

# Preference shocks to consumption goods and sectoral labor composition\*

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## Abstract

It's quite vast the literature looking for the technological reasons for sectoral labor composition while explanations based on changes in consumers' preferences have roused less interest. This paper moves into this less explored perspective, studying in which measure sectoral composition of labor units responds to changes in preferences for the different consumption goods. In order to perform our analysis, we build up time series of consumption and labor units consistent one each other and we elicit sectoral preference shocks through the analysis of the final consumption expenditure of the Italian households, aggregated according to the Coicop 2 digits classification. It emerges that sectoral labor dynamics respond positively and significantly to preference shifts. At the same time, a weak and negative relationship emerges between relative price dynamics and labor dynamics. These results, on the one hand, prompt to carry out further research on the identification of preference dynamics, and on their determinants, since their role is quite significant. On the other, they suggest to look into the determinants of price dynamics since identifying productivity dynamics through price dynamics may conduct to puzzling results and inconsistent interpretations of the linkages between sectoral consumption, labor, and price movements.

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# 1 Introduction

It's quite vast the literature looking for the technological reasons for sectoral labor composition while explanations based on changes in consumers' preferences have roused less interest. This paper moves into this less explored perspective, studying in which measure sectoral composition of labor units responds to changes in preferences for the different consumption goods. In order to perform our analysis, we build up time series of consumption and labor units consistent one each other and we elicit sectoral preference shocks through the analysis of the final consumption expenditure of the Italian households, aggregated according to the Coicop 2 digits classification. It emerges that sectoral labor dynamics respond positively and significantly to preference shifts. At the same time, a weak and negative relationship emerges between relative price dynamics and labor dynamics. These results, on the one hand, prompt to carry out further research on the identification of preference dynamics, and on their determinants, since their role is quite significant. On the other, they suggest to look into the determinants of price dynamics since identifying productivity dynamics through price dynamics may conduct to puzzling results and inconsistent interpretations of the linkages between sectoral consumption, labor, and price movements.

In order to analyze the relationship between preference and labor dynamics, we have to accomplish two main tasks: i) to elicit sectoral preference shocks; ii) to build up comparable time series of consumption and labor. We dealt with the first task relying on some theoretical assumptions. In fact, if consumers' preferences are characterized by constant elasticity of substitution, the optimization process implies that the consumption of good  $j$  with respect to the consumption of good  $i$  is an increasing function of the relative preference between the two goods and a negative function of the relative price. Since sectoral consumption and price dynamics are available, preferences can be extracted by using this relationship. The second task requires to gather data classified according to the same criteria. Consumption data are provided according to the COICOP product classification, while employment data are provided following the NACE industry-based nomenclature. Consequently, starting from the industry-based information, we had to re-classify the labor data according to the Coicop classification. Furthermore, it is necessary to extract just the labor

units that are presumed to be involved in the production of goods consumed internally and, at the same time, consumption time series should refer only to the goods that have been produced internally. On the one hand, labor data refer to the workforce involved in the entire internal production process. On the other, consumption time series include also the consumption of goods produced abroad. That implies that both employment and consumption time series need to be adjusted in order to be fully consistent one each other.

The paper is structured as follows. Section 2 provides some reference to the related literature. Section 3 shows the way we followed to build consistent time series of consumption and employment. Section 4 presents the theoretical model supporting our analysis and the method we adopted to elicit preference dynamics. Section 5 shows in which measure sectoral labor dynamics respond to preference and price dynamics. Section 6 draws conclusions.

## **2 Related Literature**

TBA

## **3 Data processing**

To achieve the aim of our work, we need to analyze time series of final consumption and labor units. In this context, the main matter is represented by the need of making these time series coherent to each other in conceptual and operative terms. This means that both have to be expressed following the same classification scheme, and have to refer to the same conceptual framework.

In this section, we illustrate the processing procedure that allowed us to define coherent time series of nominal and real (internally produced) final consumption (IPC, hereafter), and of the labor units that have been employed to produce this set of goods and services (ULAI).

Specifically, concerning the final consumption, the aim is to remove the imported component from the original information. Indeed, starting data are relative to the entire amount of final

consumption independently of the place of origin (internal or foreign) of its production. With regards to labor units, there are two matters to be overcome. First, we need to translate the starting industry-based information into product-based data. The second is represented by the need to preserve just the part of labor units that is employed to produce goods used internally for final consumption.

The refining process of the original datasets calls for using National Accounts (NA) aggregates, while stepping from industry-based to product-based data of labor units involves some manipulations of the internal production matrix. However, while NA aggregates (and relative matrices) are generally expressed in CPA product classification, final consumption aggregates are published following the COICOP classification.<sup>1</sup> Therefore, a correspondence between different classifications is needed in order to operate.

In order to complete our procedure, we utilize the following set of data: *i*) 1992-2010 time series of nominal and previous-year-price final consumption (in COICOP); *ii*) 1992-2010 data of Supply and Use tables; *iii*) 1992-2010 time series of Full Time Equivalent (ULA) units of labor (in NACE). All these datasets are produced by ISTAT.

Next paragraphs will show the method we followed to obtain coherent time series. Particularly, in the first, we present the starting information we gathered from NA and the re-classification procedures to step from CPA to COICOP classification. In the second and third, we illustrate the methods we utilized to build, respectively, refined IPC and ULAI series. Finally, in the fourth, we briefly present, for each COICOP, the trend of the defined time series of IPC, ULAI, and prices.

### **3.1 National accounts data and re-classification**

NA provide a scheme to interpret economic transactions and measure relative aggregates. Supply and Use framework is constituted by two product-by-industry (aggregates) matrices representing the supply and the demand side of the economy. The complete framework is generally available at current price, while volume measure are normally provided at a more aggregate level. Ancillary information about the economic system is provided by industry-based data on labor units and

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<sup>1</sup>We utilize COICOP-based data of consumption instead of NA(CPA)-based data because the latter dataset does not include volume information at the proper level of aggregation.

product-based data on final consumption.

Supply table contains product-based information about imports, distributive margins, taxes and subsidies, and a (product-by-industry) sub-matrix representing internal production. Use table contains product-based information about final consumption, exports, investments, change in inventories, and a (product-by-industry) sub-matrix representing intermediate consumption of the producing sector.

Industries are in this framework classified following the NACE nomenclature, while products are classified following the CPA nomenclature. These classifications have the characteristics of being fully correspondent at 4-digits level, thus providing a strong conceptual framework to analyze the technological features of the exchanges in the producing sector.

Ancillary information about labor units is classified following the NACE nomenclature and is the result of a processing of survey data in order to take into account the normalization of employment in terms of full time equivalent work position, and irregular workers.

Ancillary information about (nominal and real) final consumption is the result of a re-classification of final consumption expressed in terms of CPA (by-activity) into COICOP (by-purpose) nomenclature. This is obtained by a re-classification matrix that uses micro data to weight each 6-digits CPA and assign it into the relative 4-digits COICOP.

NA data are published at 64-by-64 level of aggregation, this meaning that information about industries and products are published at a less than 2-digits level both in NACE and CPA nomenclatures. In this context, the need for building coherent IPC and ULAI time series involves a harder effort of re-classification. Indeed, apart from peculiar elaborations (which will be dealt with in the following paragraphs), the procedure we developed to process the information about IPC and ULAI calls for developing an aggregation method to translate CPA-based into COICOP-based information.

The procedure involves three main passages. Indeed, in order to build the re-classification matrix between NA by-64 products and 2-digits COICOP nomenclatures we are called for building two different correspondence matrices: CPA vs. COICOP, and CPA vs. NA.

### **3.1.1 The CPA vs. COICOP re-classification**

The CPA vs. COICOP re-classification is obtained by studying the correspondence between 4-digits CPA and 2-digits COICOP in order to stress possible problems arising from the need of disaggregating some CPA into different COICOP.

The full correspondence between CPA and COICOP is constituted by about 3600 records, which have been analyzed to build up the correspondence matrix. As a first step each 4-digits CPA has been attached to the relative 2-digits COICOP. Once this first correspondence has been obtained, we can have two different cases: (a) the given CPA has a one to one correspondence with the given COICOP, and (b) the given CPA has a more-than-one to one correspondence with the given COICOP.

While in the former case we can easily assign a CPA to the relative COICOP, in the latter we would have the problem of disaggregating the given CPA. To cope with this matter, we developed a procedure that involves two (hierarchical) disaggregation methods. The first is represented by a qualitative analysis finalized to exclude from the procedure irrelevant (in terms of economic value) 6-digits CPA in order to reduce the impact of (4-digits) disaggregation. The second method assigns the share of the 4-digits CPA to the given COICOP based on the number of 6-digits CPA (relevant) items corresponding to the given COICOP.

### **3.1.2 The CPA vs. NA correspondence**

The CPA vs. NA correspondence does not involve similar complexities: the by-64 aggregation of NA data does not present disaggregation problems. Indeed, the re-classification matrix can be obtained by studying the one to one correspondence between CPA and NA nomenclature.

Finally, a NA vs. COICOP re-classification matrix can be built by utilizing the information of the two preceding re-classification matrices. Utilizing this procedure, therefore, we are able to re-classify each CPA-based data (production, imports, exports, employment, consumption) into a COICOP-based information.

### 3.2 Internally produced final consumption

In our work, we use two different datasets of IPC: the first contains nominal, (chain linked) volume and price time series in levels, while the second contains their annual variation rates.<sup>2</sup>

As we stressed, final consumption series (at current and previous-year prices) should include only internally produced goods. Once NA aggregates have been re-classified into COICOP nomenclature, the procedure to refine final consumption relies on the assumption that the same share of internally produced and imported goods are devoted to consumption. Under this assumption, IPC can be calculated as a share  $k$  of total consumption in the following way:

$$IPC = kC = \frac{PR - E}{PR - E + I}C$$

where  $PR$  is the value of total internal production,  $E$  the value of export and  $I$  the value of imports (all expressed in terms of the new aggregation in COICOP), while  $C$  is the final consumption reported in COICOP time series. Once final consumption at current and previous-year prices have been properly calculated, chain linked volumes are defined with the customary procedure, so as to obtain time series of nominal, chain linked volumes and prices in levels and, consequently, their annual variation rates.

### 3.3 Labor units for internally produced consumption

Building time series of labor units coherent with internally produced consumption, apart from the re-classification procedure presented in Section (3.1), involves two further matters: *i*) the need to translate (the former) industry-based into product-based information, which also allows us to take into account the structure of secondary productions; *ii*) the need to exclude the labor units not employed to produce  $IPC$ .

With regards to the first issue, labor unities data are available by industry at 2-digits level of NACE classification. In order to translate this information in CPA nomenclature, we utilize

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<sup>2</sup>In order to keep the additivity along the procedure, data are processed taking into account real series at previous-year prices, while relative chain-linked volumes are defined once internally produced final consumption time series have been obtained.



the internal production matrix, which provides a product-by-industry information about internal production. Particularly, the procedure is constituted by two steps. The first is represented by defining a pseudo-productivity for each industry starting from the information of the internal production matrix (by-industry) and labor unity series. As shown in Figure 1 (Internal production matrix and pseudo-productivity), therefore, by summing the production by industry and then dividing the result by the amount of labor unities (by industry), it is possible to define a level of (pseudo) productivity characterizing the whole set of products and services (principal or secondary) that are produced by the given industry.

FIGURE 1. HERE

Supposing the same pseudo productivity in every principal or secondary production in the given industry, we can obtain a distribution of labor units along the column. Indeed, as shown in Figure 2, the productivity is assigned (by-industry) to each cell of the internal production matrix so as to obtain the amount of labor units that are employed in the production of the given product in the given industry. Then, by summing up by product, we can measure the amount of labor units that are employed to produce the given product (or service).

FIGURE 2. HERE

This first elaboration, therefore, allowed us to obtain a CPA-based information about labor units. Once a COICOP-based data have been built through the re-classification method presented above, we finally can complete the procedure by maintaining in the time series only the labor units involved in the production of *IPC*, *ULAI*. These represent a share of the total units of labor (*ULAT*), specifically:

$$ULAI = \frac{PR - E}{PR - E + I} \times \frac{C}{PR} \times ULAT$$

where the first ratio on the right hand side is given by the available internal production over the resources internally available, and the second ratio is given by total final consumption over

total production elaborated starting from CPA-based information and aggregated according to COICOP classification.

### 3.4 Trend of aggregates

Following the procedure described above, we obtained IPC and ULAI time series. Starting from (nominal and real) IPC series we are able to build up time series of price indexes for each COICOP. In this paragraph, we illustrate the trends over time of the different relevant aggregates defined. Particularly, we analyze nominal internally produced final consumption, price indexes and units of labor connected with the internally produced final consumption.

FIGURE 3. HERE

Figure 3 shows, for each COICOP, the comparison between the consumption share in 1992 and 2010.<sup>3</sup> Food, beverage and tobacco (-4%), clothing (-3%), furnishings (-2%), and miscellaneous products and services (-1%) had a decreased over the time span of the analysis while, conversely, a increases can be observed for housing (+6%), hotel and restaurants (+3%), and communications (+1%). Finally, health care, transport, and education do not show relevant change.

FIGURE 4. HERE

Figure 4 shows, for each COICOP, the trend of the ratio between the sectoral price level and the consumption price level. In this context, we can observe a particularly strong fall of Communication and Health relative price while the relative price of Housing has been continuously growing. It is worth noticing that Food presents a U-shaped trajectory of the ratio, which is characterized by an initial decrement, followed by an increment starting from 2000. Miscellaneous and Transport have more or less the same relative price at the beginning and the end of the period.

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<sup>3</sup>Starting from the 12 classes defined by the 2-digits COICOP, we aggregated the first two (food, and beverages and tobacco) and included recreational services into miscellaneous.

Figure 5 shows trends of variation of the employment share of ULAI for each COICOP. In the analyzed time-span, employment share experimented an increase for housing, transport, communications and miscellaneous products and services, while for the other COICOP we can observe a reduction. Particularly, food beverage and tobacco (-2.2%), and clothing (-1.3%) had a relevant reduction of their employment shares. Conversely, transport (+1.6%), and miscellaneous products and services, showed relevant increases.

FIGURE 5. HERE

## 4 Eliciting preference shocks

In this section we elicit preference shocks using a simplified general equilibrium model where consumers' preferences are characterized by constant elasticity of substitutions among differentiated consumption goods. Since data are available for only a 18-years time period, the exclusion of non-homothetic elements should turn out to be not particularly relevant.<sup>4</sup> As most of the formalizations used in this field, we assume that the choice among the different consumption goods is not affected by intertemporal elements, for example habit formation in sectoral consumption is excluded. It follows, that we can focus on just the static optimal conditions that characterize the choice among the differentiated consumption goods.

Let us assume that the consumption bundle can be represented by a CES aggregator defined over  $n$  types of goods as follows:

$$C_t = \left( \sum_{i=1}^n \alpha_{j,t}^{\frac{1}{\theta}} C_{j,t}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}},$$

where  $C_t$  is the consumption bundle at time  $t$ ,  $C_{j,t}$  indicates the amount of consumption of the sectoral good  $j$ ,  $\alpha_j$  is the preference weight of good  $j$ , and  $\theta > 0$  is the elasticity of substitution

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<sup>4</sup>The choice of omitting non-homothetic elements is due to the fact that their inclusion would have required to apply non-linear estimation methods involving not only growth rates but also level data. That would have created serious difficulties in identifying sectoral preference shocks.

among consumption goods. Under this formalization the optimal conditions require:

$$\frac{C_{j,t}}{C_{i,t}} = \frac{\alpha_{j,t}}{\alpha_{i,t}} \left( \frac{p_{j,t}}{p_{i,t}} \right)^{-\theta}, \quad \forall j \neq i, \quad (1)$$

which implies that the consumption of good  $j$  with respect to the consumption of good  $i$  is an increasing function of the ratio between the preference weights of good  $j$  and good  $i$  and a decreasing function of the price of good  $j$  measured in terms of good  $i$ , where  $p_{j,t}$  and  $p_{i,t}$  are the corresponding nominal prices. In dynamics terms, we get:

$$\tilde{c}_{ji,t} = \tilde{\alpha}_{j,t} - \tilde{\alpha}_{i,t} - \theta \tilde{p}_{ji,t}, \quad \forall j \neq i \quad (2)$$

where a generic  $\tilde{x}_{j,t}$  is equal to  $\ln(X_{j,t}) - \ln(X_{j,t-1})$  and a generic  $\tilde{x}_{ji,t}$  is equal to  $\ln\left(\frac{X_{j,t}}{X_{i,t}}\right) - \ln\left(\frac{X_{j,t-1}}{X_{i,t-1}}\right)$ .

At this point we can build  $n$  systems, how many the sectors are, each one composed of  $n - 1$  relationships, each time choosing a different sector  $i$  to normalize the time series and letting  $j$  vary across the other  $n - 1$  sectors. Proceeding in this way, we can estimate the following relationships:

$$\tilde{c}_{ji,t} = \tau_{i,t} - \theta \tilde{p}_{ji,t} + \varepsilon_{ji,t}, \quad \forall j \neq i$$

where  $\tau_{i,t}$  represents a dummy variable for the system  $i$  and  $\varepsilon_{ji,t}$  is the residual of the relationship  $j$  of the system  $i$ . All the systems have been estimated simultaneously in order to impose a unique estimate for  $\theta$  by using iterated feasible generalized least square estimation. Table 1 reports the estimate for  $\theta$  and the  $R^2$  for each system  $i$ .

TABLE 1. ESTIMATION OF THE ELASTICITY OF SUBSTITUTION

$\hat{\theta}$	$R_1^2$	$R_2^2$	$R_3^2$	$R_4^2$	$R_5^2$	$R_6^2$	$R_7^2$	$R_8^2$	$R_9^2$	$R_{10}^2$
.59	.55	.67	.52	.62	.75	.61	.91	.54	.52	.51

The subscript under the R-squared indicates which set of relationship the statistics refers to. For example, the subscript 3 indicates that the

R-squared has been calculated considering the equations built using the dynamics of sector 3 to normalize data.

The time dummy variables represent the intercepts of the regression in each period, then they

measure the average sectoral elements at each time  $t$ . Referring to the theoretical model this means that  $\tau_{i,t} = \sum_{j=1}^{n-1} \frac{\tilde{\alpha}_{j,t}}{n-1} - \tilde{\alpha}_{i,t}$  with  $j \neq i, \forall t$ . That implies that the following relationship

among the different time dummy variables must be verified,  $\tau_{i,t} = -\sum_{j=1}^{n-1} \tau_{j,t}$  with  $j \neq i, \forall t$ .

This constraint has been taken into account in the estimation process by imposing that the time dummy variables of the system obtained normalizing with respect to the Miscellaneous sector was equal to the opposite of the sum of the time dummy variables characterizing the other systems. If, for each time period, we gather the time dummy variables estimated in the different systems  $i$  we get (omitting any symbol indicating that they are estimates and not the true values)  $\tau_t = Za_t$  where

$$\tau_t = \begin{array}{|c|} \hline \tau_{1,t} \\ \hline \tau_{2,t} \\ \hline \dots \\ \hline \tau_{n,t} \\ \hline \end{array}; \quad Z_{ij} = -1 \text{ if } i = j \text{ and } Z_{ij} = \frac{1}{n} \text{ if } i \neq j; \quad a_t = \begin{array}{|c|} \hline \tilde{\alpha}_{1,t} \\ \hline \tilde{\alpha}_{2,t} \\ \hline \dots \\ \hline \tilde{\alpha}_{n,t} \\ \hline \end{array}.$$

Because of the constraint affecting the relationship among the different time dummy variables, matrix  $Z$  is not invertible and we had to drop out one variable (in each time period). In operative terms, that implies that the system can be solved in terms of the preference shocks characterizing one sector. In order to be fully consistent with the following estimation process, we solved the system imposing  $\tilde{\alpha}_{10,t}$ , that is the preference shock of the Miscellaneous sector, equal to zero. Through this procedure we get  $a_t$ , which can be interpreted as the vector of the shocks to the relative preference weights of the different sectors with respect to sector Miscellaneous.

In order to verify if the procedure fits well the observed data we compare the observed sectoral consumption shares with those obtained through the simulation of the theoretical model. In this simplified framework, expenditure shares  $s_j$  are given by:  $s_{j,t} = \frac{\alpha_{j,t} p_{j,t}^{1-\theta}}{\sum_{i=1}^n \alpha_{i,t} p_{i,t}^{1-\theta}}, \forall t$ . In order to build up the time series of the  $\alpha_j$  it is necessary to obtain the starting values of the different  $\alpha_j$ . We applied the previous equation, which links the expenditure shares to preferences and prices, taking the data of the reference year, 1992, where all prices are normalized to unity. Thus, we opted for  $\alpha_{j,1992} = s_{j,1992}, \forall j$ . Successively, the level values are obtained by applying  $\tilde{\alpha}_{j,t}$  to the

corresponding  $\alpha_{j,t-1}$ . Figure 6 (Preference Shares) reports the dynamics of preference weights calculated in terms of share,  $\frac{\alpha_{j,t}}{\sum_{i=1}^n \alpha_{i,t}}$ ,  $\forall t$ .

FIGURE 6. PREFERENCE SHARES

It emerges that Food and Clothing have been the sectors which experienced the strongest fall in preference share (almost 3 percent points) while Housing and Restaurants have acquired more than 2 percent points.

Finally, using the time series of the sectoral prices and the time series of sectoral  $\alpha_j$  it is possible to simulate the path of the sectoral consumption shares. Figure 7 (Observed and simulated changes in sectoral consumption) reports the percentage change in the shares of both the simulated and the observed time series. All the sectoral shares are replicated quite well.

FIGURE 7. OBSERVED AND SIMULATED CHANGES IN CONSUMPTION SHARES

## 5 Estimation

At this stage we can analyze how sectoral labor responds to relative price and preference changes. Since preference time series are expressed in terms of relative growth with respect to Miscellaneous sector, also the other series will be organized in this way. Then, our dependent variable is given by the labor growth rate of each sector less the labor growth rate of the Miscellaneous sector, and similarly for the price variable. First of all we calculate the average growth rate of each sectoral variable to figure out if the sectoral variables move in the same or opposite direction. Results are reported in Table 2 (Average growth rate).

TABLE 2. AVERAGE\_GROWTH RATE

sector	1	2	3	4	5	6	7	8	9
$\tilde{n}_{i,10}$	-2.19	-4.09	0.63	-2.03	-0.75	-0.54	1.25	-1.12	-1.99
$\tilde{p}_{i,10}$	-0.14	-0.39	1.76	-0.39	-1.12	0.25	-4.87	-1.42	0.48
$\tilde{\alpha}_{i,10}$	-1.12	-2.00	0.90	-1.41	1.14	-0.22	3.78	0.76	1.38

The subscript under the R-squared indicates which set of relationship the statistics refers to. For example, the subscript 3 indicates that the

R-squared has been calculated considering the equations built using the dynamics of sector 3 to normalize data.

This statistics shows that in 6 over 9 cases labor and price average growth rate have the same sign. The same is true for labor and preference. The former result is consistent with the idea that relative prices mirrors (inversely) relative productivity and that labor should shift towards less productive sectors.

The following step is to regress labor on price and preference. We run fixed effect (FE), random effect (RE) and feasible generalized least square (FGLS) with heteroskedasticity and cross sectional correlation. In each case (when possible) we run different estimations with and without sectoral and time dummy variables.

Table 3 (Estimation Results) reports the estimates with the standard deviations of the coefficient of price and preference variable.

TABLE 3. ESTIMATION RESULTS

	FE		RE		FGLS	
	no dummies	with dummies	no dummies	with dummies	no dummies	with dummies
$\tilde{p}$	-.24** (.10)	-.15 (.18)	-.18** (.09)	-.15 (.18)	-.08 (.08)	-.11 (.12)
$\tilde{\alpha}$	.66*** (.13)	.74*** (.13)	.63*** (.11)	.74*** (.13)	.59*** (.06)	.73*** (.09)

\*\*\* Significant at 1%. \*\* Significant at 5%. \* Significant at 10%.

The following results emerge. Relative preference shocks affect always positively and significantly labor dynamics. Under all the estimation procedures the estimated coefficients indicate

that labor reallocation reacts quite quickly and in the same direction to relative preference shocks. The results concerning the effect of relative price dynamics are less clear. The coefficient linking labor to prices is significantly negative when no dummy variables are included while becomes not significant when dummy variables are introduced. This result contrasts the idea that labor and productivity should move in opposite direction or, at least, it highlights that such a relationship does not emerge at annual frequency.

## 6 Conclusion and discussion

This paper represents a first step to disclose the relationship between shocks to sectoral consumption preferences and sectoral labor composition. To carry out our object we had to elicit preference shocks from the time series of individual consumption by purpose and we had to build up time series of consumption and labor consistent one each other. We found that there is a positive and strong relationship between the dynamics of the sectoral labor composition and the relative preference dynamics. The link between labor composition and relative price emerged to be more puzzling and weak, suggesting that the identification of price dynamics with productivity dynamics could be misleading at this level of aggregation. This work highlights the relevance of investigating the preference dynamics even if they have been often disregarded in the multisectoral approach. In fact, starting from the analysis of "demand side", that is the final consumption expenditure, we obtained the preference time series that resulted to explain significantly the sectoral labor composition. Anyway, with respect to the approach followed in this paper, it would be necessary a deeper investigation of also the "supply side", that is the production process, in order to provide a more comprehensive explanation of the sectoral composition of both consumption and labor.

## References

TBA



# FIGURE 1

	1	...	...	i	...	...	64	
1	$P(1,1)$				$P(1,i)$			$P(1,64)$
⋮								
⋮								
⋮								
j	$P(j,1)$				$P(j,i)$			$P(j,64)$
⋮								
⋮								
64	$P(64,1)$				$P(64,i)$			$P(64,64)$
<b>P</b>	<b><math>\Sigma i=1</math></b>					<b><math>\Sigma i=i</math></b>		<b><math>\Sigma i=64</math></b>
<b>ULA</b>	<b><math>U_i=1</math></b>					<b><math>U_i=i</math></b>		<b><math>U_i=64</math></b>
<b>P/U</b>	<b><math>\Sigma i=1/U_i=1</math></b>					<b><math>\Sigma i=i/U_i=i</math></b>		<b><math>\Sigma i=64/U_i=64</math></b>

Figure 2

	1	...	...	i	...	...	64	ULA
1	$P(1,1)/P_{U_i=1}$			$P(1,i)/P_{U_i=i}$			$P(1,64)/P_{U_i=64}$	$\Sigma j=1$
⋮								
⋮								
⋮								
j	$P(j,1)/P_{U_i=1}$			$P(j,i)/P_{U_i=i}$			$P(j,64)/P_{U_i=64}$	$\Sigma j=j$
⋮								
⋮								
⋮								
64	$P(64,1)/P_{U_i=1}$			$P(64,i)/P_{U_i=i}$			$P(64,64)/P_{U_i=64}$	$\Sigma j=64$

FIGURE 3 Expenditure shares in consumption goods

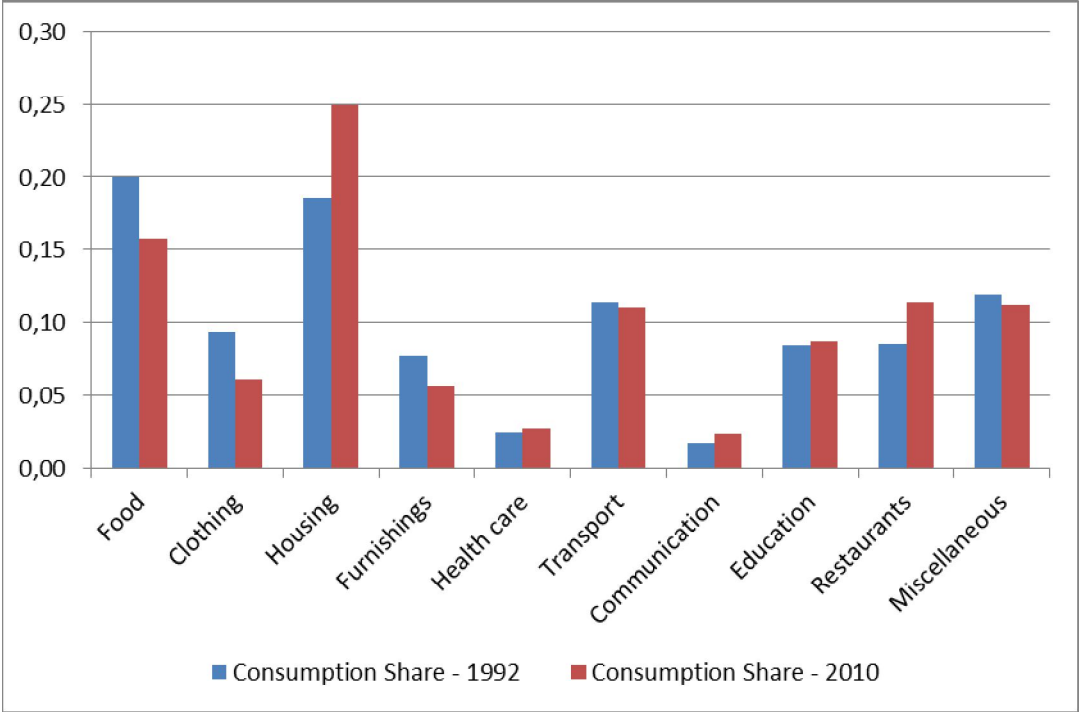
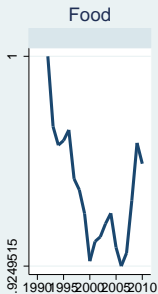
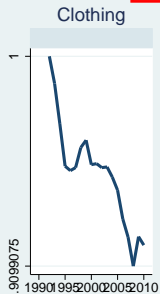


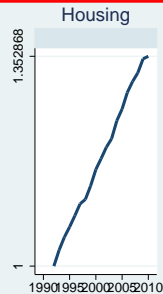
Figure 4 Relative Prices



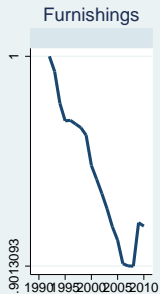
Graphs by id



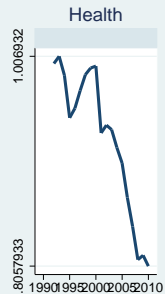
Graphs by id



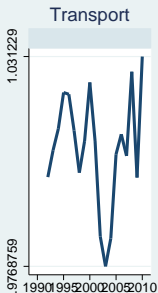
Graphs by id



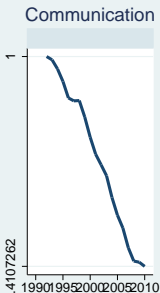
Graphs by id



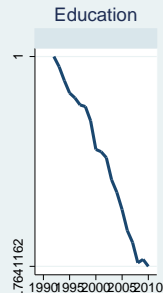
Graphs by id



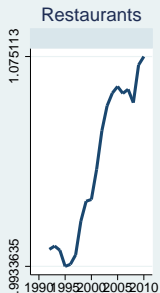
Graphs by id



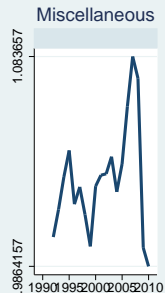
Graphs by id



Graphs by id



Graphs by id



Graphs by id

Figure 5 Variations in employment shares (in percent points)

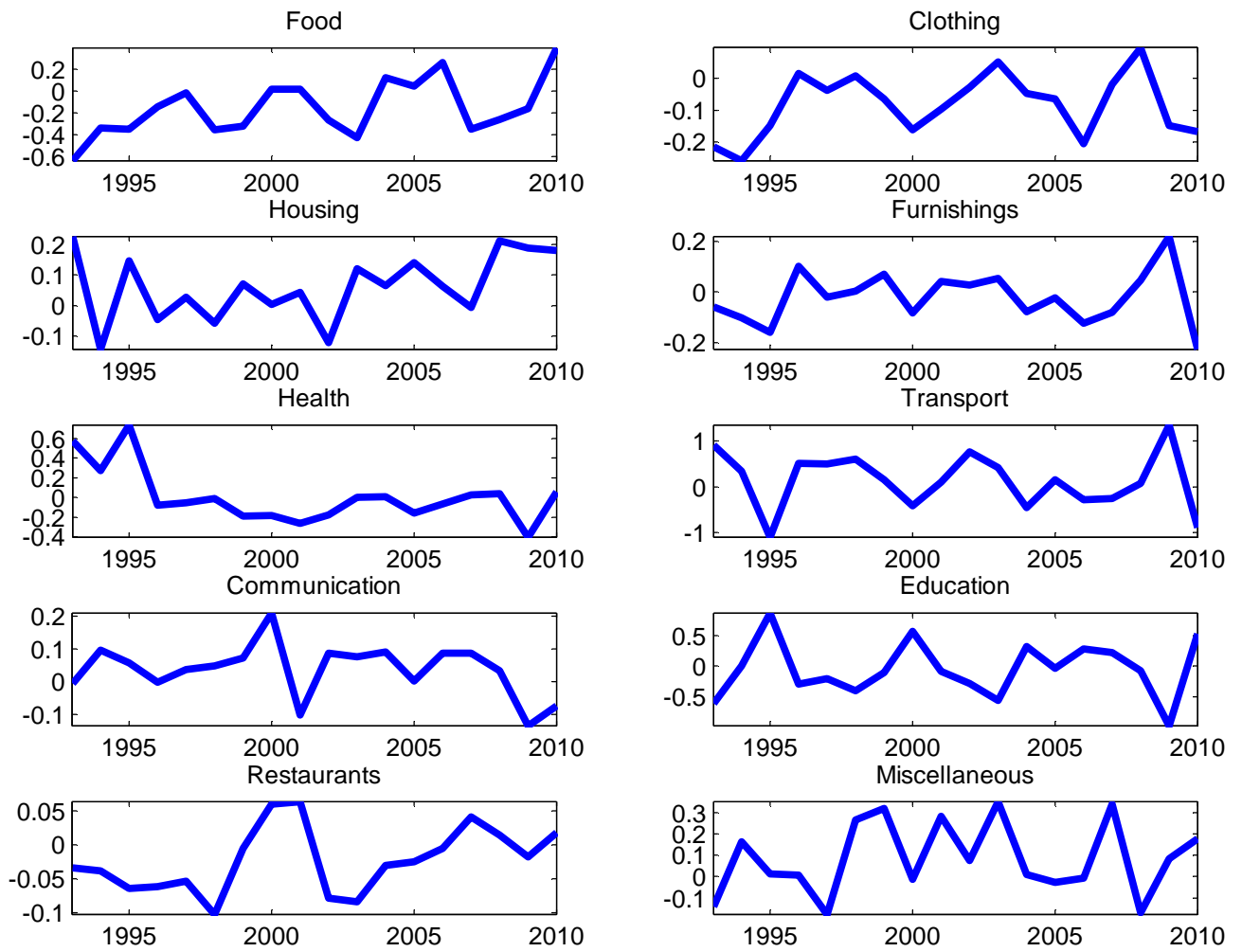


Figure 6 Preference Weights Shares

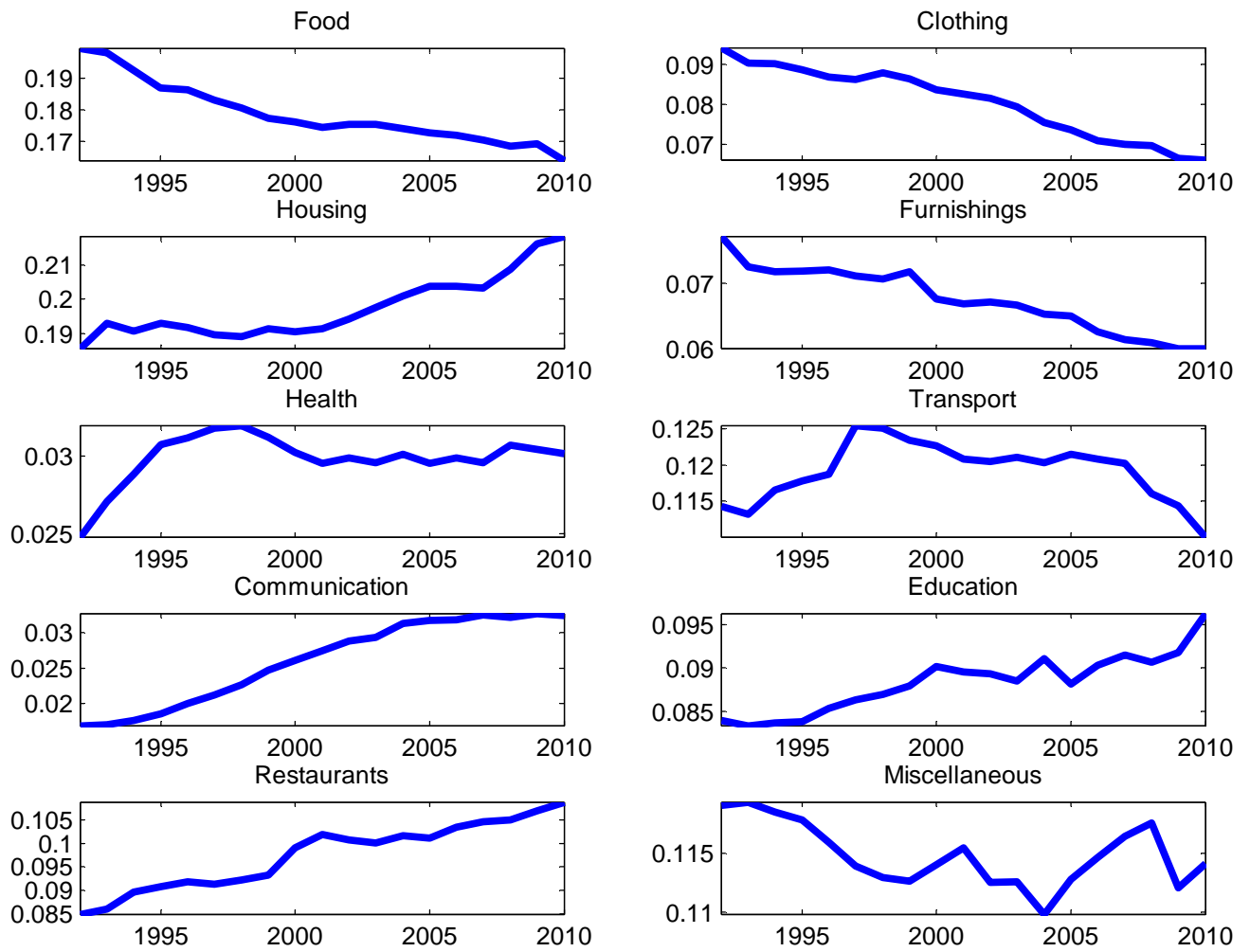


Figure 7 Variations in Consumption Shares - Observed and Simulated Time Series, in percentage points

