x'$$

The supply interpretation of the input-output framework

- In later works, Ghosh comes back with the notion that **the allocation model is related to scarcity of inputs**, but leaving aside the idea that its only purpose is for a planned economy (A. Ghosh 1964, 112).

- The supply driven model remained in the toolkit of input-output researchers for two more decades. At some point, some scrutiny over the underlying assumptions was undertaken and criticism started to arise.

- Oosterhaven (1988) **deemed the supply model implausible**, as it implies that “(…) the essential notion of production requirements, i.e., the production function, is actually abandoned.” (Oosterhaven 1988, 207).

The supply interpretation of the input-output framework

- There are theoretical reasons for why this could be the case. **For any set of sectoral growth rates that are not equal, fixing the *H* matrix means a varying *A* matrix, and vice versa**.

- The question of “abandoning” the production function may need to be reconsidered with the introduction of inventories. **The use of stocks could be a buffer between the supply and demand driven models** (Oosterhaven 1988, 212–15).

- The article of Oosterhaven sparked a long controversy. Rose and Alison (1989) tested empirically the joint stability of the production and allocation coefficients, and found very small discrepancies.

The supply interpretation of the input-output framework

- Dietzenbacher (1997) proposed to **vindicate the Ghosh model** as a price model. In doing so he restated the problem in an attractive manner to us:

  "Suppose that the value added (or the input of, say, labor) in sector j is increased by one unit. Using the supply-driven input-output model this induces an increase of the output in each sector. Hence, **in any sector other than the jth, the production is increased without any increase in the value-added terms (such as labor and capital)**." (Dietzenbacher 1997, 630).

- Why would new production occur, **if no value added is created in any sector other than the one that triggered the action**?

The supply interpretation of the input-output framework

- Dietzenbacher critic is very appealing **from the standpoint of the Labor Theory of Value**. Here, value added is the total amount of **direct labor unfolded by the labor power in the production process**. Marx calls it *product of value* (Marx 2002, 1:256–57):

$$V = cc + \underbrace{cv + p}_{\text{value added}}$$

- If no more direct labor is unfolded, the only thing that we can conclude is that **the productive power of labor has changed** in all the other sectors that will use the input.

- Perfectly supply-induced productivity adjustments sound too good to be true. Also, normal intensity of concrete labor is a determinant of abstract labor (i.e. value). If the intensity of the labor process changes, **it must be transient, not permanent**.