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

Author: Santiago Capobianco[1].

Abstract

The aim of this paper is to explore the possibility of bringing a temporal dimension to input-output multipliers. In particular, we are interested in forecasting quarterly final demand components from a series of sectoral value added. The Monthly Estimator of Economic Activity (EMAE) is one of the most important *economic situation* indicators provided by the National Institute of Statistics and Censuses (INDEC) of Argentina. It's a leading indicator for economic activity, and anticipates the evolution of quarterly national accounts. Using Gosh's supply multipliers, it is possible to forecast the evolution of final demand components from the year 2004 to 2023. In addition, these estimations are improved by constructing a *time dimension*, a quarterly distribution for the effects of the multipliers. Two alternatives are presented. First, we explore a distributed lag model (DLM) with no restrictions over the coefficients. Afterwards, we demand that the supply multipliers are not to be modified by the coefficients of the regression, so all betas must sum to unity and be non-negative. This transform the DLM model into a *quadratic optimization problem*. The results shows that final demand forecast can be improved by considering this temporal distribution. Specially in the case of Argentina's (mostly agricultural) exports, when the creation of value added tends to be lagged from its commercialization.

1 National University of Tres de Febrero (Argentina) and Ministry of Economic Affairs (Argentina). Email: capobiancosanti@yahoo.com.ar

Introduction

Forecasting economic aggregates is a key requirement for almost all policy makers. Public administrations, international organizations, private enterprises and institutions, they all somehow rely on a set of assumptions over the future course of demand, supply and economic activity.

From the mid 1970's and onwards, with the consolidation of the Box-Jenkins methodology, *time series analysis* has become the primary tool used for short and medium term forecast (Urbisaia and Brufman 2000, 13–16, 79–81, 167–71). This approach exhibits a much greater emphasis in accuracy than the more theoretically grounded paradigm of the Cowles Commission (Qin 2013, 4–23). Computational power has become increasingly cheap, and the general availability of time series data, produced by the same information technology revolution, certainly contributed to the consolidation of this family of methods. Particulary, autoregressive integrated moving average models (ARIMA) and vector autoregression models (VAR) dominate the mainstream landscape of short term and medium term forecast[2]. The one notable exception to this trend is principal component analysis.

In parallel to the ascent of time series models, input-output framework was also widely used for projection purposes, especially for long term forecast. One of the seminal papers in this respect is Cornfield *et al* (1947a; 1947b), whom projected the level of final demand needed to achieve full employment in the USA, by the year of 1950. Soon after, the question about the convenience of using input-output matrices for such a task arose. The comparison of input-output projections against other simpler methods (like mere extrapolation, or multiple regression against GDP and time) was tackled by Leontief (1949), Barnett (1951) and Arrow (1951). The verdict at that time was that input-output was not the best performer (Barnett 1951, 12; Arrow 1951, 5–6), but it was a promising technique that "(…) insures consistency among the projections for the various industries and guards against forecast which are mutually incompatible in our existing technology." (Arrow 1951, 7).

In Argentina, the first input-output table ever produced was immediately put to use by Balboa (1958). The method was quite similar, but the aim was slightly different: to forecast the requirements of domestic production and, more important, *intermediate imports*, needed to meet certain projected levels of final demand, for the years of 1962 and 1967 (Balboa 1958, 52–70). Again, the same debate was recreated, with some researchers arguing against the efficiency of input-output forecasting. The considerable statistical effort needed to compile an input-output matrix must be compensated with an accuracy at least greater than other simpler methods (Brodersohn and Guissarri 1968, 743–50).

Building an input-output matrix is not an easy endeavor, as everybody is aware of. But things certainly have improved since the 1950's. The internalization of the input-output framework in the core of the Production Account, inside the System of National Accounts 1968 (SNC 1968), was a major milestone for both fields of research (Capobianco 2023, 86–87, Annex A). With the 1993 revision of the SCN, a regular flow of annual supply and use tables could be available, if the system was fully implemented. This has contributed to alleviate part of the burden that researchers and institutions bear when constructing input-output tables.

For Leontief (1949, 221–22), the empirical contrast of input-output projections was, *at the same time*, an empirical contrast of the hypothesis of constant linear production coefficients[3]. In this context, any discrepancy could be explained as a change in the production function, attributable to more circumstantial causes, like price fluctuation and market conditions, or more structural ones,

2 For a context about ARIMA and VAR models see Gujarati and Porter (2010, 773–89).

3 This was also true for Rey and Tilanus (1963, 462), for whom the systematic errors could be corrected with trend corrections to the technical coefficients.

like technological change (Adams and Stewart 1956, 450–51). The question about the *stability* of the coefficients and its relation with projection error will continue to pop up in future research about input-output forecasting[4].

The future of both econometrics and input-output analysis was one of articulation and integration. The first "theoretical bridge" for this interaction was given by Keynesian macroeconomics[5]. Econometric forecast of final demand started to be feed into the standard input-output open model, like in the Brookings or Wharton econometric models of the US economy (P. P. Ghosh, Ghose, and Chakraborty 2011, 3–8). Also, the construction of an income-consumption linkage (employment-output requirements and endogenization of consumption) that overcomes some of the restrictive assumptions of the standard input-output model, called for the need of parameter estimation (S. J. Rey 2000, 273–76). At the pinnacle of this trend (end of the 1970's), it was seen as a complete integration of Keynesian demand and income with Leontief's inter-industrial flows, that will allow for full supply and demand interactions (Beaumont 1990, 167). For some authors, this was not quite the case (Beaumont 1990, 175–79).

Later on, the change in theoretical preferences of mainstream economics (moving away from Keynesianism to monetarism and rational expectations theory) didn't stop the articulation between input-output and econometric methods. But it did change its nature. With the rise of Computable General Equilibrium (CGE) models, econometric tools interacted in a different way with the input-output framework (Miller and Blair 2009, 423–27, 679–82). Instead of a broader macro-econometric model for final demand aggregates and labor cost, the new articulation came mostly in the form of specifying elasticities that are statistically based, for production and consumption maximizing functions.

In present times, input-output analysis and other techniques like multiple regression, or time series analysis, are more seen like *complementary* approaches than competing ones[6]. The use of econometric techniques is particularly strong in regional science, and in environmental input-output[7].

The temporal dimension in input-output analysis

The most traditional interpretation of the Leontief inverse (L) is a static one, without regards for time lags in multiplier effects. Total output resolves into a series of production process that are all happening in *parallel*, and *simultaneously*, whit the same production function.

The temporal dimension of input-output models was first thought in conjunction with the problem of introducing fixed assets and inventories stocks to the model (Miller and Blair 2009, 639–45). In Leontief's seminal work about dynamic systems, he presents the concept of a *capital stock matrix by unit of output* (B), that comprises all buildings, machinery, tools and inventories needed to meet a year of total output. Given this new matrix, and the production coefficients (A), a system of linear difference equations is solved, where future (or present) final demand have impact in present (or future) output, depending if the model is forward or backward looking (Leontief 1966, 220–26). 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). Latter on, in the decade of 1980, numerous attempts were made to reconcile production (and distribution) time

4 For example, Matuszewski, Pitts, and Sawyer (1963) proposes a row correction factor for the domestic and imported matrices, that implies perfect forecast accuracy. This scalar can be interpreted as a measure of instability of all row coefficients (Matuszewski, Pitts, and Sawyer 1963, 427). It can be seen that such a correction is very similar to the first step of a RAS adjustment procedure.

5 For a very extensive review of integrated macro-econometric and input-output models see Ghosh *et al* (2011).

6 Leontief himself has sometimes posed the problem in terms of two rival techniques, relating the use of multiple regression with the restricted availability of economic data to only time series aggregates (Leontief 1949, 218).

7 For example, Wang, Zhao and Wiedmann (2019) uses panel regression and input-output analysis to forecast carbon emissions embodied in China-Australia bilateral trade.

lags with the static input-output model (Miller and Blair 2009, 653–54).

One of those attempts is Romanoff and Levine (1981; 1986), with the development of sequential inter-industry models (SIMs). They begin with the notion of *industry interval*, that comprises all time elapsed since start of production to final delivery[8]. The SIM interpretation makes use of the power series approximation of the Leontief inverse (*L*), but assumes that every power of *A* comprises a *uniform* and *synchronized* industry interval (Romanoff and Levine 1981, 182–83). Next, they specify two polar forms of inventory management and information flow, that will give birth to two different families of models: *anticipatory* and *responsive*. Either "(…) production precedes a fully known demand stimulus (…)" or "(…) production responds to a known demand stimulus (…)" (Romanoff and Levine 1981, 181). This allows them to explain present intermediate consumption, in terms of a past, or future, total output. Furthermore, with a mix of anticipatory and responsive industries, present intermediate consumption depends upon both of them (Romanoff and Levine 1981, 184).

Another approach to this problem was presented by Mules (1983), who also performs a temporal decomposition of the power series approximation of *L*. Mules assumes that each round of this process "(…) takes a finite period of time." (Mules 1983, 199), and the effects are given by the direct coefficients matrix (*A*) only[9]. The key element introduced are binary matrices for specified sectoral time lags that inhibit some of the coefficients of *A* from working in some periods. Therefore, given a finite time window, this temporal decomposition will yield total effects that are strictly lower than the total effect of the Leontief inverse (Mules 1983, 202–3).

Subsequently, Romanoff and Levine (1986) refined the SIM model, to accommodate it for multi-interval industry production periods, transportation delays, inventory handling and capacity expansions. In this context, the authors proposed a time distribution for each of the production coefficients. The *L* matrix is disaggregated into temporal layers, but for each one, every coefficient is different (Romanoff and Levine 1986, 80–81). Nevertheless, the approach is quite demanding in terms of information. For that, only tentative examples are given to the reader (Romanoff and Levine 1986, 83–85). More recently, He *et al* (2022) presented an algorithm to estimate the temporal layers of production coefficients (with responsive industries only), using linear regression over a set of simulated productions and final demands.

Another recent approach over the time dimension of input-output analysis is the *seasonal* decomposition proposed by Avelino (2017). It is indeed true that the "(…) loss of information that the temporal aggregation imposes on the annual technical coefficients by suppressing the distinct economic structure in each period (…) biases the technical coefficient matrix." (Avelino 2017, 2). In this novel work, annual inter-industrial flows are decompose into intra-year (quarterly) tables, that are internally and temporally consistent. Then, a *seasonal* production structure arises (Avelino 2017, 7–12). In turn, this translate to changing backward and forward linkages along the year, specially for agricultural activities (Avelino 2017, 15–18).

Our approach to the time dimension will not try to (explicitly) decompose the *A* matrix, or any production coefficient. Conditional to the fact that all required inventories (and means of production) are available, *production time* does not depend on any input[10]. It is totally a characteristic of the production process itself[11].

8 Industry interval can be further broken down into production interval and shipment interval. This quite resembles to Marx's production time and circulation time (Marx 2009, 4:143–49).

9 "A system for modelling input-output responses to an initial impact which does not use the Leontief inverse is proposed (…)" (Mules 1983, 197).

10 "Maintenance of material input inventory allows production to be initiated prior to purchasing inputs." (Romanoff and Levine 1981, 182).

11 At this point, it feels convenient to recover the insightful characterization of the industrial production processes made by Georgescu-Roegen (1969). They can be thought as a replication of partial processes where "(…) all these operations are performed *simultaneously and in a special arrangement*." (Georgescu-Roegen 1969, 516 original italics). The replication and arrangement of all the steps tends to minimize the idleness of what Georgescu-Roegen calls "fund factors", i.e. the working force and all tools and equipment (Georgescu-Roegen 1969, 515–22). In

This does not mean that there are no reasons for production coefficients to vary across time, on a regular basis (apart from technological change)[12]. For us and for now, the question of changing production coefficients will be put aside. Rather than production and distribution time affecting the input coefficients, like in the SIM or Mules models, we will try to capture the temporal (quarterly) distribution of the *given* total effect of an input-output multiplier. The direction will be forward looking, in the sense that, for example, future consumption will depend on present production. The chosen multiplier is one with a somewhat controversial history.

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, 59). In this kind of situations, technical coefficients play a minor role in determining input ratios, according to Ghosh perspective[13].

The allocation of intermediate inputs occurs following a designated matrix quota (H)[14], that makes it a linear function of sectoral production (x). So, given a vector (v) of "(..) net national income generated (…)" (A. Ghosh 1958, 61), total outlays can be uniquely determined. And thus, also final demand available for consumption, investment or foreign trade. This can be expressed in the usual matrix form[15]:

$$\begin{aligned} v' \cdot (I - H)^{-1} &= x' \\ v' \cdot G &= x' \end{aligned} \qquad [1]$$

Where G is known as the Ghosh inverse. The elements of G tell us "(…) the percentage increase in industry i total output due to an initial exogenous one percent increase in industry j output (...)" (Miller and Blair 2009, 548). For that reason, it is also referred as a direct output-to-output multiplier. 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[16].

After Ghosh's work, the supply driven model remained in the toolkit of input-output researchers for two more decades. Most applications where related to supply restrictions of critical inputs (Miller and Blair 2009, 547–48). At some point, some scrutiny over the underlying assumptions was undertaken and criticism started to arise.

In Oosterhaven (1988), we found a clear example of those critics. For this author, the supply driven model "(…) takes demand for granted, i.e., demand is supposed to be perfectly

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regard to inputs, for an optimal factory process "(…) *there is no time-lag between input and output flows*." (Georgescu-Roegen 1969, 520 original italics). If the replicated process cannot, by some reason, be arranged in line (like in agricultural production), it must be replicated in *parallel*, imposing idleness in factor funds, and time lags between input and outputs (Georgescu-Roegen 1969, 522–28).

12 Indeed, we just review one reason for this to happen, in the seasonal input-output decomposition.

13 The author somehow implies that in a market economy, the production function is an optimal technical combination.

14 In past works by the author of the present paper, the allocation matrix was interpreted as a redefinition of physical quantities, such as all sectoral output is equal to unity. This where given the name of "abstract quantities" (Capobianco 2012, 7).

15 Following the usual notation, upper case letters are matrices, lower case letters are column vectors, apostrophe (') means transposition, hat (^) means a diagonal matrix, tilde (~) means estimated, *u* is a unit (sum) vector, and lower bold case is a scalar.

16 "(…) in the short run excess capacity is not evenly distributed over the different industries and this impedes the free flow of supplies in response to a change in the composition of final demand." (A. Ghosh 1964, 112).

elastic.”. In the limit, “(…) purchases are made, e.g., of cars without gas and factories without machines.”. Altogether, this implies that “(…) the essential notion of production requirements, i.e., the production function, is actually abandoned.” (Oosterhaven 1988, 207). There are theoretical reasons for why this could be the case. For any set of sectoral growth rates that does not meet very specific conditions[17], fixing the *H* matrix means a varying *A* matrix, and vice versa. The worst scenario for the joint stability of both types of coefficients is the case of very *uneven* sectoral growth rates. On this basis, the allocation approach is basically rejected for anything rather than descriptive use of forward linkages (Oosterhaven 1988, 209–12).

At the end of his critic, Oosterhaven proposes two refinement of the allocation model, that he restricts to supply constrains situations or centrally planned economies (Oosterhaven 1988, 212–15). One element stands out from both of them: the use of stocks as a buffer between the supply and demand driven models[18]. In the real world, to buy or to sell an item does not necessarily mean to *immediately* use it, either for production or final demand. And in reverse, to productively consume an item does not mean that it was just bought a minute ago. It is indeed true that Ghosh’s model assumes that all inputs *eventually* are processed and passed on. But the time that takes for them to complete this journey may vary, like we will see in a moment. The question of “abandoning” the production function may need to be reconsidered with the introduction of inventories[19].

The article of Oosterhaven sparked a long controversy, that extends to this day[20]. Some time later, Dietzenbacher (1997) re-examined the issue, with the objective of vindicating the allocation approach as a *price model*, that yields the exact same results as Leontief’s dual[21]. In doing so, we think he restated the problem in a more precise manner, that could serve better to the objectives of this work:

> “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 *j*th, the production is increased without any increase in the value-added terms (such as labor and capital).” (Dietzenbacher 1997, 630).

17 Only if outputs from all sectors change at the same rate, then the matrices *H* and *A* will be jointly stable (Rose and Allison 1989, 452–53). This “turnpike” growth rate, as Miller and Blair calls it (Miller and Blair 2009, 651–52), has a long history in twentieth centuries debates over Theory of Value and growth models. It is the same as von Neumann’s coefficient of expansion of the whole economy, and Shaikh’s rate of pure expanded reproduction. In the latter, the composition of net output is the same as total cost, production inputs plus the wage basket of goods (constant and variable capital in Marx’s terms), and also total output. Again, this equal composition between total product and net product, is the same as in Sraffa’s “standard” commodity (Capobianco 2023, 53–54, Annex A).

18 Interestingly, the author finds some resemblance with the sequential inter-industry models (SIMs) of Romanov and Levine, and thinks that a link between the two approaches can be established (Oosterhaven 1988, 214).

19 Oosterhaven is totally aware of this: “Imagine an economy with a shortage only in the supply of primary inputs to the first sector, where all sectors hoard capital, labor and intermediate inputs of all other sectors except those of sector 1. (…) In this very specific case, the notion of production requirements can be maintained as the hoards will serve to satisify those requirements (…)” (Oosterhaven 1988, 207–8). We must add that almost every sector in modern economies is operating always with some sort of inventories and idle capacity. Then, the issue turns into a matter of grade.

20 Soon after, Rose and Alison (1989) tested empirically the joint stability of the production and allocation coefficients, and found very small discrepancies; small enough to consider the supply driven model still plausible. Also, Gruver (1989) restricted the use of Gosh’s approach to small changes of primary inputs, where its validity could be theoretically established. In a reply, Oosterhaven (1989) reject them both.

21 This is also true. In the end, it is all a matter of *assuming fixed prices or fixed quantities*: “The requirement is that the initial, exogenous change is interpreted as being caused by price changes.” (Dietzenbacher 1997, 635). It can be proven that Leontief’s dual also has an interpretation with fixed prices, that yields the same results as Ghosh’s allocation model. Also, the classic demand driven input-output model could be interpreted, with fixed quantities, into a *demand-pull price model*, where variations in final demand result into price variations that climb upstream into the productive structure. All of this was neatly put down by Oosterhaven (2023), following an original proposal of demand prices determining ‘factor’ prices, made by Davar (1989).

The reason why this restatement is so attractive to us is that it poses the problem strictly in terms of value added. Oosterhaven's critic could be circumvented by appealing to inventories. And that still holds here. But, Dietzenbacher is asking a deeper question: why would new production occur, if *no value added is created* in any sector other than the one that triggered the action?[22] To answer this, we need first to introduce an interpretation of Ghosh's allocation model, within the framework of the Labor Theory of Value (LTV).

As it can be deducted from its name, in this line of thought, labor is the *sole* source of all value created in capitalist production. The form in which new value appears is as "(…) *surplus value of the product above the value of the factors that has been consumed in generating said product* (…)" (Marx 2002, 1:252, original italics, own translation), which is called *surplus value*. The consumed factors are, of course, the means of production and the labor power. An important qualitative difference arises between these two. The value of the means of production (*cc*) does not modify its magnitude, and only *reappears* in the value of the product (*V*). In contrast, the consumption of the labor power has a twofold consequence. First, it *replaces* all the value contained in the *means of subsistence* (c*v*) needed for her or his reproduction (Marx 2002, 1:208–9). And second, it creates the aforementioned surplus (*s*). This gives:

$$V = cc + \underbrace{cv + p}_{\text{value added}} \qquad [2]$$

In this context, *value added* can be understood as the total amount of direct labor *unfolded* by the labor power in the production process[23]. It comprises the remuneration of the labor power, and also all future profits, rents and derived incomes. For this, Marx calls it *product of value* (Marx 2002, 1:256–57). Going down the production chain, a *fraction* of this output will reappear later as the value of an intermediate input (*cc*), in the gross output of other industries. Given a vector of all value added and a matrix of this *reappearances* fractions (allocations), total output of all sectors can be recreated (as in equation [1])[24].

Let's say that, for whatever reason, *only one sector* is modifying (increasing) its output, and we assume that further down *it will be used.* What does that mean in the context of the LTV? If *no more direct labor is unfolded*, i.e. no product of value (value added) is created, the only thing that we can conclude is that *the productive power of labor has changed* (risen in this case) in all the other sectors that will use the input[25]. So, a variation in the output of one sector can tell us, under the assumption of a *varying productivity of labor*, the impact in the output of other sectors[26]. Also, the reader must note that, for any other than labor, all technical relations can remain unmodified (thanks to inventories).

How *plausible* is this interpretation of Ghosh's allocation model? Well, it depends. For small enough differences in sectoral output variations, this becomes *empirically* a non-issue, like

22 "In whatever way output turns out to be produced and allocated among sectors it surely makes little sense that value–added is not responsive to a general system reallocation." (Guerra and Sancho 2010, 2).

23 The identification of value added with the sum of necessarily product and surplus product is quite usual in empirical Marxism (Shaikh and Tonak 1994, 41–45). Also, value added is assimilated as the monetary expression of direct labor in the so called *New Interpretation* (Duménil 1983; Foley 1982). In all of this, we are abstracting ourselves from the existence of any non-capitalist commodity production and nonproductive activities (in the marxian sense).

24 In a way, this interpretation has some common points with De Mesnard (2009), who argues that Ghosh's model can only be a value (prices times quantities) model, not a prices or quantities model alone (De Mesnard 2009, 366–67). We don't agree with the latter, since variations in value can be thought as product of variation in prices, or in quantities.

25 "The same labor, therefore, no matter how much the productive power changes, always yields *the same magnitude of value* in the *same periods of time*. But in the *same period of time* it supplies *use values in different quantities*: more, when the productive power of labor increases, and less when it decreases." (Marx 2002, 1:57, original italics, own translation).

26 This is true for any combination of variations that are not all equal (see note N° 17).

Rose and Alison (1989, 454–56) already pointed out. Having said that, perfectly *supply-induced* productivity adjustments sound too good to be true. In practice, when increasing output, *some* layout and organizational improvements could be implemented. In the opposite case, unexpected fall of supply may cause *idleness* in means of production and labor power. However, there is a subtle theoretical point that must be addressed here.

Let us rephrase the question. Given the labor power[27], is there any reason why productivity may vary *with changing availability* of inputs? The most intuitive answer would be *yes*, with a *changing intensity* of the labor process. That would have solved our problem, if it were not that *normal intensity* of concrete labor is a determinant of abstract labor[28], i.e. value. Any *permanent* increase in normal intensity of the labor process (or longer working days[29]) for any type of concrete labor, will materialize itself in more use values, but also in *more value*. So, in order to be theoretically consistent, all changes in labor intensity must be *transient*, not permanent variations in the normal intensity of the labor process[30].

When interpreted in this context, Ghosh's allocation model becomes a quite useful device, for planed or market economies all alike. Value added is *value*, that is *created* in each sector and then provided to all the others. It can point, for example, the need for more productivity growth in sectors that will be facing an increasing availability of inputs. Furthermore, it can give an intuition, in the short run, for changes in sectoral output, due to *induced changes* in labor productivity.

Information sources and methodology

In this section, we will go over all information sources used and we will present our methodology for forecasting final demand components, with a "forward looking" temporal distribution. All calculation and graphics were done using the R language and environment for statistical computing (R Core Team 2022). 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).

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[31], and it is expressed in quantities index numbers with base 2004 = 100. The first thing that we want to analyze is how *unbalanced* was growth during the period 2004-2023. This can be seen in Figure N°1.

27 Guerra and Sancho (2010, 12–17) presented a 'closure' for the supply driven model, that could be interpreted as an endogenization of wages and salaries. In this case, new value added could be created, but only in the form of retributions to the working power. This interesting alternative is analogous to the closure of the demand driven model for some class of final demand. For now, we will let this alternative aside and keep the model in its simpler form.

28 "Socially necessary labor time is the time required to produce any use value, under the normal production conditions in a given society and with the average degree of skill and intensity of work." (Marx 2002, 1:48, own translation).

29 These two phenomena have equal effect: increased labor expenditure by the labor power (Marx 2003, 2:498–500, 636–39).

30 To be more precise, they need to correspond with transient variations of the sectoral rate of surplus value. The *average* rate of surplus value is not modified. No new value is created, and also the value (price) of the labor power stays equal. For a more detailed description of values as a result of a process of equalizing rates of surplus value, see Capobianco (2023, chap. II).

31 The aggregation of sectors matches the ISIC rev. 3.1 industrial classification, at the level of section ("letters"). They are the following: Agriculture, hunting and forestry (A); Fishing (B); Mining and quarrying (C); Manufacturing (D); Electricity, gas and water supply (E); Construction (F); Wholesale, retail trade and repair (G); Hotels and restaurants (H); Transport and communications (I); Financial intermediation (J); Real estate, renting and business activities (K); Public administration and defence (L); Education (M); Health and social work (N); Other community, social and personal service activities (O).

The matrix should be read, by columns, as the ratio of sectoral growth of the column sector over the row sector. 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”. But, if we let these two aside, a more balanced growth appears to have occurred between all the other sectors. It is not our objective to give and explanation for this behavior, so we move on.

The EMAE is our “source” time series. Our target is final demand, by component, which is also elaborated and published by INDEC, as part of the quarterly national accounts. This time series is provided at 2004 *constant market* prices, with a seasonal adjustment. Final demand components available are: household consumption, public consumption, gross fixed capital formation (from now on investment) and exports. Both consumption and investment comprise national and imported production. In the case of consumption, there is no available disaggregation of origin, and thus it is not possible to subtract imports from it. In contrast, 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.

Figure N°1. 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

Source: Own elaboration based on INDEC. Given yield variations for climatic conditions, the rate of growth of “Agriculture, hunting and forestry” was calculated with a triennial mean. Matrix visualizations were made with the *corrplot* package (Wei and Simko 2021).

The last input-output matrix published by INDEC dates back to the year 1997 (INDEC 2001). Since then, there is no “official”[32] symmetric table of intersectoral flows. Having said that, in

32 Nonetheless, this void was filled by many other researchers and institutions whom build updated versions, or

the year 2021, INDEC resumed the publication of annual Supply and Use Tables (SUT)[33]. The first SUT available was from the year 2018 (INDEC 2021). An industry-by-industry input-output matrix, with fixed product sales structure (type "D") (European Commission and Eurostat 2008, 297), was constructed using this SUT. The matrix is expressed at basic prices. Later, it was aggregated to match the sectors of the EMAE series. The allocation coefficients were calculated, and the Ghosh inverse was obtained.

The EMAE series needed some treatment prior to its utilization. It was converted from index numbers to constant prices (millions of AR$), using base year value added from national accounts. That turned it into a series at *constant basic* prices. Finally, the series of total output could be reconstructed from sectoral value added (following Equation [1]). For all observations (*n*):

$$v_t' \cdot G = \tilde{x}_t' \quad \text{for } t = 1, 2, \ldots n \qquad [3]$$

Recall that final demand was expressed at market prices. So, to ensure consistency in the estimates, taxes (less subsidies) over products must be added. Aliquots for product taxes could be directly derived from the 2018 SUT. Nevertheless, this figure included export tariffs. Thereby, the latter was independently estimated from foreign trade data. Then, the result was subtracted from the total taxes (less subsidies) over products. In the end, two vectors of aliquots were made (*q*): one for investment (*in*), household (*hc*) and public consumption (*pc*), with taxes over products; and one for exports (e*x*), with export tariffs. In addition to taxes (less subsidies) over products, value added tax should also be included. Unfortunately, we do not have yet constructed an estimate for this element.

Total final demand components (***f***) where estimated using 2018 input-output matrix participation (as a diagonal matrix *P*) across all sectors, with the corresponding taxes in each case included.

$$\text{for } t = 1, 2, \ldots n \begin{cases} \tilde{x}_t' \cdot \hat{P}^{hc,pc,in} \cdot (u + q^{hc,pc,in}) & = \tilde{\boldsymbol{f}}_{\boldsymbol{t}}^{\boldsymbol{hc,pc,in}} \\ \tilde{x}_t' \cdot \hat{P}^{ex} \cdot (u + q^{ex}) & = \tilde{\boldsymbol{f}}_{\boldsymbol{t}}^{\boldsymbol{ex}} \end{cases} [4]$$

All of this resulted in four time series estimated in levels, with a monthly frequency. The following step is to aggregate them to a quarterly frequency, in order to match final demands, which are a quarterly time series (total observations diminish from 240 to 80).

Results

Let's begin by exploring the correlation between our crude estimates, with no temporal adjustment, and the original final demands series. In Figure N°2 we can see the plot of the four components, and the coefficient of determination.

What immediately strikes the eye is that the estimates for the supply driven model are consistently below the observed values. This "underestimation" is particularly gross in the case of exports. There could be multiple explanations for this phenomenon[34]. Partially, it could be attributed to the lack of the value added tax, in the case of household, public consumption and investment. Regarding exports, the main explanation, we believe, is that the severe drought of the year 2018

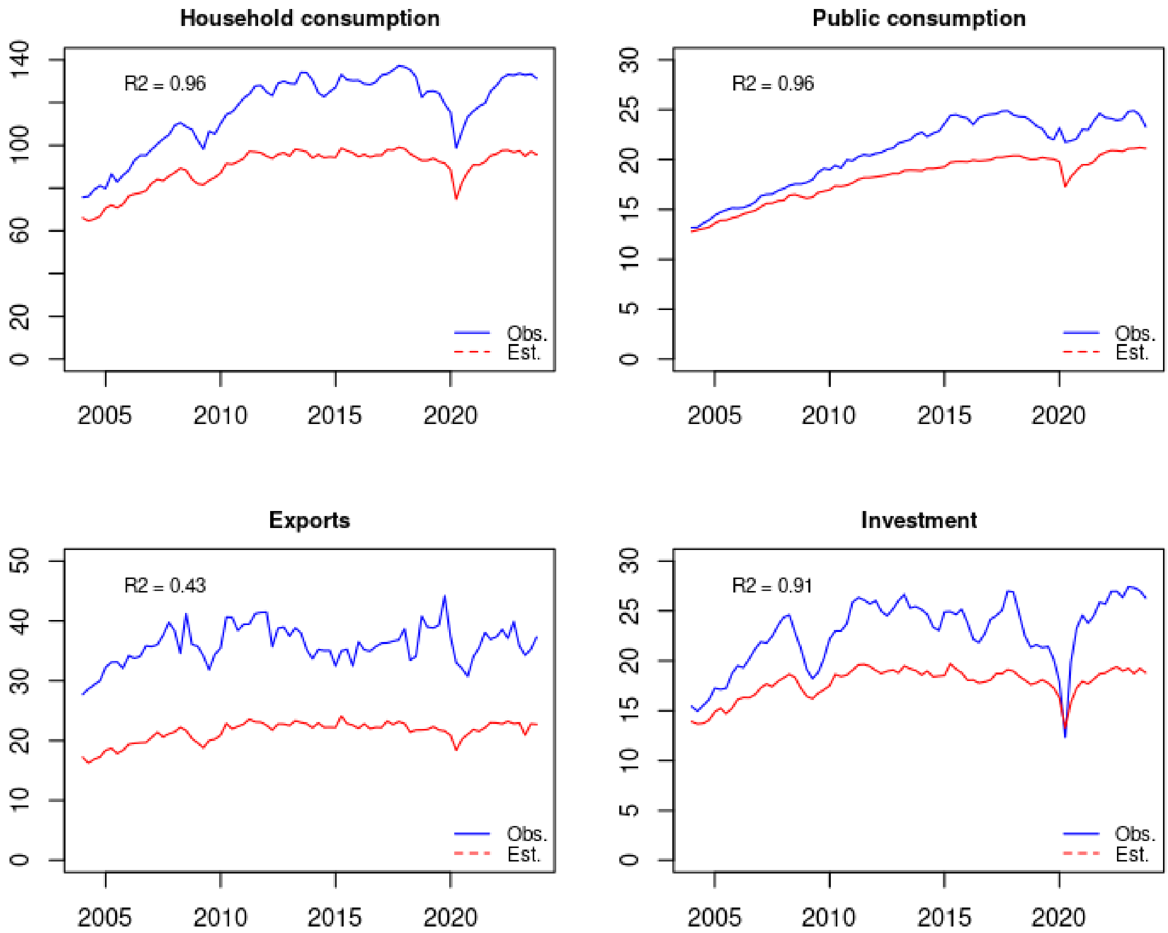
compiled them starting from the Supply and Uses Tables avalilable for the year 2004.

33 "Supply and use tables (SUT) form a central part of the system of national accounts. Their main use is to act as an integration framework for balancing the national accounts (…). They also constitute the data base from which (…) macroeconomic models and impact analysis can be derived in the form of symmetric input-output tables." (European Commission and Eurostat 2008, 295).

34 The magnitude of the underestimation is slightly bigger than what the figures show. The reader should be aware that we are not modeling changes in inventories, which is another important part of quarterly final demand. For all the period 2004-2023, inventory builds are positive for a total amount of approximately 200 BN AR$.

acts like a “fall of productivity”, that affects the estimation for the entire period.

Figure N°2. Final demand components, Argentina 2004-2023. Observed vs. estimate. Billions of AR$ 2004.



Source: Own elaboration based on INDEC.

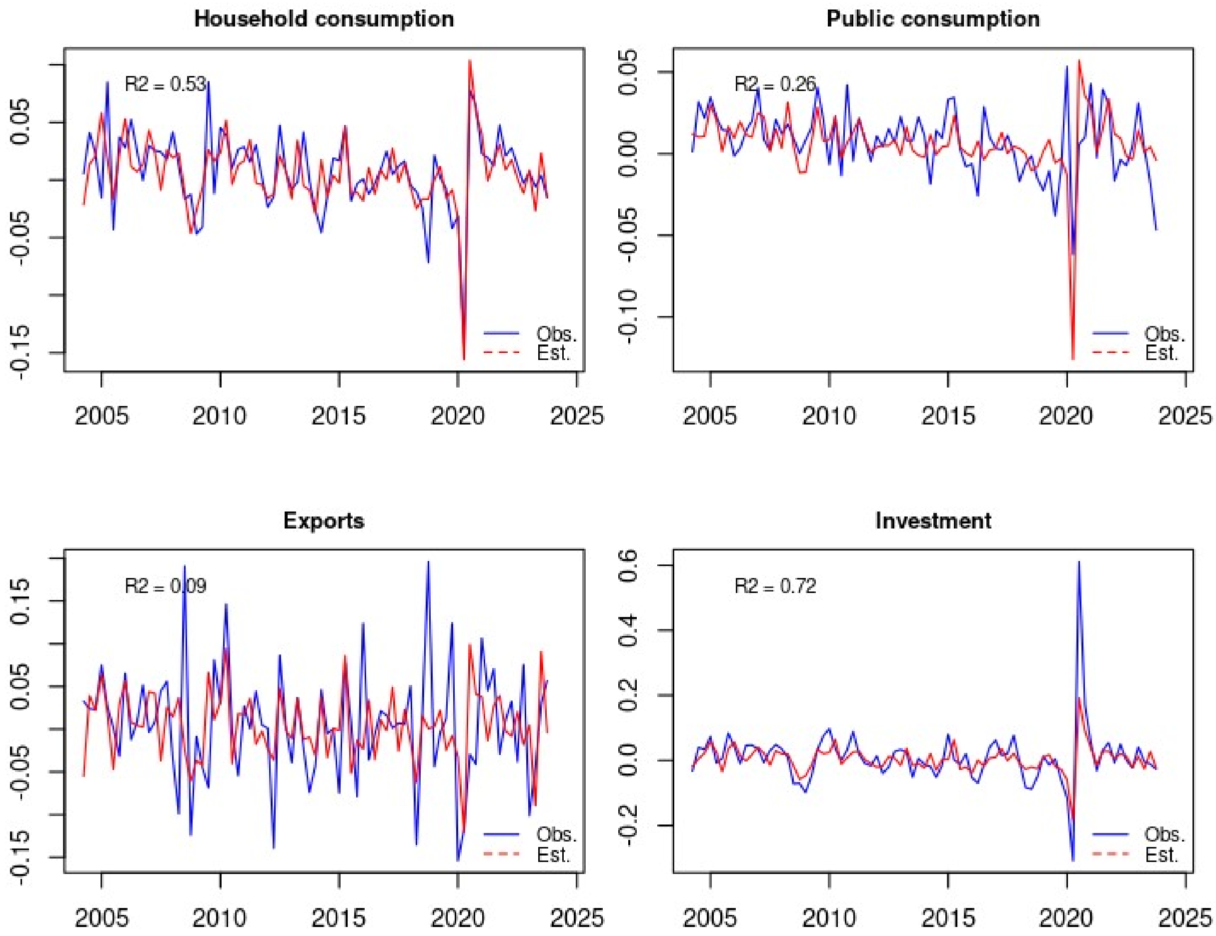
Letting that aside, at a first glance, there seems to be some correlation between the observed values and the estimates. The coefficient of determination is rather high in three cases (household consumption, public consumption and investment), but not so with exports. Nevertheless, we should not give yet too much importance to this indicator. It is a well known fact in econometrics that correlation tends to be rather higher when time series are expressed in levels[35]. A greater deal of reliability in short term predictions will be achieved by transforming our time series into variations[36]. This is shown in Figure N°3.

Now the landscape has changed. The most accurate short term prediction is the one for investment, followed by household consumption. Considering the relative high weight of construction inside investment, this result should not be a surprise. On the other end, the accuracy of exports just falls apart.

35 Sometimes, this argument is put in therms of “spurious correlation”. We do not think that this is the case here.

36 That is, take the first difference against the last period, and divide it by this value: $\triangle f_t^i = \dfrac{f_t^i - f_{t-1}^i}{f_{t-1}^i}$.

Figure N°3. Final demand components, Argentina 2004-2023. Observed vs. estimate. Variations against last period.



Source: Own elaboration based on INDEC.

Why is this happening? One possible explanation could be that national accounts aim to register value added *when it's created*, in the process of production. At the same time, they register its final use *when its sold* (in this case, exported). If a time lag between these two moments exists, a short term prediction would be harmed. In general, if it were possible to capture the normal temporal distribution of final uses, in relation to when value is created, it could, hypothetically, improve the accuracy of predictions. Let's explore this path.

The first approximation to the temporal dimension is fitting a *finite distributed lag model* (DLM)[37], to each observed final demand component. It is finite in the sense that the number of lags is not infinite, and we need to specify them with some criterion (Gujarati and Porter 2010, 623). As we already mentioned, the SUT that were used to construct the input-output matrix corresponded with a yearly time frame. So, 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:

$$\begin{aligned}&\text{for } i = hc, pc, ex, in: \\ &\quad f_t^i = \beta_0 \cdot f_t^i + \beta_1 \cdot f_{t-1}^i + \beta_2 \cdot f_{t-2}^i + \beta_3 \cdot f_{t-3}^i + e_t^i\end{aligned} \qquad [5]$$

37 For some context in distributed lag models see Gujarati and Porter (2010, 617–52).

The result of the fitted models can be seen in Figure N°4. There are many things to point out from the results. First, 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[38].

Figure N°4. Summary statistics of DLM for final demand estimates[39].

	Dependent variable:		*Dependent variable:*
	hc		pc
$\widetilde{hc}_t$	0.826*** p = 0.000	$\widetilde{pc}_t$	0.569*** p = 0.000
$\widetilde{hc}_{t-1}$	0.251*** p = 0.004	$\widetilde{pc}_{t-1}$	0.142 p = 0.155
$\widetilde{hc}_{t-2}$	0.029 p = 0.731	$\widetilde{pc}_{t-2}$	0.154 p = 0.123
$\widetilde{hc}_{t-3}$	0.101 p = 0.235	$\widetilde{pc}_{t-3}$	0.003 p = 0.973
R^2	0.608		0.363
Adj. R^2	0.586		0.328

	Dependent variable:		*Dependent variable:*
	ex		in
$\widetilde{ex}_t$	0.668*** p = 0.0004	$\widetilde{in}_t$	1.914*** p = 0.000
$\widetilde{ex}_{t-1}$	0.548*** p = 0.004	$\widetilde{in}_{t-1}$	−0.345** p = 0.011
$\widetilde{ex}_{t-2}$	0.060 p = 0.744	$\widetilde{in}_{t-2}$	−0.023 p = 0.860
$\widetilde{ex}_{t-3}$	0.376** p = 0.049	$\widetilde{in}_{t-3}$	0.054 p = 0.685
R^2	0.236		0.752
Adj. R^2	0.194		0.738

Source: Own elaboration based on INDEC.

All and all, the hypothesis contrast for the regression coefficients must not be of much concern to us, yet. There are other important considerations that must be addressed first. Let's take a look at the total sum of the coefficients, the "long term multiplier" of distributed lags (Gujarati and Porter 2010, 619), in Figure N°5.

38 But this is also subject of further consideration, as the probable presence of multicollinearity increases standard error in relation to coefficients, and so the *t* values (Gujarati and Porter 2010, 624).

39 The tables of summary statistics were made using the *stargazer* package (Hlavac 2022).

Figure N°5. Sum of all coefficients ("long term multiplier") of DLM.

hc	pc	ex	in
1.206	0.869	1.652	1.600

Source: Own elaboration based on INDEC.

The important thing that arises in Figure N°5 is that the total sum of the estimated betas does not add up to unity. It is not far from it, but it must be exactly one. The reason behind this imperative is simple. If we allow the total sum of the betas to diverge from unity, we are not performing anymore a temporal distribution of a certain input-output multiplier. We are indeed changing its total magnitude, and therefore, backtracking over the assumptions of the input-output model. In short words, we are almost *leaving the input-output framework*. It is essential to secure total non-negativity of all betas, and also the total sum must add up to unity. Then, the original multiplier effect will remain unchanged.

In conclusion, it is necessary to redo the estimation in the light of the above considerations. 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.* The restrictions that we want to incorporate are the *constraints functions,* with their corresponding bounds. Rephrasing Equation [5], and incorporating the desired constraints:

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

$$\min g(b_i) = \|\tilde{F}_i \cdot b_i - f_i\|_2^2 = b_i' \cdot \tilde{F}_i' \cdot \tilde{F}_i \cdot b_i - 2 \cdot f_i' \cdot \tilde{F}_i' \cdot b_i + f_i' \cdot f_i \qquad [6]$$

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

Equation [6][40] poses the constrained least square problem as a QP. 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. The optimal temporal distribution of supply multipliers can be seen in Figure N°6.

The results shown in Figure N°6 are very insightful. 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 output multiplier does not impact in the same period. But it is also true, to some extend, for household and public consumption. Investment is the only final demand component where the output multipliers fully impact in the same period.

40 For notation purposes (the use of the transpose operator), in this equation we left aside temporal references (since its a matrix representation of a least square problem), and changed the meaning of the subscript from temporal values to categories of final demand.

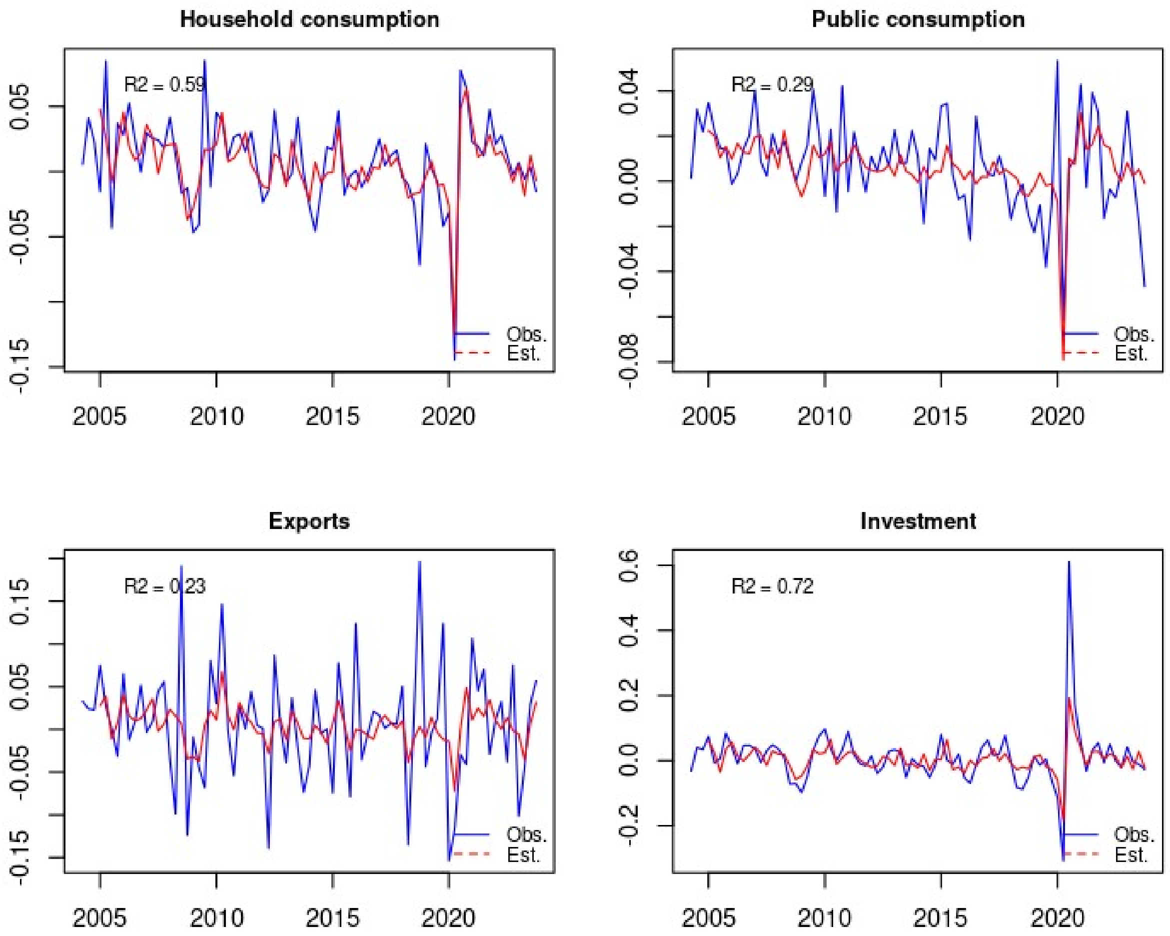
Figure N°6. Optimal temporal distribution of supply multipliers, by final demand categories.

	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

Source: Own elaboration based on INDEC.

Taking the optimal temporal lags (OTL) and using them for re-estimating the final demand components, yield the following forecast (Figure N°7). The predictive power is better that in our crude estimates of Figure N°3. They are also very similar to the results of the DLM. However, we argue that OTL is more congruent with the framework of input-output analysis and its assumptions. Given the aggregation of the matrix used (only fifteen sectors), we believe that the fit of the models is adequate.

Figure N°7. Final demand components, Argentina 2004-2023. Observed vs. estimate with OTL. Variations against last period.



Source: Own elaboration based on INDEC.

Conclusion

In this essay, we explored the possible interactions between input-output analysis and the econometric approach to time series. It is certainly not the first time, since we also exposed a rich tradition of crossovers between the two fields. In the beginning, they maybe saw each other as competing techniques. But make no mistake, the future of input-output and econometrics is still one of *integration*.

In a sense, input-output can play a role that is somehow analogous to what principal component does in short term forecast. Leontief or Gosh's inverses can be thought as *linear transformations* that extract a special kind of information from a set of time series, prior to its utilization in another model or workflow. The additional benefit is that input-output provides a clear *economic interpretation* of the outcomes.

In our example, the explained variance of final demand 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. Overall, this highlights the fact that, combining input-output projections with OTL gives us a meaningful interpretation to the error term of the final combined forecast[41].

One of the reasons for a relatively low explained variance could be, obviously, that the allocation (or technical) coefficients may have changed in the span of twenty years[42]. Technological change, economies of scale, and other factors can indeed change the matrix of inter-industry transactions. A possibility could have been to quarterly balance the matrices, with some biproportional technique. But, that would (maybe) stand in the way of capturing the phenomenon of *temporal lags*, that we just presented.

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. Furthermore, the proposed framework for estimating optimal temporal lags could be extrapolated to the more common demand driven model, provided that the information is available. It still stands the question of the *statistical significance* of the optimal distribution. This, and the question of changing coefficients, could be addressed in future works.

41 Another way of saying this is that a very high fit could also be non desirable, since it does not left any space for other effects to enter the scene.

42 The same thing could be said for the relative participation of final demand component in the outputs of every industry.

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