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Research article

Constant price input-output and productivity surplus

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Abstract: In this paper we showed that the results of input-output impact analyses can vary significantly depending on whether current prices or constant prices are used, particularly when the deflation method differed from the conventional double deflation approach. We quantified the transfer of productivity surplus from constant price input-output tables obtained by applying appropriate price indices through a single deflation method. Focusing on the Spanish economy during the period 2010–2019, we analyzed the redistribution of this surplus among sectors. We algebraically defined the rule for distributing productivity gains across sectors in response to an exogenous demand shock. Due to the presence of forward and backward productivity linkages, sectors may experience productivity gains or losses, irrespective of where the demand shock originates.

Keywords: Input-Output; constant prices; single deflation; productivity surplus; Spain

JEL Codes: C67, D24, D57, E31

1. Introduction

Economic impact analysis ever more frequently relies on constant price Input-Output (I-O) tables. The reasons lie in their ability to better capture structural and technological change while avoiding price-biased results. Various techniques exist for obtaining constant price I-O, but the conventional and most widely used is the double deflation approach. This method calculates gross value added at constant prices by subtracting intermediate consumption at constant prices from output, also measured at constant prices. Essentially, in this approach, the value added is obtained as a residual, therefore abstracting from the different nature of its components (labor and capital) that would require appropriate price indices. The advantage of using double deflation lies in its relative simplicity, low data requirements, and the fact that it ensures the I-O system to remain balanced in constant prices. However, previous research has suggested that an I-O system measured in constant prices may inherently reflect imbalances that correspond to productivity changes (see, e.g., Babeau (1978); Kendrick (1961)). These gains (or losses) can only be captured if each component of the I-O table (intermediates, labor, capital, consumption, exports, etc..) is deflated by the most appropriate price index without any adjustments to artificially preserve equilibrium in the system.

Several contributions in the literature have employed I-O–based approaches to derive productivity measures, laying the foundations for the analytical perspective adopted in this paper. Early studies, such as Flexner (1959), demonstrate that productivity improvements between the base and current periods imply that changes in input quantities no longer match changes in output quantities. Babeau (1978) further shows that, under constant price aggregation, the balancing residual within the I-O system represents the total productivity surplus. This has been decomposed to measure the transfer of productivity surplus from firms to households and its distribution between household groups.

A more systematic framework was proposed by Fontela (1989) and Fontela (1994), who developed the total factor productivity approach. In this formulation, a fully deflated I-O system serves as the accounting structure for measuring productivity gains and the corresponding transfers of productivity surplus among economic agents. The interindustry framework enables the identification of productivity transfers among industries and from firms to households. Furthermore, the full I-O system allows the measurement of workers' productivity gains and transfers of surplus from workers to capital owners or from capital owners to households, providing a view of how efficiency gains permeate the entire economic system.

Extensions of this framework have further expanded its analytical reach. Antille and Fontela (2003), for instance, apply it to the case of Switzerland, identifying the role of exchange rates in mediating cross-country redistribution of productivity gains. More recently, Garau (2022) refines the single deflation approach by differentiating between productivity generated under conditions approaching perfect competition and the surplus created by firms' market power, which enables them to impose higher markups and generate extra profits. This allows us to separate the efficiency-driven and rent-based components of the productivity surplus.

This paper pursues a twofold objective. First, it contributes to the input-output impact analysis literature by comparing multipliers derived under alternative deflation methods. In doing so, the paper emphasizes that the magnitude and interpretation of multipliers effects can vary substantially depending on whether the analytical framework is expressed in current or constant prices, particularly when accounting for productivity gains. Building in the Spanish input-output tables for the period 2010–2019, we construct a constant price I-O accounting system and compare the results obtained under single and double deflation, thereby extending earlier exercises such as Dietzenbacher and Hoen (1998) while proposing a different assumption on I-O identities in constant prices.

Second, the paper advances the understanding of how productivity gains and losses propagate across sectors in response to demand shocks. This is achieved through the extension of prior work on productivity surplus (Fontela, 1994; Garau, 2022). By algebraically deriving a distribution matrix of productivity gains, the analysis identifies sectors that, when directly affected by a demand shock, act as sources of productivity for the rest of the economy, as well as those that primarily absorb gains generated elsewhere. This approach reveals that certain sectors may experience productivity losses even when they are the direct target of a positive demand stimulus.

Contrary to conventional productivity measures, the paper underscores that productivity surplus analysis provides a unique perspective on the mechanisms through which productivity changes in one industry transmit throughout the economy via intermediate linkages.

The remainder of the paper is structured as follows. Section 2 discusses the different alternatives of the constant price framework and the issue of unbalanced systems under constant price I-O. Furthermore, it presents the distribution rule of productivity surplus between sectors. Section 3 describes the data sources and their treatment to obtain single deflated I-O tables. Section 4 presents the results of the application to Spain of both the impact analysis divergence and the distribution of demand-driven productivity gains. In Section 5, we draw our final remarks and conclusions.

2. Constant price I-O

Traditionally, impact analysis has relied on nominal balanced I-O tables, and therefore, current price multipliers have been the conventional approach for many years. However, since the 1990s, there have been attempts to reproduce and use physical or constant I-O tables as an alternative to ordinary monetary and current price I-O tables. Deflated I-O tables may reveal hidden trends or refute general beliefs of structural or technological change (Garau et al., 2010). For example, when measured at constant prices, the increase in the share of tertiary economic activity in the economy seems overestimated (Kander, 2005; Savona and Ciarli, 2019). In periods of high inflation, the use of constant price I-O tables avoids price-biased results (Chóliz and Duarte, 2006; Pereira López and de la Torre Cuevas, 2023). Furthermore, some authors argue in favor of using physical tables, such as Hubacek and Giljum (2003) or, in their absence, constant price tables (Hoen, 2002), as they would produce more accurate results. Ultimately, constant prices ensure that the total factor productivity measures technological change rather than price increases in intermediate inputs, labor, and capital (Miller and Blair, 2009; Peterson, 1979).

Among various deflation techniques, the most widely used method to construct constant price tables is the conventional double deflation approach (Dietzenbacher and Hoen, 1998; Dietzenbacher et al., 2013; Wu and Keiko, 2015; Rampa, 2008), which produces an equilibrating and balanced system of accounts at constant prices. It consists of deflating the elements of the I-O table by sector in some base year prices and computing their constant price value added as a residual, balancing the table by subtracting the deflated intermediate inputs from the total deflated output (Durand, 1994). Despite its wide use, double deflation is recognized as an effective method only under restrictive conditions (Garau et al., 2010).

The double deflation method deflates I-O tables as if each sector comprises only one commodity, inducing a problem of aggregation bias (Dietzenbacher and Hoen, 1999). Only in rare cases do sectors produce a single commodity where all buyers pay the same price for it (Folloni and Miglierina, 1994). In some particular circumstances, double deflation may produce value-added sign flips, becoming negative, whenever the deflated total intermediates exceed the deflated total output of any sector (Pereira López and de la Torre Cuevas, 2023).

In light of these challenges, alternative approaches have been proposed in the literature. These include techniques such as the row-column adjustment sum (RAS) method[1] and further developments

[1]Originally meant as a system to update and balance I-O tables, is now a widely used alternative to double deflation as it provides cell-specific deflators, solving the double deflation aggregation bias problem (see for instance Dietzenbacher and Hoen (1999) or the

such as the generalized RAS (GRAS) algorithm (Junius and Oosterhaven, 2003), and the Path-RAS (Pereira López and de la Torre Cuevas, 2023) and the "subjective" weighted least-squares (SWLS) (Rampa, 2008). These methods allow for a more flexible and disaggregated treatment of price variation across cells and components of the I-O table.

This literature starts by defining the I-O accounting equilibrium equation where **I** is the identity matrix, **A** the technical coefficient matrix[2], **x** a vector of output, and **y** a final demand vector[3]:

$$x = (I - A)^{-1} y \tag{1}$$

In Equation (1), $(I - A)^{-1}$ is the Leontief inverse matrix, which generates the amount of output required by each sector after a unit increase in final demand. Conventionally, irrespective of the deflation method used, when converting Equation (1) in constant prices, the same identity holds for constant price values:

$$\overline{x} = (I - \overline{A})^{-1} \overline{y} \tag{2}$$

where $\overline{x}$ is the output vector at constant price, $(I - \overline{A})^{-1}$ is the Leontief matrix evaluated in constant prices, and $\overline{y}$ is the deflated final demand vector.

Dietzenbacher and Temurshoev (2012) provide an application of constant price multipliers proposing three deflation methods that yield similar impact predictions. In another study, Harmston and Chow (1980) argue that there is no evidence supporting the preference for constant multipliers as the ones with superior forecasting power. Following Kendrick (1961), a constant price system of accounts is unbalanced by nature, and the disequilibrium between input and output evaluated in constant prices can be seen as the source of productivity gains (Babeau, 1978; Flexner, 1959; Fontela, 1989). From this perspective, enforcing balance in constant price tables may hide structural changes effects driven by shifts in relative price differences that in turn reflect changes in total factor productivity (TFP) (Ngai and Pissarides, 2007).

In consideration of this literature, let us now consider a full I-O system where **Z** is the matrix of intermediate flows, **l** is the labor vector, vector **k** capital, **m** represents the vector of imports, **f** is the final demand vector, and **e** represents the vector of exports. The variables are expressed in nominal terms and the following equilibrium between input and output holds:

$$Z'i + m + l + k = Z + f + e \tag{3}$$

However, when the system is deflated using a single deflation method, the above identity no longer holds. This method deflates every element of the I-O table at current prices using the appropriate price index (i.e., producer prices for intermediates, consumer prices for final demand, return to capital, wages, etc.) and without using artificial balancing methods such as RAS, for example. Since even value-added vectors are deflated by their own price vector and not as a difference between constant output and constant intermediates, single deflation converts the table from a balanced to an imbalanced

recent work of Matsushima et al. (2024)

[2]The technical coefficient matrix represents the amount of inputs required by each sector to produce a unit of output.

[3]Matrices are denoted in bold capital font, vectors in bold lower-case font. Vectors are columns, by definition. Scalars are denoted in italic font. The superscripts indicate transposition when denoted with " " or sectoral identification when denoted with c and r. A bar above any letter denotes that the variable is in constant prices. A summation vector of ones is denoted by I, and it varies in dimension across equations.

system of accounts. This means that $\overline{Z}'\mathrm{i} + \overline{\mathrm{m}} + \bar{\mathrm{l}} + \bar{\mathrm{k}} \neq \overline{Z} + \bar{\mathrm{f}} + \bar{\mathrm{e}}$ and, therefore, the Leontief model as previously mentioned in Equation (2) is not able to replicate the initial value of production in constant prices:

$$\overline{\mathrm{x}} \neq (\mathrm{I} - \overline{\mathrm{A}})^{-1}\overline{\mathrm{y}} \tag{4}$$

In a single-deflated I-O table, there is no equilibrium between demand and supply. The difference is represented by productivity gains or losses in the economy as originally found in Fontela (1989). This has, therefore, implications when calculating constant price multipliers. Expressing $\overline{\mathrm{x}}^{\mathrm{c}}$ as the vector of the total constant price input, such that $\overline{\mathrm{x}}^{\mathrm{c}} = \overline{Z}'\mathrm{i} + \overline{\mathrm{m}} + \bar{\mathrm{l}} + \bar{\mathrm{k}}$ and $\overline{\mathrm{x}}^{\mathrm{r}}$ as the vector of the total constant price output obtained as $\overline{\mathrm{x}}^{\mathrm{r}} = \overline{Z} + \bar{\mathrm{f}} + \bar{\mathrm{e}}$, it results that $\overline{\mathrm{x}}^{\mathrm{c}} \neq \overline{\mathrm{x}}^{\mathrm{r}}$. This implies that under a single deflation method, the matrix of technical coefficients can alternatively be defined as:

$$\overline{\mathrm{A}}^{\mathrm{r}} \text{ where each element } \mathrm{a}_{\mathrm{c,r}} = \frac{\bar{\mathrm{z}}_{\mathrm{c,r}}}{\overline{\mathrm{x}}^{\mathrm{r}\prime}}$$
$$\overline{\mathrm{A}}^{\mathrm{c}} \text{ where each element } \mathrm{a}_{\mathrm{c,r}} = \frac{\bar{\mathrm{z}}_{\mathrm{c,r}}}{\overline{\mathrm{x}}^{\mathrm{c}}}$$

where $\mathrm{z}_{\mathrm{c,r}}$ is the cell-specific constant price I-O value for each combination of sectors c or r, $\overline{\mathrm{x}}^{\mathrm{c}}$ is the total input of sector c, and $\overline{\mathrm{x}}^{\mathrm{r}\prime}$ is the transposed vector of the total constant price output of sector r. Separately using $\overline{\mathrm{A}}^{\mathrm{r}}$ and $\overline{\mathrm{A}}^{\mathrm{c}}$, we can generate two alternative balanced Leontief models in constant prices[4]:

$$\overline{\mathrm{x}}^{\mathrm{r}} = (\mathrm{I} - \overline{\mathrm{A}}^{\mathrm{r}})^{-1}\overline{\mathrm{y}} \tag{5}$$

$$\overline{\mathrm{x}}^{\mathrm{c}} = (\mathrm{I} - \overline{\mathrm{A}}^{\mathrm{c}})^{-1}\overline{\mathrm{y}} - (\mathrm{I} - \overline{\mathrm{A}}^{\mathrm{c}})^{-1}\mathrm{t} \tag{6}$$

If the technical coefficients are defined as $\overline{\mathrm{A}}^{\mathrm{r}}$, we can obviously obtain a balanced constant price Leontief model as in Equation (5) while using the matrix $\overline{\mathrm{A}}^{\mathrm{c}}$, and the conventional Leontief model should be adjusted to include the productivity gains **t** as shown in Equation (6). The vector **t** is obtained as the difference between outputs and inputs in constant prices $(\mathrm{t} = \overline{\mathrm{x}}^{\mathrm{r}} - \overline{\mathrm{x}}^{\mathrm{c}})$ such that $\overline{Z}'\mathrm{i} + \overline{\mathrm{m}} + \bar{\mathrm{l}} + \bar{\mathrm{k}} + \mathrm{t} = \overline{Z} + \bar{\mathrm{f}} + \bar{\mathrm{e}}$. Essentially, **t** represents the extent to which constant price disequilibrium has been transformed into productivity surplus or losses. This additional balancing vector **t** has been called by Babeau (1978) and Fontela (1994) total factor productivity surplus (TFPS hereafter).

We have now obtained two alternative Leontief models based on a single deflated constant-price I-O model derived from Equations (5) and (6), besides the constant-price model developed in previous literature. The two constant prices multipliers are defined as $\overline{\mathrm{L}}^{\mathrm{r}} = (\mathrm{I} - \overline{\mathrm{A}}^{\mathrm{r}})^{-1}$ as in Equation (5) for rows and $\overline{\mathrm{L}}^{\mathrm{c}} = (\mathrm{I} - \overline{\mathrm{A}}^{\mathrm{c}})^{-1}$ as reported in Equation (6) for columns.

2.1. TFPS and the distribution rule across sectors

When the economy experiences an external demand shock, the magnitude of the TFPS changes. In this section, we identify algebraically the link between the effect of a demand shock and the distribution of productivity across sectors. We build upon the work of Fontela (1989) and Fontela (1994) on TFPS to solve for t. We depart from Equations (5) and (6) to derive an expression for the productivity gains,

[4]Since t is defined as the difference between output and input, to obtain $\overline{\mathrm{x}}^{\mathrm{c}}$, vector t must be substracted from the column-constant output after it has been pre-multiplied by the column-constant Leontief inverse matrix.

such as $\overline{x}^r - \overline{x}^c = \left(I - \overline{A}^r\right)^{-1}\overline{y} - \left(I - \overline{A}^c\right)^{-1}\overline{y} + \left(I - \overline{A}^r\right)^{-1}t$. We then obtain $t = \overline{L}^r\overline{y} - \overline{L}^c\overline{y} + \overline{L}^c t$ that, with algebraic manipulation, brings to Equation (7):

$$t = \left(I - \overline{L}^c\right)^{-1}\overline{L}^{rc}\overline{y} \tag{7}$$

where $\overline{L}^c = \left(I - \overline{A}^c\right)^{-1} > 0$ and $\overline{L}^r = \left(I - \overline{A}^r\right)^{-1} > 0$ are the multipliers calculated under two specification of technical coefficients while $\overline{L}^{rc} = \overline{L}^r - \overline{L}^c \lesseqgtr 0$ represents the differences between the two alternative multipliers. Equation (7) tells us that productivity surplus can then be determined from a demand-driven model where the matrix $\left(I - \overline{L}^c\right)^{-1}\overline{L}^{rc} = S$ can be interpreted as a distribution matrix of productivity gains among sectors. Each element of the matrix $s_{r,c}$ can be positive or negative and tell us the distributed productivity from sector r to sector c or whether the sectors are absorbing from or transferring productivity to the other sector of the economy.

$$S = \begin{bmatrix} s_{11} & s_{12} & \cdots \\ \vdots & \ddots & \\ s_{n1} & & s_{nn} \end{bmatrix}$$

If $s_{r,c} < 0$, it means that sector r is losing surplus, distributing it to either sectors c or outside the domestic economy, while if $s_{r,c} > 0$, sector r is taking advantage of sector c, either absorbing productivity from it or from outside the domestic economy[5]. For instance, if s_{11} is negative, it means that a final demand shock of 1 unit performed in sector $r = 1$ generates a productivity loss in the same sector of an amount s_{11}. Generalizing, all elements on the diagonal tell us the productivity generated, redistributed, or absorbed in a sector r when the same sector is perturbed. The sum across all columns gives us the total productivity surplus transferred or absorbed when all sectors of the economy are perturbed simultaneously. The sum across all rows tells us the productivity surplus generated in the whole economy when a single sector r is perturbed.

We can now derive the changes in productivity Δt associated with changes in constant price final demand $\Delta\overline{y}$ from the distribution matrix S:

$$\Delta t = S\Delta\overline{y} \tag{8}$$

The matrix S thus converts 1 unit of additional final demand expenditure into changes in productivity of each sector of the economy[6]. An economic sector n can gain productivity to the detriment of another sector or transfer productivity to the benefit of another sector. We can have the following two cases:

- $\Delta t_n > 0$; sector n is experiencing an increase in productivity, no matter where the constant demand shock occurs. Sector n is gaining productivity from other economic sectors.
- $\Delta t_n < 0$; sector n suffers a productivity loss despite any positive demand shock, even if directly experienced by the sector itself. Sector n is transferring productivity to other economic sectors.

[5] As shown in Equation (3), imports and exports are determining elements in the evolution of TFPS.
[6] A 2-sector algebraic and numerical example is available in Appendix C.

3. Data

This empirical analysis draws data for the period 2010–2019[7] from a range of sources depending on the considered variable. The 2019 Spanish I-O table was obtained from the Spanish National Statistical Office (Instituto Nacional de Estadística, INE (2024a)). The table provides comprehensive information for 64 sectors, organized according to the classification of economic activities (NACE rev.2). Price deflators are collected from four different sources: INE, Eurostat, EU KLEMS and the Penn World Table. Table 1 shows the index and the source of each deflator used for the application of the single deflation method[8].

Table 1. Price deflator data sources

Intermediate goods deflators	Construction, manufactures, and services	Producer's price index	Eurostat (2024)
	Agriculture	Agricultural output price index	Eurostat (2024)
Demand-side deflators	Households and government consumption	Consumers' price index	Eurostat (2024)
	Investment	All assets price index	EU KLEMS (2024)
	Exports	Export price index	INE (2024b)
Supply-side deflators	Labor	Labor cost index	Eurostat, 2024
	Capital	Calculations for capital deflator	Penn World Table (2025)
	Taxes	Intermediate goods price index	INE (2024b)
	Imports	Import price index	Eurostat (2024)

The analysis was conducted by applying the average deflator for each variable as a general case for all unavailable sectoral deflators. The deflator used for intermediate goods is the producer's price index consistently applied at the row level[9]. The deflator for household and government consumption is obtained from the consumer price index, which provides results in the classification of Individual Consumption by Purpose (COICOP). To obtain the NACE Rev. 2 equivalent index to match the I-O classification, a conversion was carried out by using a correspondence matrix (Cai and Vandyck, 2020) that translates the classification into products by activity (CPA)[10] for the Spanish economy. Export and import price deflators are available only for industry sectors. For the rest of the sectors, the approach diverges. Since exports are mainly derived from domestic production, exports have been deflated by

[7]The period was selected according to data availability.

[8]All price indices are available in Appendix A.

[9]The possibility of constructing cell-specific deflators from previous-year-price (pyp) Supply and Use Tables (SUTs) was considered, following the methodology proposed by Garau (2022). However, this approach was not feasible due to data limitations, as Spanish pyp SUTs are available only from 2017. The analysis in this paper deliberately spans a longer period to capture structural productivity changes across the maximum number of years available. Using the producer's price index ensures methodological consistency while allowing for a longer-term analysis of productivity dynamics.

[10]Each CPA code matches one NACE Rev. 2 category.

producer price indices. On the other hand, since the origin of all imports cannot be directly determined, non-industrial imports (which account for approximately 15% of all imports) are considered constant for the period taken into account. Since taxes do not present a specific sectoral deflator price index, they are deflated by the average intermediate goods price index obtained from INE. Labor inputs are deflated by the labor cost index as it provides the most comprehensive coverage for the required sectoral disaggregation and incorporates both wages and employers' social contributions, offering the closest empirical approximation to the national accounts concept of labor compensation.

Finally, given the particular nature of capital, its deflation process must be addressed explicitly. Capital is not directly measurable as it is a composite of different produced goods over time (Sraffa, 1961). This means there is no price for capital, and it must be determined jointly through a price system that takes into consideration three elements: a bundle of heterogeneous and previously produced commodities, multiplied by both their price and a profit rate. This relationship can be understood through the following equation:

$$\mathrm{p} = \mathrm{a_n w} + \mathrm{pA}(1 + \mathrm{r}) \tag{9}$$

where p is a vector of output prices, w is the wage rate, $\mathrm{a_n}$ is the vector of direct labor per unit of output, and r is the profit rate.

To derive this relationship, an estimate of the profit rate is required. For this purpose, we draw on the dataset provided by Basu et al. (2022), who offers internationally comparable estimates of profit rates for a wide range of countries over the period 1960–2019. In their framework, the profit rate is defined as:

$$r_{jt} = \Pi_{jt}/K_{jt} \tag{10}$$

where Π_{jt} denotes the profit income of country j at time t, and K_{jt} represents the corresponding capital stock. The Spanish profit rates for 2010 and 2019 are 6.8% and 7.2%, respectively[11].

4. Results analysis

4.1. Nominal vs Constant price multipliers: an application to the Spanish economy

To ensure comparability with previous literature (Dietzenbacher and Temurshoev, 2012), we directly compare the three output multipliers obtained through the three alternative deflation methods with the output multiplier computed using the nominal I-O table. In Table 2, we present key statistics related to the percentage differences between the three constant price multipliers ($\overline{\mathrm{L}}^{\mathrm{r}}$, $\overline{\mathrm{L}}^{\mathrm{c}}$, $\overline{\mathrm{L}}$) and the nominal multiplier (L). Additionally, we are interested in the differences between the two multipliers derived from the two alternative single deflation methods ($\overline{\mathrm{L}}^{\mathrm{r}}$ vs. $\overline{\mathrm{L}}^{\mathrm{c}}$)[12].

Table 2 includes, for each of these differences, the minimum, first quartile (Q1), median, mean, standard deviation, third quartile (Q3), and maximum. Figure 1 shows the distribution of the sectoral percentage between the same differences. A detailed examination of these statistics reveals important information on the distribution and variability of these differences.

[11] While Basu et al. (2022) also provide data on sectoral profit rates, their disaggregation does not cover the 64 sectors of the Spanish table. Consequently, in this study we employ the national profit rates, introducing the sectoral variation in the capital price by weighting it with the technical coefficients matrix as displayed in Equation (9).

[12] All four multipliers disaggregated by Nace Rev. 2 classification are reported in Appendix B.

Table 2. Percentage change between alternative multipliers.

$(\overline{L}^r - L)/L\%$	Value	$(\overline{L}^c - L)/L\%$	Value
Min	–13.7	Min	–1.5
Q1	0.0	Q1	0.8
Median	1.3	Median	1.5
Mean	1.6	Mean	1.4
St. Dev.	3.1	St. Dev.	1.1
Q3	3.9	Q3	2.1
Max	9.6	Max	4.9
$(\overline{L} - L)/L\%$	Value	$(\overline{L}^r - \overline{L}^c)/\overline{L}^c\%$	Value
Min	–15.7	Min	–17.7
Q1	–2.0	Q1	–1.5
Median	0.0	Median	0.0
Mean	0.2	Mean	0.1
St. Dev.	3.3	St. Dev.	3.4
Q3	2.3	Q3	1.6
Max	6.7	Max	7.9

In the case of $(\overline{L}^r - L)/L$, the minimum value is –13.7, while the maximum is 9.6, suggesting an important range of deviation. This insight is confirmed by a standard deviation of 3.1, that reflects significant variability in the data. The first quartile (Q1) is 0.0, while the third quartile (Q3) is 3.9. The median value is 1.3, and the mean is 1.6, both of which indicate an important difference between the nominal multipliers and the constant multipliers by rows. Observing Panel A, there is a slight positive skew, which means that some sectors experience higher than average positive differences, with the right tail of the distribution extending beyond 5. However, this skew is caused by a minority of sectors, as the mean is very close to the median. The Figure 1 also shows a moderate dispersion (from about –5 to 7), which could have significant implications on any impact analysis.

The difference $(\overline{L}^c - L)/L$ exhibits a narrower range of values, with a minimum of –1.5 and a maximum of 4.9. The standard deviation of 1.1 indicates less variability compared to $(\overline{L}^r - L)/L\%$. The Q1 is 0.8, suggesting that the lower 25% of the data is still relatively close to zero. The median and mean are 1.5 and 1.4, respectively, showing a similar difference to $(\overline{L}^r - L)/L$. However, when observing Panel B, the concentration of the data makes it the least skewed distribution and with less variability, suggesting that $\overline{L}^c$ represents the closest single deflation approximation to the nominal multiplier L. In fact, the constant multiplier by columns shows a narrower dispersion.

For $(\overline{L} - L)/L$, the minimum value is –15.7, and the maximum is 6.7. The Q1 is –2.0, and the Q3 is 2.3, with the standard deviation being 3.3. The median is at 0, reflecting a balanced distribution around zero, while the mean is slightly positive at 0.2 suggesting that the sectors with positive changes have a slightly stronger impact on the average. Panel C shows positive skew, with a long right tail. Many sectors experience positive percentage changes, with an important portion exceeding 5. The widest dispersion (from about –6 to 7) highlights the highest volatility of sectoral impact of the double

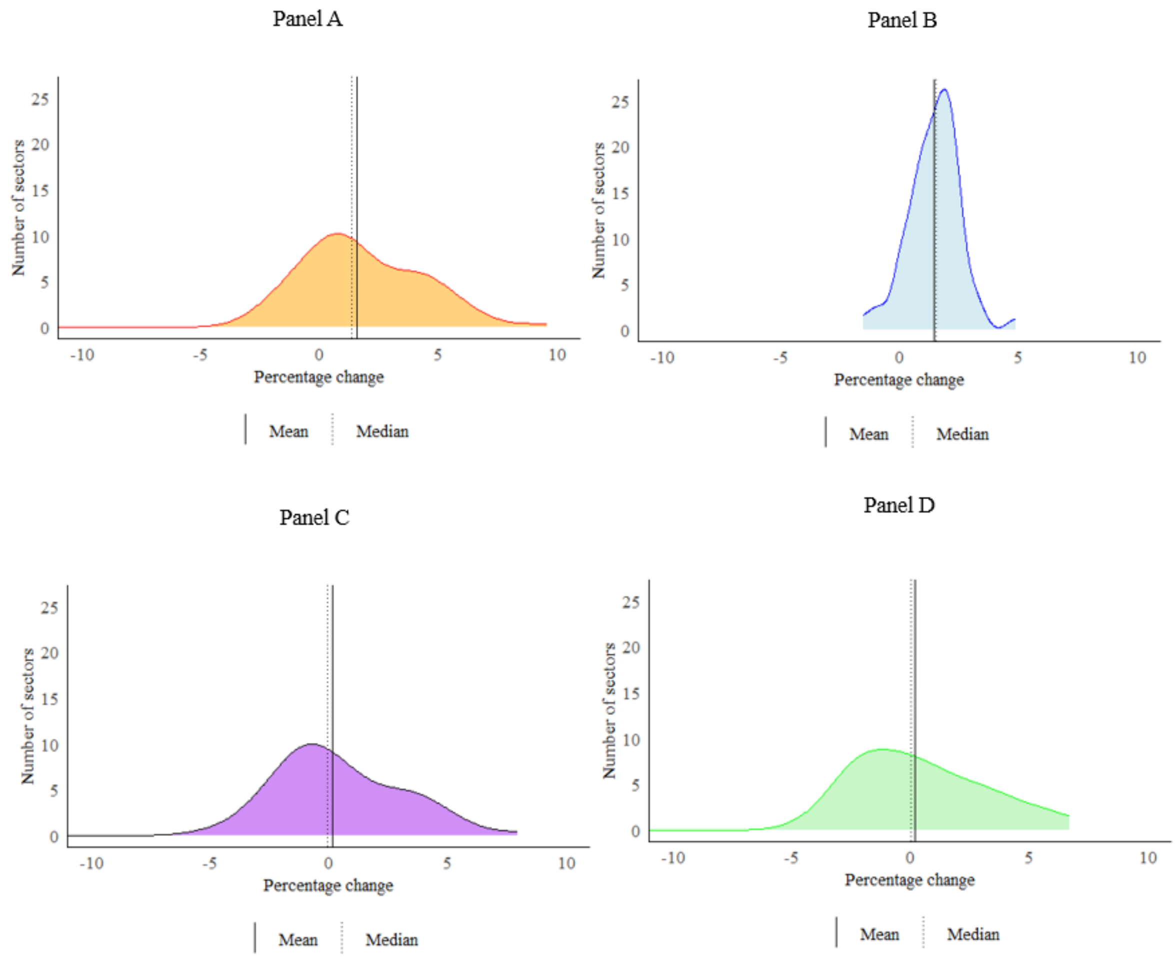

Figure 1. Distribution of the sectoral percentage differences between alternative multipliers.

Note: Figure 1 replicates the pattern of Table 2. Panel A corresponds to $(\overline{L}^r - L)/L$; Panel B corresponds to $(\overline{L}^c - L)/L$; Panel C corresponds to $(\overline{L} - L)/L$; Panel D corresponds to $(\overline{L}^r - \overline{L}^c)/\overline{L}^c$. For visual purposes, some outliers have been excluded from Panel A, C, and D.

deflated multiplier $\overline{L}$ with respect to the nominal multiplier L.

$(\overline{L}^r - \overline{L}^c)/\overline{L}^c$ shows the greatest overall range, with a minimum of –17.7 and a maximum of 7.9. The Q1 is -1.5, and the Q3 is 1.6, with a standard deviation of 3.4. The median is 0, and the mean is 0.1, both very close to zero, suggesting a relatively balanced distribution. The results of the distribution between these two multipliers corroborate from another perspective, the existence of significant differences between the estimates.

The smaller values of the mean and median found in $(\overline{L} - L)/L$ with respect to the row-constant and column-constant applications seem to partially confirm previous literature according to which double-deflated-constant and nominal multipliers either show negligible differences, as in the work of Dietzenbacher and Temurshoev (2012)[13], or do not provide enough evidence to support the use of one

[13] In general terms, we obtained larger differences than those obtained in Dietzenbacher and Temurshoev (2012). This can be due to higher price variations determined by a different geographical application (Denmark vs Spain) and a different time interval taken into consideration (2000–2007 vs 2010–2019 period).

or the other, as in Harmston and Chow (1980). However, this result provides the first fundamental implication of this analysis. In fact, even if this is applicable to the average effect applied to the whole economy, a sectoral examination of the multiplier suggests a different interpretation. While the double deflation method presents the smallest mean and median, its higher dispersion among all three constant alternatives makes the sectoral impact analysis more volatile. This means that the reason behind the average effect being the closest to the nominal result is determined by the high positive and negative sectoral differences rather than a similar behavior of the multiplier in nominal and double-deflated terms.

When single deflation is applied, we observe higher changes in both median and mean compared to the nominal multiplier. Both alternatives ($\overline{\mathrm{L}}^{\mathrm{r}}$ and $\overline{\mathrm{L}}^{\mathrm{c}}$) show that single deflation affects the differences between nominal and constant multipliers. Meanwhile, in particular, $\overline{\mathrm{L}}^{\mathrm{c}}$ shows the smallest and symmetrical changes overall and the least variability; an average impact divergence of around 1% from the nominal counterpart confirms the importance of using constant multipliers as the appropriate application to provide a good measure of structural change and productivity and avoid price-biased results, even in the case of single deflation.

Finally, we see that using one deflation methodology or the other presents an important impact on the results of any shock analysis. In fact, despite the use of any alternative method, the results show a high sectoral heterogeneity in the multipliers' estimates.

4.2. *Demand shocks and productivity gains*

In this section, we perform two sets of illustrative simulations to quantify the distribution of productivity gains across sectors in the Spanish economy arising from a) a final demand shock applied separately to each sector in turn (Shock 1), and b) a final demand shock applied to all sectors except one, in turn (Shock 2). These two shocks allow us to isolate each element of matrix S, as described in Section 2.1. The first shock identifies the TFPS that the perturbed sector absorbs or transfers to other sectors and itself. Conversely, the second shock provides insights into the productivity gains or losses a sector may experience due to a demand shock in the rest of the economy. The shocks are performed using Equation (8). Since the shock implemented is of one unit, this analysis essentially collapses to an analysis of backward and forward productivity linkages of the computed matrix S.

In Figure 2[14], we present the TFPS distribution resulting from separately shocking each sector[15]. The x-axis represents the TFPS values for the non-perturbed sectors, while the y-axis shows the TFPS values for the perturbed sector. Essentially, the y-axis corresponds to the diagonal elements of the matrix **S**, while the x-axis depicts the row sums excluding the diagonal elements of the matrix **S**. The horizontal red line indicates the average TFPS across the perturbed sector, and the vertical blue line marks the average TFPS for the non-perturbed sectors. We can thus divide the figure into 4 quadrants. We separate the quadrants with respect to the average values in the x- and y-axis, and not in positive-negative values (axis origin zero). This is due to the total TFPS for the period being negative, making the deviation from null TFP transfer a more trivial exercise, as many sectors will cause a productivity loss for themselves and/or for the rest of the economy. In particular, the total TFPS for the period is

[14] Legend: ● = Agriculture, Mining and Quarrying; ▲ = Manufactures; ◆ = Construction; ■ = Services.

[15] For visual purposes, the sector for food products, beverages and tobacco products C10 – 12($-0.015; -0.041$), coke and refined petroleum products C19($0.031; 0.063$), electricity, gas, steam and air conditioning D35($0.030; -0.112$) water transport services H50($0.033; 0.008$), air transport services H51($0.042; -0.121$) and telecommunications services J61($0.004; 0.352$) have been excluded from Figure 2.

–1.67 billion euros[16].

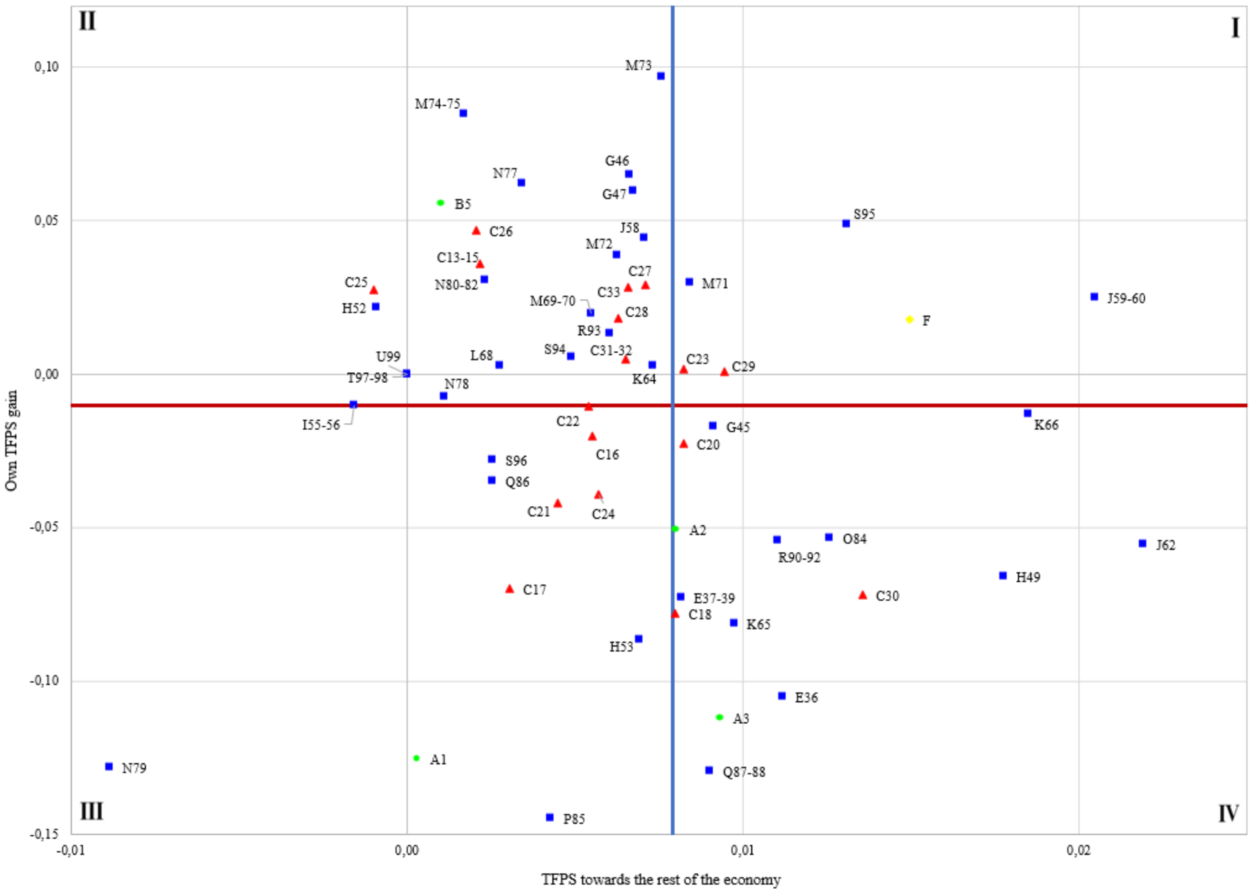

Figure 2. Productivity gains toward own sector vs spillovers (Shock 1).

In quadrant **I**, we have the sectors that generate positive above-average TFP spillovers toward the rest of the economy while gaining productivity themselves. The negative trend of TFPS for the period 2010–2019 implies that sectors generating above-average TFP for both themselves and the rest of the economy are nearly absent from the economy. In this quadrant, for example, a positive demand shock occurring in the construction sector (F) generates a positive TFP injection in the rest of the economy and productivity gains in its own sector.

Sectors in quadrant **II** experience a TFP gain caused by an exogenous positive shock while draining productivity from the rest of the economy. Sectors in this quadrant tend to experience a productivity stimulus within themselves, while other sectors experience a loss in productivity through spillover effects. For example, the manufacturing of fabricated metal products (C25) increases its productivity by around 0.027 of every unit of demand that it experiences, while it reduces the overall economy's productivity by 0.001.

In quadrant **III**, we have the sectors that, after an exogenous positive stimulus, generate an above-average TFP transfer from their own and the rest of the economy. Sectors in this quadrant experience productivity losses within the sector and cause productivity declines in others. The spillover effects

[16]A sectoral TFPS disaggregation is available in Table B.2 of Appendix B.

propagate a shock that may negatively alter key input markets. For example, a positive demand shock occurring in the agricultural sector (A1) generates negative TFP withdrawal from the rest of the economy and productivity losses in its own sector.

Finally, sectors in quadrant **IV** experience an above-average TFP transfer from their own but are able to generate positive productivity gains on the rest of the economy. In this case, for example, the computer programming, consultancy, and related services sector (J62) suffers a high productivity loss caused by a positive demand shock that translates, however, into a TFP boost toward other sectors.

Albeit it may seem counterintuitive, there are several elements that explain why an increase in final demand can lead to a decrease in productivity, among others, resource misallocation toward already unproductive sectors, inflationary pressures in key input markets driven by the demand shock itself, sectoral rigidities, or diminishing returns to scale (Hsieh and Klenow, 2009; Jones, 2013). While sector-specific analysis should be implemented to explore which of these reasons lie behind the productivity loss in each of these sectors, the results for quadrants I and II reveal critical policy implications. This suggests that demand-side policies directed toward sectors below the horizontal red line will not improve productivity and should be avoided while seeking longer-lasting effects on sectoral productivity by intervening on the supply side.

Observing Figure 2 as a whole, we see a situation of high sectoral heterogeneity in terms of productivity in the Spanish economy for the period 2010–2019. While this result calls for sector-specific targets when designing economic policies, some conclusions can still be drawn from the analysis. First, the primary sector (A1-3) exhibits a clear pattern of own-TFPS loss. As stated previously, this paper does not pretend to explore the reasons behind all sectoral behavior. However, this result is consistent with a sector traditionally characterized by lower productivity, greater vulnerability to inflationary trends, and high dependence on intermediate inputs for technological change. Second, except for certain outliers, the manufacturing sectors (C) appear to show a more resilient response to demand shocks in productivity terms. In fact, the productivity pattern in most manufacturing sectors is similar to the average of the economy. On the other hand, the services sector shows the highest heterogeneity, and no clear pattern can be observed. This is partly due to the wide diversity of activities provided in the sector. However, there is still significant divergence even when grouping service activities by branch. For example, the transportation branch (H) displays at least one sub-sector in each quadrant. Finally, it is important to note that the average direct effect (y-axis) of the demand stimulus on each sector is a -0.010 transfer per unit, generating an average negative productivity impact on the overall economy. However, the average spillover effects, shown on the x-axis, present a positive productivity impact on the rest of the economy by 0.008 per unit of demand shock. This result suggests that the productivity spillover effects partially offset the strong impact of the negative direct effect of the demand shock on the economy.

Figure 3[17] represents backward and forward productivity linkages[18], without the direct impact of the shock toward the perturbed sector[19]. In this sense, we present the TFPS distribution resulting from

[17]The same legend applies for Figure 2 and 3.

[18]In a standard I-O analysis, a demand shock leads to an increase in production through forward and backward production linkages. The level of sectoral interconnection is measured and defined as strong or weak based on the sector's ability to push other sectors to generate additional production. In Figure 3, backward and forward linkages are directly related to the creation or absorption of TFP through sectoral transfers. Based on this, strong productivity linkages may not match strong forward and backward linkages in standard production terms.

[19]Again, for visual purposes, some sectors have been excluded from Figure 3. These sectors are mining and quarrying $B5(0.001; 0.095)$, food products, beverages and tobacco products $C10-12(-0.015; -0.031)$, coke and refined petroleum products $C19(0.031; 0.063)$,

separately shocking each sector, and then shocking all sectors of the economy except the one previously shocked, in turn. Essentially, the y-axis corresponds to the column sums of the matrix **S**, while the x-axis depicts the row sums of the matrix **S**. In both cases, we exclude the elements of the diagonal from the counting. The vertical blue line shows the average amount of TFPS that each affected sector transfers to other sectors, illustrating backward productivity linkages. The horizontal red line shows the average TFPS transferred from all affected sectors to the only non-perturbed one, representing forward productivity linkages. The figure is then divided again into four quadrants according to the average values on the x- and y-axes.

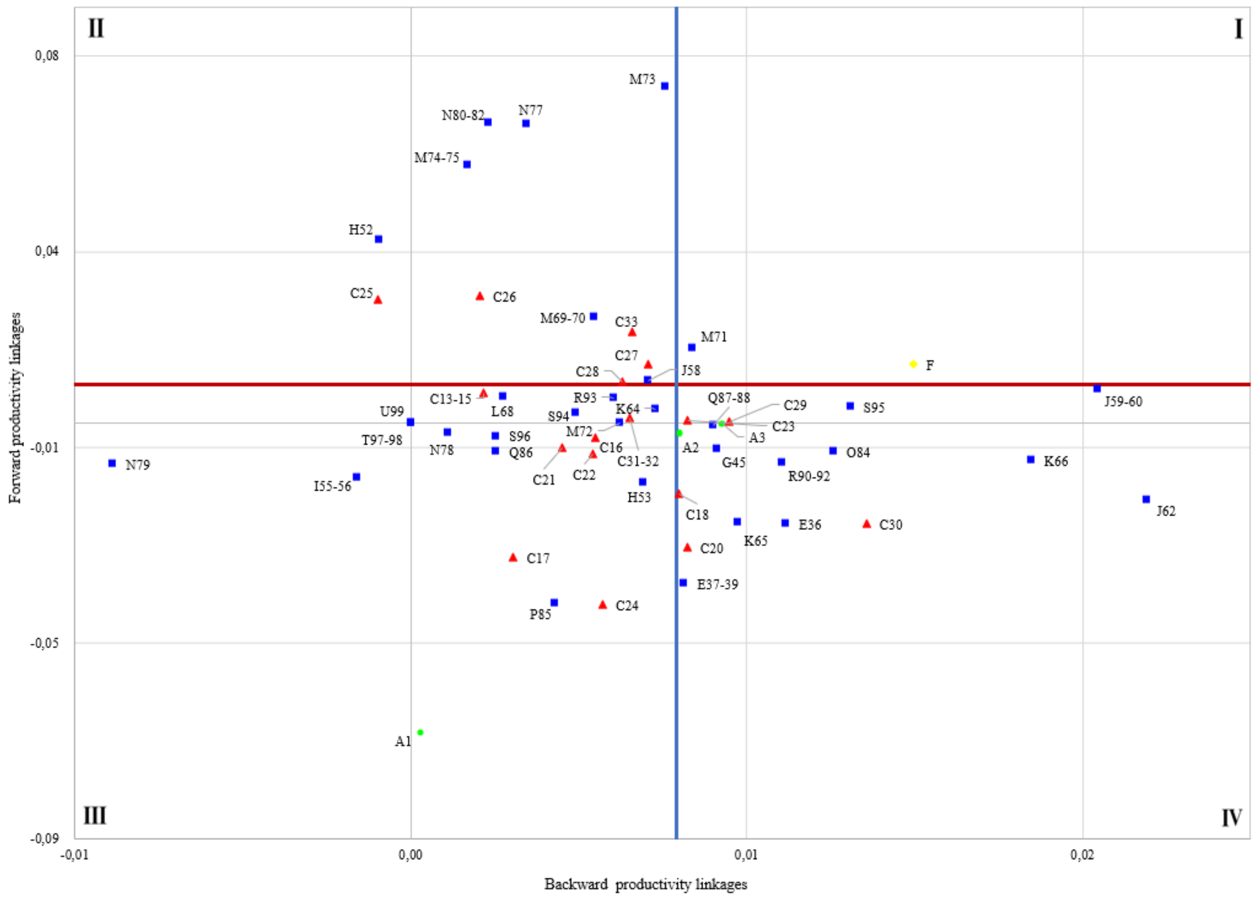

Figure 3. Backward and Forward productivity linkages.

In quadrant **I**, sectors generate and receive a TFP transfer toward and from the rest of the economy. For example, the construction sector (F) generates a 0.015 productivity gain toward the rest of the economy for each unit of demand shock it receives, while absorbing a 0.012 productivity of every unit of exogenous demand each sector of the rest of the economy receives.

In quadrant **II**, sectors experience a relative TFP surplus caused by a shock in the rest of the economy, while being unable to do the same toward the rest of the economy when experiencing a shock themselves. These sectors tend to present backward productivity linkages that cause TFP losses, while

electricity, gas, steam and air conditioning D35(0.030; –0.137), wholesale trade services G46(0.007; 0.164), retail trade services G47(0.007; 0.090), land transport services H49(0.018; –0.086), water transport services H50(0.033; 0.008), air transport services H51(0.042; –0.024) and telecommunications J61(0.004; 0.311).

forward linkages tend to cause positive productivity gains.

Sectors in quadrant **III** present forward and backward productivity linkages that cause productivity losses in other sectors while being drained of productivity from a shock in the same other sectors. For example, the agricultural sector (A1) generates a negative withdrawal of TFP from the rest of the economy while experiencing a productivity loss due to a shock in the rest of the economy. Despite the sectors present in this quadrant may possess strong production linkages with the rest of the economy, this relationship worsens productivity both in a forward and backward sense. In fact, these sectors may heavily rely on inputs from other sectors but fail to use them efficiently. Due to these inefficiencies, the backward linkages translate into productivity losses for upstream industries, leading to a sub-optimal allocation of resources and reducing overall productivity growth (Jones, 2013). Moreover, some of these sectors may be relatively efficient internally but highly vulnerable to the evolution of the economy for their own productivity, suggesting the need for resilience and diversification policies to reduce their exposure to external shocks.

In quadrant **IV**, sectors suffer a TFP loss from a shock in the rest of the economy (negative forward linkages), while generating a TFP surplus in the rest of the economy from a shock in itself (positive backward linkages). For example, the transport equipment sector (C30) generates a 0.014 productivity gain toward the rest of the economy for each unit of demand shock it receives, while it loses a 0.021 productivity of every unit of exogenous demand each sector of the rest of the economy receives.

This sectoral distribution delivers interesting outcomes. The high sectoral heterogeneity observed in Figure 2 is maintained when we substitute own-TFP with forward productivity linkages. This result not only reinforces the need for a combination of demand and supply-side policies to tackle negative productivity spillovers but also the call for sector-specific policies that take into consideration the sectoral specificities any economy presents. Moreover, except for a few outliers, the manufacturing branch (C) tends to be positioned closer to the average effect and, in many cases, between the origin and the average of each effect. Once again, this result confirms the resilience of this branch, with limited productivity effects when shocks affect the branch itself and weaker backward and forward productivity spillover effects on the rest of the economy. Another interesting aspect of Figure 3 is that sectors are nearly absent from quadrant **I**. This would suggest that no sectors are capable of generating positive productivity transfers to other sectors while also obtaining positive productivity spillovers from the rest of the economy. However, comparing the axes with the origin, we observe different circumstances. Between the origin and the average, we observe a substantial number of sectors. In fact, as in the case of backward productivity linkages mentioned earlier, the forward productivity linkages average is also slightly positive. Again, this generates an offset of the total negative effect of TFPS during the period.

5. Conclusions

This paper contributes to two key branches of the I-O literature. First, it provides new insights into economic impact analysis using I-O models, and second, it advances the I-O approach to productivity measurement, drawing on a neoclassical interpretation of total factor productivity (Solow, 1957). We demonstrate that results of I-O impact analyses can vary significantly depending on whether a framework in current prices or constant prices is used. We further extend the single deflation approach by algebraically defining the distribution of productivity gains after an exogenous shock, establishing a link between demand and productivity.

Through the construction of a distribution matrix, we are able to both measure the aggregate changes in total productivity gains or losses and explore its sectoral distribution produced by the shock on the economy. We shed light on the structural mechanisms underlying productivity transmission within economies. The observed pattern of productivity linkages reveals that sectors differ in their capacity to generate and absorb productivity gains, depending on their price dynamics. The asymmetric productivity propagation highlights that the impact of demand shocks extends beyond the directly affected sector, influencing the distribution of productivity throughout the entire economy. Because of the presence of forward and backward productivity linkages, sectors may experience an increase or loss of productivity, no matter where the constant demand shock occurs. Additionally, sectors may experience a productivity loss even if they are the target of a positive demand shock. In that case, those sectors are transferring productivity either to other economic sectors or outside the domestic economy.

This finding carries significant policy implications. Linking demand shocks to productivity may be the first step toward identifying potential inefficient fiscal policy and resource misallocation. When evaluating the effect of a fiscal policy, policymakers must recognize that increases in output might occur alongside stagnating or even declining productivity levels. Moreover, the effectiveness of demand-side interventions depends on the sectoral ability to generate productivity.

Building on these insights, future research could benefit from extending the present framework by decomposing TFPS transfers into efficiency-driven redistribution and sectoral market power arising from imperfect competition.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Author contributions

All authors contributed equally to the conceptualization, methodology, analysis, and writing of the article.

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Conflict of interest

All authors declare no conflicts of interest in this article.

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