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Evidences from Italy

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"Bisogna saper distinguere tra semplificare e banalizzare: chi semplifica toglie consapevolmente il superfluo, chi banalizza toglie inconsapevolmente l'essenziale."

(A. Moro)

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Introduction

This thesis is an attempt to contribute to Italian literature on health economics in causal framework. Despite the increasing awareness of ruling class that is time to enforce the National Health System to achieve higher efficiency levels and to make the public system bearable, there are few contributions in scientific literature that study Italian context, maybe due to scarce availability of data.

This thesis deals with two big concerns for public regulators: cost-containment policies and waiting times for elective surgeries.

The first part regards cost-containment policies and the introduction of unified authorities responsible for purchases of goods and provision of services at local level. The aim of the first part is to measure the efficacy of these new authorities in terms of costs reduction.

The straightforward policy implication is that if the unification of local health authorities can help administrations to perform scale economies, this would be a successful stimulus to other administrations to adopt the same hint and therefore create a virtuous cycle.

The second chapter refers to waiting times for elective surgeries, especially their relation with the combination of capacity constraints, demand for and supply of elective treatments. From a policy perspective, it is critical to establish the extent to which demand and supply respond to waiting time. For example, if demand is highly elastic, an exogenous increase in supply will only have minimal effect in reducing waiting times. In turn, this will make policymakers more reluctant to fund additional resources. Similarly, if supply is elastic, an exogenous increase in demand will imply that waiting time will increase only to a small extent.

In both chapters we use public and free administrative data and widely known econometric approaches (Instrumental Variable regression and Synthetic Control) to try to establish causal relations between important factors in healthcare sector and try to fill the gap between literature on Italian health care sector and scientific production concerning other OECD and European Countries.

Our findings are emerging at a sufficient extent, especially given the fact that we are not aware of many other studies that use administrative data in Italian context and quality of data is not always satisfying, even if increasing.

Cost-Containment Policies in Healthcare Sector: the example of ESTAV in Tuscany

Andrea Riganti¹

Abstract

This paper investigates the impact of the establishment of local authorities that act as purchase managers in Tuscany from 2005, replacing the former Local Health Authorities. These new authorities are responsible for the provision of goods and for the management of services; they are aimed at saving money and enhancing a more efficient allocation of resources. In order to assess the impact in terms of cost containment we use the Synthetic Control Procedure to create from the donor pool of all Italian Regions and Local Health Authorities a weighted average that could resemble the exposed units in terms of expenditures before 2005, when ESTAVs were settled. We project the path of expenditures of these "Synthetic" units in the post-intervention period with optimally assigned weights and we measure differences with respect to the real path of the cost variables. We also compute permutations to conduct valid inference: results are appearing for most of the outcome variables, are robust at classical significance levels and are homogeneous across different Local Health Authorities. Purchases of pharmaceuticals account for high share of total expenses and are the ones that deserve more attention in policy discussion. In addition they require further analysis since the effect of the policy seems not to be in the desired direction for this specific item.

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1 Introduction

Cost-containment policies and efficient allocation of resources in healthcare sector are one of the major concerns in OECD countries, where a significant share of public balance is devoted to financing health sector, especially in publicly funded systems (Armeni and Ferrè, 2014, Folland et al., 2007, Feldstein, 2012).

The Italian National Health System (NHS) is Regional based, is funded thought general taxation, provides full coverage in public hospitals for all citizens and is DRG-reimbursement type, i.e. public providers receive money according to volumes of treatment performed.

Aging population (Lindeboom, 2006), the increase in waiting times (Siciliani and Hurst, 2005) and the rise of unhealthy behaviours in the population (Kenkel, 2006, Cawley et al., 2009) contribute to increase public expenditure for health. It is therefore crucial to keep public expense under control when these drivers are increasing, as in the Italian case.

In the last decades Italian Regions have dealt with strict budget constraints, and have pursued different policies to face increasing demand for public service and avoided financial collapse of the system. Some of them created unified regional authorities with duties such as purchasing of goods and supplying of services, in order to save money by exploiting economies of scale and achieve efficient allocation of resources. (Furnari et al., 2016).

When specific authorities with duties on purchases of goods and provision of services are established within a certain area we call this process *Collaborative purchasing* or *collaborative supply chain* (Marsilio et al., 2016). There is a huge literature that underlines theoretical framework and use empirical applications also in health sector, where efficient allocation of resources and collective purchasing systems are crucial to keep public expenses

under control. (Bovaird, 2006; Schotanus et al., 2009, Nollet and Beaulieu, 2003; Tella e Virolainen, 2005).

Collaborative purchasing is in general related to cost reduction (Johnson, 1999; Muse et al., 2010). The first underlining mechanism is the most obvious one: bigger public authorities can exercise more influence on the market with respect to smaller ones and can achieve cost containment results thanks to market power. Moreover they are able to perform scale economies. (Johnson, 1999; Schotanus, 2005). In addition bigger and more experienced public providers can reduce transaction costs (e.g. administrative costs, tender procedure costs), train and hire employees at a higher level of expertise and reach e higher level of standardisation of procedures¹ (Marsilio et al., 2016).

Tuscany was the first among Italian regions to create in 2005 three unified supply providers, followed in subsequent years by other Regions. There are seminal papers that describe Regional heterogeneous institutional setting (Brusoni and Marsilio, 2007, Amatucci and Mele, 2012) or investigate differences and similarities between Italian and EU-national frameworks (Marsilio and Mele, 2010), but we are not aware of papers that study in causal framework or econometric specification the impact that this kind of policy have determined. The aim of this chapter is to assess the impact of the introduction of these local authorities in terms of saving, giving a contribution in the existing literature.

Despite the existing literature on causal effect is wide, it is often difficult to measure the impact of a policy introduction in a causal specification (Cerulli, 2015) in particular when sample size is small. We have a too limited number of observations to use well-studied policy evaluation techniques, and moreover would be very difficult to test classical hypothesis (e.g.

¹ In Marsilio et al., 2016, are descripted in detail some relevant aspects of possible channels for cost increase after a centralisation procedure.

parallel trend assumption) with such a heterogeneous sample. We try to solve these problems using the Synthetic Control Procedure (Abadie and Gardeazabal, 2003, Abadie, Diamond and Hainmuller, 2010, 2011 and 2013). Synthetic Control (SC) is a relatively new approach which extends the widely known and traditional counterfactual models (e.g. Difference-indifferences) when parallel trend assumption cannot be assumed without loss of generality, by building a theoretical unit of observation from a convex linear combination of control units (Abadie and Gardeazabal, 2003, Abadie, Diamond and Hainmuller, 2010, 2011 and 2013, Eren and Ozbeklik, 2011, Hinrichs, 2012, Billmeier and Nannicini, 2013, Xu, 2016). We refer to the exposed unit as the one that experience the treatment or the introduction of the policy. The idea behind this model is that a weighted average of unexposed (or control) units based on their covariates would resemble in an appropriate way the exposed unit and in turn produce a counterfactual unit comparable with the original one.

SC method has been mainly used to evaluate the consequence of natural disasters (Cavallo et al., 2013, Coffman and Noy, 2012, Du Pont IV and Noy, 2012, Lynham, Noy and Page, 2012), where the natural disaster is viewed as random and unpredictable shocks happening in a single or a limited number of countries. Due to non-comparability across countries SC method is adequate to estimate the effect of a policy change that cannot be anticipated, as in the natural disaster case, combining units with a set of control weights aiming to reproduce the exposed region. In later extension of SC method, it has been used to evaluate effects on wage compensation for professionals of health (Okeke, 2009), universal coverage reform on health outcomes (Courtemanche and Zapata, 2014), insurance market reform (Lo, 2013) and minimum wage studies (Dube and Zipperer, 2013).

Given the large heterogeneity across Italian Regions, SC procedure seems to be optimal since it allows us to obtain an unbiased estimate of the treated – or exposed – unit and to measure the effect through a difference between real values and pointwise estimates. We therefore use the SC method to assign weights to the unexposed units in the sample so that they could resemble Tuscany before the policy was introduced and then use these weights to build a theoretical prevision of Tuscany's expenditures after policy implementation. We can thus compare the theoretical Tuscany with real values of expenses and through differences between these two outcomes measure the real policy effect.

The chapter is structured as follows: Section 2 and 3 highlight some key elements for the Italian Health care sector and the type of data we use. Section 4 describes in detail SC procedure, whilst Section 5 articulates descriptive and inferential results. Section 6 concludes and discusses some policy implications.

2 Italian and Tuscany Health System

Italian constitution states that "*The Republic safeguards health as a fundamental right of the individual and as a collective interest, and guarantees free medical care to the indigent.*²" The Italian NHS was founded in 1978 and the Ministry of Health is nowadays assisted by some internal agencies, which aims are to safeguard human health, workers at their workplace, coordination of NHS, veterinary medicine and food security.

In particular the Ministry fixes general rules for preventive medicine, diagnoses, care and rehabilitation for both people and animals. It also monitors Regions and Local Health Authorities (L.H.A.s) conducting clinical research in health care sector.

The Italian Healthcare system is publicly-funded through general and regional taxation and is a DRG-type system, which means that public providers receive money according to several different factors e.g. volumes, number of performed intervention, quality and complexity of the provided care, waiting times and target achievements³.

Italy is divided into nineteen Regions and two autonomous provinces: in 2001 a Constitutional reform decentralised healthcare sector at regional level and gave regions the freedom to choose the type of healthcare model, generating great variability in institutional arrangements across regions. From now on we therefore consider Autonomous Provinces of Trento and Bolzano as Regions since they have the same duties and rights in healthcare sector other Regions have. Regional healthcare systems have to meet the so-called Essential Levels of Assistance (L.E.A.) annually defined and updated by the Ministry of Health. Regional administrations are responsible for strategic planning (e.g. building new hospitals or agreements with Universities), organisational scheme, resources allocation strategy,

² Art.32 Italian Constitution

³ Legislative Decree n.300/1999 and subsequent modifications

budgetary policy, regulatory scheme between private and public sector, co-payment rules for citizens. Heterogeneity in regional policies has emerged driven by differences in co-payment schemes, unified booking centres and promotion of private health insurance, providing a fragmented framework with regional disparities.

Regional administrations settle within each region LHAs and define their jurisdictional territory. LHAs depend from Regional government in terms of funding and control, and are local providers for health care, prevention campaigns, general practitioners (GP) provision and veterinary medicine.

The total number of Italian LHAs has reduced from 227 in 1997 to 136 in 2013. Some Regions (Valle d'Aosta, Autonomous Province of Trento, Autonomous Province of Bolzano, Marche and Molise) have only one LHA operating within its district at the end of 2013. Two regions, Veneto and Friuli Venezia Giulia, have a health governance structure disaggregated at sub-provincial level. The remaining Regions have defined LHA boundaries coinciding on average with Provincial ones.

Moreover, within each LHA operate in general more than one public hospital; regional administrations are allowed by law to decide whether hospitals are subject to regional or local control through LHAs. In the former, hospitals are called Hospital Authorities (HAs), depend from Regional Administration in terms of funding and are free from territorial duties, whilst in the latter they are not autonomous from LHAs responsible for the site hospitals are operating. There is huge heterogeneity across Regions in the definition of the regulatory scheme between public and private hospitals, LHAs and HAs which reflects not only heterogeneity in internal need of the population, but also different approaches in the provision of care.

In the last decades reduction in transfers from national government to regional administrations have caused Regions dealing with strictly balance constraints which has in turn determined heterogeneous reduction strategies of expenses between administrations, seeking of a more efficient allocation of resources, and a decrease in transfers from Regional Administrations to LHAs and HAs. The most commonly used policy was local unit reduction and the creation of specific authorities with responsibilities in cost containment and efficient allocations of resources.

Until 2005 in Tuscany were operating twelve LHAs until regional government decided to appoint to three territorial authorities LHAs duties and tasks on administration, accounting, provision of goods and services, management. These were called *Enti per i Servizi Tecnico Amministrativi di Area Vasta* – ESTAV⁴, i.e. *Authorities for Technical and Administrative Services for Extended Area* and act as commission centres in behalf of Local Health Authorities and Teaching Hospitals. Moreover, they are subject to all national and regional disposals that regulate purchases of the Authorities themselves. The aim of regional administration was to improve quality of care and increase free access to care for residents through corruption contrast, efficient allocation of resources, scale economies.

In order to simplify the notation and to stress the idea that ESTAVs are nothing more than bigger LHAs operating on bigger portion of regional area, we indicate the North-West Tuscany ESTAV as the new "LHA of Pisa", the Central Tuscany ESTAV as the new "LHA of Florence" and the South-East ESTAV as the new "LHA of Siena".

⁴ The three ESTAVs namely are: North-West Tuscany (former LHAs of Massa – Carrara, Livorno, Lucca, Viareggio, Pisa and HA of the city of Pisa), Central Tuscany (former LHAs of Prato, Pistoia, Florence, Empoli, HA Careggi and HA Meyer) and South-East Tuscany (former LHAs of Grosseto, Siena, Arezzo and HA of the city of Siena)

3 Data

We collect balance sheets of LHAs and HAs from Ministry of Health databases⁵. Some LHAs are settled at sub-provincial level i.e. they are in general smaller than administrative Italian provinces. Moreover, as detailed in Section 2, almost all regions changed their territorial structure (i.e. aggregation process) over the time span considered. Given the big heterogeneity across and within regions, combined with the fact that different LHAs and HAs can coexist within each province, we would ideally aggregate data at provincial level in order to have an administrative unit of observation and availability of covariates. There are although few cases in which LHAs are bigger than the correspondent province and essentially are the cases of regional LHAs: in such cases we opt for a Regional aggregation of covariates. In addition there are few other cases in which administrative provinces are smaller than the correspondent LHA, (e.g. in Sardegna and for provinces of Bari and Barletta in Puglia) and we opt for LHA aggregation of provincial covariates. We can thus refer to unit of observations as LHAs without any loss of generality, since the healthcare sector building block are by definition Local Health Authorities, irrespectively by Regional or Provincial aggregation. In Appendix A1 we provide the definition of our unit of observation.

Balance sheets are available in Ministry of Health database from 1997 to 2013. Thus, we sum balance items for all LHAs and HAs within each LHA (or unit of observation as detailed above), obtaining a panel dataset of 1564 observations (92 units for 17 years) for each expenditure item. Balances were made comparable with some reclassification procedures since 1997. Up to 2013 five different versions of balances were promoted with different codifications.

⁵http://www.salute.gov.it/portale/temi/p2_6.jsp?lingua=italiano&id=1314&area=programmazioneSanitariaLea& menu=dati.

We focus on the categories of expenses related to: (*i*) *Pharmaceutical goods*, such as pharmaceuticals, blood sacks, blood-derived, low-calorie, haemodialysis, vaccines and chemical products, medical devices, prosthetic, diagnostic and surgical materials; (ii) *Veterinary* goods and vaccines for animals; (iii) *Foodstuff* goods and food services; (iv) *Living* goods and services, i.e. wardrobe and cleaning goods and services; (v) *Combustibles*, carburant, propellants, lubricants and heating services; (vi) *IT*, stationery materials and data management services; (vii) *Maintenance* goods and services.

Every item is multiplied for a constant-per-year coefficient according to the year in order to have all variables expressed in PPP Euro at year 2010 prices. In addition our outcome variables are standardized by population dimension and logs are taken.

From ISTAT (the Italian National Institute of Statistics) we derive and include population distribution as potential shifters of public expenditure i.e. proportion of under 14, over 65 and over 80 years old on the total number of residents, population density (inhabitants per squared kilometre) and average number of residents per municipality⁶.

From Ministry of Finance⁷ database we obtain the GDP per capita for every region in any given year of observation. We also calculate the proportion of non-taxpayers on the total number of residents aged between 15 and 64 years old as measure of people at the expenses of regional population, since official statistics for unemployment rate are not available at provincial level from 1997.

The Ministry of Health⁸ annually publishes the Annual Report of Hospital Discharges from which we compute some volumes of treatment variables. These variables are available at regional level and we are able to standardise them according to the population dimension for

⁶ Relevant data can be fount in dati.istat.it in Population and Families section.

⁷ http://www.finanze.gov.it/opencms/it/statistiche-fiscali/

⁸ http://www.salute.gov.it/portale/temi/p2_6.jsp?id=1237&area=ricoveriOspedalieri&menu=vuoto

each unit of observation. These variables are the total number of hospital discharges and the total number of days in hospital for elective patients but also for rehabilitation and long-stay patients. We also include the average stay, measured in days, as potential covariate.

Lastly, we include quality of care indicators provided by the Ministry of Health and available at Regional level. We include the average stay standardised by complexity of treatment, the case mix variable to control for severity of admissions, the share of complications after surgeries on the total number of surgeries performed as a measure of quality and a performance indicator. Ideally we would have more quality and efficiency indicators but unfortunately data are not available for the years considered at disaggregated level. We also add the standardised-by-complexity performance index to be able to compare different Regions over time.

4 Econometric Specification

4.1 Synthetic Control Procedure

We use the Synthetic Control Procedure (SC) as presented in Abadie and Gardeazabal. (2003), Abadie et al. (2010, 2015) to measure the effect of the settlement of ESTAVs in Tuscany regional healthcare sector in terms of cost containment.

SC was proposed to compare a single "treated" or "affected by the policy" unit and a set of "non-treated" or "non-affected" units, and it can be considered an extension of Difference-in-Difference method to compare one unit against a group of untreated units. From now on we use the term "treated" to indicate any unit that have experienced policy change (i.e. the introduction of ESTAV and "untreated" as the remaining ones. We consider one single ESTAV – or LHA – as exposed unit and all other untreated units in our dataset as unit in the donor pool. We find the weights for the single treated LHA as a convex linear combination of untreated LHAs in the donor pool in pre-intervention period and we apply those weights to the post-intervention period, de facto computing a theoretical trajectory for the outcome variable if "any intervention would have occurred" or more precisely, what would have happened to LHA expenditures if any intervention or policy change happened.

We thus compare the theoretical LHA outcome path, built as a linear combination of past values of other units, with the real values of the outcome variable. If it is possible to measure a positive difference between the theoretical LHA and the real one in terms of the outcome (cost) variable after the policy was introduced, we conclude that the policy intervention have caused a reduction in expenditures, so the policy has reached the predetermined goal. Vice versa, if there is a negative difference between the theoretical and real outcome variable, the policy has just worsened the situation. We expect that the introduction of LHAs has lowered the aggregate level of expenses in a single area, i.e. we expect to find positive differences between the theoretical and real values.

We consider J + 1 units where only the first one is exposed to policy intervention. We consider T as the total number of years of observation, with $T_0 = (t_0, t_1, ..., t_k)$ being the number of years in the pre-intervention period, and $T_1 = (t_{k+1}, ..., T)$ the years after the policy implementation. Let Y denote the cost variable, measured over the time span considered for all units in the sample and affected by the policy change in year k. Suppose we can observe Y_{jt}^N the outcome variable under any policy intervention and Y_{jt}^I the outcome variable after policy introduction. For every unit unaffected by the policy, but also for unit 1 before policy implementation, $Y_{jt}^N = Y_{jt}^I = Y_{jt}$. For unit 1 and after policy introduction in year k we can only observe Y_{1t}^I . The SC procedure aims at measuring the impact of the policy for any given year after year k for the affected unit from the difference between the real value and what would have happened in absence of treatment as follows:

$$Y_{jt} = Y_{jt}^N + \left(Y_{jt}^I - Y_{jt}^N\right) D_{jt} = Y_{jt}^N + \alpha_{jt} D_{jt}$$

Where $\alpha_{jt} = Y_{jt}^I - Y_{jt}^N$ is the effect of the policy introduction and D_{jt} is a dummy variable equal to 1 in presence of the new policy and 0 otherwise.

$$D_{jt} = \begin{cases} 1 & if \ j = 1 \ and \ t > k \\ 0 & otherwise \end{cases}$$

It follows that $\alpha_{1t} = Y_{1t} - Y_{1t}^N = Y_{1t}^I - Y_{1t}^N$. We do not observe the outcome in absence of intervention for unit $1 Y_{1t}^N$, indeed we observe $Y_{1t} = Y_{1t}^I$. Thus we need to provide an estimate of α_{1t} to assess the policy change.

It is straightforward that α_{1t} has a causal interpretation and denote the impact of the policy introduction, since it represents the difference between what has really happened and what would have happened in absence of the policy.

As in Abadie et al. (2010) we define $T_1 = T - T_0$ as the number of post-intervention periods and we let Y_1 be a $(T_1 \times 1)$ vector of cost outcome for the exposed unit. Let Z_1 be a $(1 \times r)$ vector of r potential exogenous linear combination control variables measured on the affected unit by the policy unit and let $X_1 = (Z'_1, Y_1)$ be a $((T_1 + r) \times 1)$ vector of outcome values and linear combination of exogenous shifters for the affected unit. Similarly we define Y_0 as a $(T_1 \times J)$ matrix of outcome variables for J unaffected units in pre-intervention period, and Z_0 as a $(J \times r)$ vector of r potential exogenous linear combination control variables for the same set of control units. We can thus define $X_0 = (Z'_0, Y_0)$ as a $((T_1 + r) \times J)$ matrix of outcomes and exogenous covariates. We can estimate $W^* = (w_2, ..., w_{J+1})$ as the $(1 \times J)$ vectors which minimise

$$||X_1 - X_0 W||_V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$$

where *V* is a $(r \times r)$ symmetric and positive semidefinite matrix. We minimize this difference with constraints $\sum_{j=2}^{J+1} w_j = 1$ and $w_j \ge 0 \forall j$.

Let us note that *V* can influence minimisation procedure. *V* is chosen so that it minimizes the Root Mean Square Prediction Error (RMSPE) of the synthetic control estimator. Once V^* and W^* are chosen, we can use the derived weights to estimate

$$\hat{Y}_{1t}^{N} = \sum_{j:2}^{J+1} w_{j}^{*} Y_{jt}$$

with $t \in (k, ..., T)$ and obtain

$$\hat{\alpha}_{1,t} = Y_{1t}^{I} - \widehat{Y_{1t}^{N}} = \left(Y_{1,k+1}^{I} - \widehat{Y}_{1,k+1}^{N}, \dots, Y_{1T}^{I} - \widehat{Y}_{1,T}^{N}\right) = \left(\hat{\alpha}_{1,k+1}, \dots, \hat{\alpha}_{1,T}\right)$$

The estimated average effect of the policy is given by the mean of all effects across all years:

$$\widehat{\alpha}_1 = \frac{\sum_{t:k+1}^T \widehat{\alpha}_{1t}}{T-k}$$

4.2 Inference and Multiple Treated Units

Following Cavallo et al. (2013) we use permutation techniques to compute significance values for the estimates SC procedure provide. We routinely apply the SC procedure to all units in the donor pool assuming that each of them had experienced in year k the same policy implementation our previous-affected unit did. We obtain J SC ($T_0 \times 1$)vectors of estimates, one for each unit. These vectors are nothing but the effects that would have been obtained by having randomly assigned the policy to the sample units along the time span considered. We calculate the proportion of effects that overcome the estimated effect for the affected unit over the total J + 1 number of effects for each year considered. We interpret this proportion as a p-value, as in the following:

$$p_t = \Pr(\hat{\alpha}_{jt} \ge \hat{\alpha}_{1t}) = \frac{\sum_{j:2}^{J+1} I(\hat{\alpha}_{jt} \ge \hat{\alpha}_{1t})}{J}$$

where $\hat{\alpha}_{jt}$ is the estimated effect for the generic *j* region at time $t \in (k + 1, ..., T)$ when the policy intervention is randomly assigned to county *j*.

We draw inference on $\hat{\alpha}_1$, the average effect on the entire post-intervention period for the affected unit. We consider, for each year t after policy introduction, the total number of possible "placebo" averages (N) and we calculate the empirical p-value reported as p_t i.e. the proportion of "placebo" averages that exceeds the estimated average effect.

$$p = \Pr(\hat{\alpha}_g \ge \hat{\alpha}_1) = \frac{\sum_{g:1}^N I(\hat{\alpha}_g \ge \hat{\alpha}_1)}{N}$$

Where *N* denotes the total number of possible placebo averages $N = \prod_{j=2}^{J+1} J!$ and *g* denotes any possible realisation obtained from any combination of placebo effects.

As proposed by Krief et al. (2015) following Abadie et al. (2010) we extend our analysis considering the fact that we have three treated units which belong to the same region and the treated units might be aggregated into a single one. We use the same SC procedure explained in Sections 4.1 and 4.2 considering as unit of observation the whole region and compare it with all other regions. This exercise is useful to assess robustness of our estimates and provides general effect of a Region versus the others, even if using aggregate data prevents us from using robust inferential techniques.

5 Empirical Results

5.1 Descriptive statistics

We calculate per capita expenditures for every item dividing the total amount spent by public providers within each LHA by the average number of residents in each territory at the beginning and at the end of each year⁹.

Tables 1.a and 1.b show outcome cost variables averaged over different time periods for Tuscany (a) and a mean of all Italian Regions (b). The overall per-capita expenditure has dramatically increased for Italian Regions from about 200 euros in 1997-1999 triennium to approximately 335 euros in 2012-2013. The magnitude of this increase is similar to the one experienced in Tuscany, where, from 220 per capita euros in 1997-1999, an increase occurs which leads to a per capita expenditure equal to 416 euros for 2009-2011 compensated by a significant reduction in 2012-2013, where the average cost per capita is about 385 euros.

Pharmaceuticals are the major determinant of overall per capita goods dynamics since they account for at least two third of total per capita expenditures in every time interval considered and their relative weight has increased over time. It follows that per capita paths are mostly driven by changes in pharmaceutical per capita expenditures.

Per capita expenditures for maintenance goods and services are, on average, constant over time both for Tuscany (27 euros per inhabitant in 1997-1999 and 35 euros in 2012-2013) and for the average of all Italian Regions (25 euros in 1997-1999 and 36 in 2012-2013), showing in both cases a small reduction between the last two intervals. Living goods and materials show a similar path in terms of a small increase in both Italian and Tuscany case. Foodstuff goods and food-related services are on average quite constant over time in Tuscany and show a little increase on average for Italian Regions. IT, combustibles and veterinary goods are the

⁹ Cost variables are expressed in Euros with reference year 2010.

less expensive and show a small but constant decrease in per capita euros in Tuscany. Veterinary goods are also decreasing in the Italian average, whilst combustibles are constant over time and IT goods and services are somewhat increasing.

Tables 1 (a) - (d) represent three-years averages of per capita expenditures for LHA of Florence (a), Pisa (b), Siena (c) and an un-weighted average of all units included in the sample (d), i.e. an average of all Italian LHAs. There are small differences within LHAs in Tuscany in terms of per capita costs at the beginning and at the end of the period considered and the comparison with overall Italian average of per capita expenditures across all LHAs reveals us that public providers in Tuscany spend more than the national average. As for the analysis at regional level, pharmaceuticals drive the aggregate cost and reflect the Tuscany over-expenses if compared with the average of local units. Also goods and services for maintenance and for food are on average higher in Tuscany rather than in other units, even if with different rates.

We can conclude that expenditures experienced an increase over time from 1997 to 2013, and this increase can be identified irrespectively at Regional or at local level. Pharmaceuticals are the major driver of public expenditures for goods and services and show a common trend between different units. Other items have a lower weight on the determining of total per capita expenditure but show interesting different path over years and across units.

In Appendix A2 we report tables for descriptive statistics on covariates such as population dimension (Tables A2.1a and A2.1b). In terms of number of residents, both Tuscany and LHAs operating in Tuscany territory are on average bigger than national averages for Regions and for LHAs. Moreover we can observe that population has increased over time and in particular Tuscany experienced a higher population growth rate since the difference was about 785 thousands in 1997-1999 and increased up to 845 thousands in 2012-2013.

As stated in previous section population composition is one of the most powerful driving force for utilisation of health services, since the elderly (or super–elderly) and the youngest deserve more care and as a consequence are more likely to demand for health care services. In Tables A2.2a – A2.2d (Appendix A2) we can see that the both the proportion of people who are over 65 years old the proportion of over 80 years old are higher in Tuscany LHAs than the Italian average, even if this difference is decreasing over time. In general, the proportion of elderly and the proportion of super elderly are increasing over time and they represent significant share of population which in turn can have an important effect for expenditure increase. Accordingly with this result, proportion of under 14 is decreasing in Italian LHAs whilst is increasing over time for Tuscany. Population density and the average number of residents per municipality are constant over time for all units considered. We also report in Tables A2.2e and A2.2f population composition and dynamics for Tuscany and other Italian Regions and autonomous provinces.

Wages for doctors and medical staff standardised by population dimension account (Table A2.3a) for 460 euros per LHA resident in 2012-2013 in Italy, wages for administrative personnel about one tenth (44 euros per capita), wages for professional service employees less than 3 euros per capita and wages for technical employees about 65 euros per capita. All these labour variables have followed similar path from 1997 to 2013 and are substantially lower than per capita expenditures for Tuscany LHA residents (Tables A2.3b-d). This difference is exactly the same if we compare whole Tuscany with the average of Italian Regions (Tables A2.3e and A2.3f). Wages of doctors and medical staff are in general defined by national contract and as a consequence we can either conclude that in Tuscany there are more doctors per residents or these doctors are paid to work more. In both cases we can assume a higher endowment of labour in Tuscany with respect to Italian average.

Tuscany (and its sub-territories in which LHAs operates) is generally richer and with lower level of unemployment if compared to other Italian Regions. Detailed results are in tables A2.4 and A2.5 (Appendix A2).

We also report utilisation rates (A2.6, Appendix A2) and complexity performance indices (Table A2.7, Appendix A2) available at regional level to control for providers heterogeneity and for quality differences.

Table 1 (a): Pharmaceuticals

		Years:	Years:	Years:	Years:	Years:	Years:
		1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2013
LHA	n	Mean S.D.					
Italy	92	113,49 39,5	136,25 44,4	171,26 53,7	199,03 56,9	222,36 66,7	220,34 72,9
Florence	1	153,91 13,1	203,35 16,1	274,17 24,8	302,05 11,7	328,55 1,9	310,79 3,6
Pisa	1	150,63 12,3	199,78 18,8	252,76 18,1	289,24 7,1	314,35 3,7	285,74 2,4
Siena	1	139,22 10,7	163,96 39,2	240,97 22,1	276,72 12,0	297,73 5,7	275,65 3,2

Notes: Euros spent by Italian and Tuscany Local Health Authorities for pharmaceutical goods and services standardised by resident population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Variables are expressed in 2010 Euros.

Table 1 (b): Veterinary goods and services

		Years:	Years:	Years:	Years:	Years:	Years:
		1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2013
LHA	n	Mean S.D.					
Italy	92	1,04 3,5	0,42 1,1	0,15 0,2	0,14 0,2	0,13 0,1	0,13 0,2
Florence	1	0,04 0,0	0,02 0,0	0,03 0,0	0,02 0,0	0,01 0,0	0,01 0,0
Pisa	1	0,70 1,0	0,06 0,0	0,06 0,0	0,03 0,0	0,02 0,0	0,01 0,0
Siena	1	0,08 0,1	0,06 0,0	0,08 0,0	0,08 0,0	0,08 0,0	0,03 0,0

Notes: Euros spent by Italian and Tuscany Local Health Authorities for veterinary goods and services standardised by resident population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Variables are expressed in 2010 Euros.

Table 1 (c): Foodstuff goods and services

		Years:	Years:	Years:	Years:	Years:	Years:
		1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2013
LHA	n	Mean S.D.					
Italy	92	11,18 3,8	12,16 4,5	12,70 5,0	13,45 5,4	13,85 5,3	13,06 5,2
Florence	1	9,46 0,7	11,49 0,6	12,88 0,3	11,83 0,8	12,55 0,3	12,38 0,2
Pisa	1	13,99 0,4	16,00 0,6	16,89 0,4	15,07 0,6	15,23 0,3	13,22 1,2
Siena	1	14,04 1,0	14,41 1,5	15,60 0,1	14,95 0,1	15,76 0,4	14,62 0,6

Notes: Euros spent by Italian and Tuscany Local Health Authorities for foodstuff goods and services standardised by resident population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Variables are expressed in 2010 Euros.

Table 1 (d): Living goods and services

		Years:	Years:	Years:	Years:	Years:	Years:
		1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2013
LHA	n	Mean S.D.					
Italy	92	19,70 11,3	22,66 11,3	25,40 11,7	28,12 11,4	29,79 11,1	28,80 11,1
Florence	1	22,62 0,2	30,94 3,5	37,19 0,8	36,61 0,9	38,37 0,5	35,69 2,1
Pisa	1	23,23 1,5	26,99 1,9	32,18 0,7	33,34 0,3	37,02 1,8	37,37 2,1
Siena	1	20,89 1,1	25,50 3,0	35,06 3,5	40,00 0,1	39,95 0,1	38,32 1,0

Notes: Euros spent by Italian and Tuscany Local Health Authorities for living goods and services standardised by resident population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Variables are expressed in 2010 Euros.

Table 1 (e): Combustibles

		Years:	Years:	Years: Years:		Years:	Years:	
		1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2013	
LHA	n	Mean S.D.	Mean S.D.	Mean S.D.	Mean S.D.	Mean S.D.	Mean S.D.	
Italy	92	5,63 3,9	4,24 3,9	3,47 3,5	3,57 3,9	3,11 3,9	3,04 4,0	
Florence	1	6,57 0,4	5,22 0,2	4,12 0,4	2,36 1,6	0,77 0,0	0,87 0,1	
Pisa	1	1,89 1,0	1,62 0,2	1,96 0,5	1,62 0,5	1,04 0,1	1,08 0,2	
Siena	1	7,13 0,7	5,55 1,1	2,59 1,2	1,55 0,1	1,38 0,1	1,55 0,1	

Notes: Euros spent by Italian and Tuscany Local Health Authorities for combustibles standardised by resident population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Variables are expressed in 2010 Euros.

Table 1 (f): Information Technologies (IT)

		Years:	Years:	Years:	Years:	Years:	Years:
		1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2013
LHA	n	Mean S.D.					
Italy	92	4,48 3,4	5,37 4,0	6,48 5,6	6,90 5,8	6,77 6,0	6,46 5,9
Florence	1	6,49 0,3	5,51 0,6	4,86 0,6	4,73 0,2	4,09 0,4	3,04 0,4
Pisa	1	5,22 1,1	8,92 1,0	6,59 1,3	5,25 0,1	4,71 0,6	3,47 0,8
Siena	1	3,97 0,1	4,35 0,5	4,05 0,4	3,31 0,4	4,39 0,2	3,35 0,5

Notes: Euros spent by Italian and Tuscany Local Health Authorities for IT goods and services standardised by resident population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Variables are expressed in 2010 Euros.

Table 1 (g): Maintenance

		Years:	Years:	Years:	Years:	Years:	Years:
		1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2013
LHA	n	Mean S.D.	Mean S.D.	Mean S.D.	Mean S.D.	Mean S.D.	Mean S.D.
Italy	92	23,51 9,9	24,30 9,2	26,34 9,7	29,02 10,9	31,48 13,9	31,61 14,7
Florence	1	27,33 0,5	29,80 0,6	29,04 1,6	31,67 0,2	33,54 0,8	32,39 1,1
Pisa	1	26,53 0,6	31,73 2,4	34,57 3,0	32,68 1,5	37,23 2,1	37,89 0,5
Siena	1	26,43 0,6	24,51 6,0	31,81 2,5	35,45 0,3	35,85 0,2	37,66 0,5

Notes: Euros spent by Italian and Tuscany Local Health Authorities for maintenance goods and services standardised by resident population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Variables are expressed in 2010 Euros.

Table 1 (h): Total

		Years:	Years:	Years:	Years:	Years:	Years:
		1997-1999	2000-2002	2003-2005	2006-2008	2009-2011	2012-2013
LHA	n	Mean S.D.					
Italy	92	179,02 59,4	205,40 64,6	245,82 74,4	280,22 79,1	307,50 90,2	303,44 96,8
Florence	1	226,42 12,9	286,33 18,8	362,28 24,5	389,26 10,0	417,88 2,7	395,16 7,5
Pisa	1	222,19 12,7	285,10 23,9	345,02 20,3	377,23 5,3	409,60 4,6	378,78 7,1
Siena	1	211,77 10,5	238,32 50,8	330,16 26,8	372,06 12,3	395,14 6,0	371,19 4,9

Notes: Euros spent by Italian and Tuscany Local Health Authorities for total goods and total provision of services standardised by resident population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Variables are expressed in 2010 Euros.

5.2 Synthetic Control: a brief reminder

Sections 5.3-5.5 contain results for Synthetic Control procedures for LHA of Florence (Section 5.3), Pisa (5.4) and Siena (5.5). For each LHA and for each cost variable we estimate a separate model assigning weights to Italian LHAs in the donor pool in order to minimise differences between outcome trajectory before 2005 and the weighted linear combination of outcome variables of others LHAs. We therefore apply the same weights to outcome variables measured at Local level after 2005, obtaining pointwise estimates of *what would have happened* to relevant outcome variable in absence of ESTAV creation. Weights are assigned to LHAs but also to relevant variables (*W** and *V** matrices, section 4.1). To compute our estimates we include all Italian LHAs with the only exclusion of the ones that operate in Tuscany, since they have experienced the same cost-containment policy in 2005 and this would violate the assumption that units in donor pool do not have to experience the same policy. In section 5.6 we use the same model to estimate results for Tuscany and compare outcome variables with a weighted combination of outcome variable themselves in aggregated Italian Regions and Autonomous Provinces.

The structure of each of the following (5.3-5.6) sections is the same: is shown a table which compare simple averages over years of covariates in the pre-treatment period for the relevant LHA, and a weighted average (weights are assigned as reported in Section 4.1) of covariates measured at LHA level separately for each outcome variable. These tables are useful to investigate whether the (weighted) average of covariates in pre-treatment period is reproducing original values in LHA of interest.

In addition we provide for each LHA and for each balance two different graphical representations: the left-hand one represents the real path of expenditures (blue line) with the SC convex combination of LHAs (red line), while the right-hand one shows differences

between the two mentioned. We expect the two lines are overlapping in both figures before 2005 and are diverging after.

In Appendix A3 we also provide tables with real and SC estimates from which we obtain these figures.

5.3 Synthetic Control: Florence

Table 2 reports predictor balance of covariates. In the first column we calculate the 1997-2005 average of covariates for LHA of Florence so the real means over time for the covariates included. In the following columns we report the average outcomes weighted with SC weights in the same time interval for the units included in each donor pool. As we have previously noticed the pre-treatment goodness of fit is on average quite good for each variable. Good balance between covariates and real averages in the interval 1997-2005 reveals that SC estimate is adequate to represent LHA of Florence.

Figure 1 represents pharmaceutical cost variable: we note an unexpected effect, since the real trajectory is on average above the estimated SC line. It seems that the policy caused an increase in pharmaceutical expenditures that we wouldn't have observed without policy implementation.

Figure 2 represents purchases of veterinary goods. Due to non-constant trend in pre-treatment period the goodness of fit is too poor and the SC estimates have poor predictive effects.

Foodstuff goods and services are represented in Figure 3. The pre-policy introduction series is perfectly matched by the SC linear combination of LHAs, since real and synthetic lines coincide in left-hand part of the Figure, i.e. their difference is zero. The effect of the policy is positive in the first years while is weaker in the last part of the time span considered.

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Albeit the difference between the real and the Synthetic lines is negligible for living goods and services (Figure 4) there is no policy effect. As we can note from right-hand part of Figure 4 the difference between the two lines seems random and there is no clear indication on any effect.

There is a significant cost decrease for combustibles *et similia* as we can see from Figure 5. The pre-policy real line is very well approximated by the SC combination and from 2006 there is a substantial reduction in terms of costs, moreover the trend is decreasing also in the weighted combination of LHAs.

The discrepancy between real and synthetic lines is monotonically increasing over time for IT goods and services as we can see in Figure 6. The synthetic line is quite flat after 2006 but the real trajectory is dramatically decreasing and reveals us that ESTAV introduction had a positive effect on this variable.

For what concern maintenance goods and services (Figure 7) the pre-treatment fitting is poor and conclusions can not be strong as previous outcomes.

		Outcome:	Outcome:	Outcome:	Outcome:	Outcome:	Outcome:	Outcome:
	Florence	Pharmaceuticals	Veterinary	Food	Living	Combustibles	IT	Maintenance
Acute admissions	19.46	18.76	17.86	18.61	18.25	17.91	18.20	18.16
Rehabilitation admissions	15.29	15.08	13.96	14.87	14.55	13.73	14.10	13.21
Long-care term admissions	11.18	13.45	11.61	11.77	10.45	10.72	11.35	10.50
Acute total days	21.31	20.57	19.68	20.41	20.03	19.65	20.01	19.97
Long-care total days	14.88	17.80	15.48	15.96	13.69	14.41	15.32	13.55
Rehabilitation total days	18.47	18.25	17.19	18.08	17.61	16.80	17.34	15.94
Prop. over 80 y.o.	5.65	5.99	5.63	4.55	5.42	4.19	4.56	4.72
Prop. over 65 y.o.	21.77	22.90	22.11	19.20	21.39	18.03	18.61	19.60
Prop. under 14 y.o.	11.85	11.40	11.80	13.70	12.10	14.93	14.81	13.71
Share of non-working people	24.60	22.46	23.50	29.62	24.15	31.11	24.62	28.53
Average stay	7.48	6.92	7.31	7.09	7.13	6.76	6.95	7.37
Performance Index	0.98	0.96	0.98	1.02	1.00	1.00	0.99	1.03
Case mix control	1.10	1.04	1.08	1.01	1.06	0.99	0.97	1.02
Share of complications	32.13	30.87	32.26	28.31	30.09	28.70	28.28	31.19
GDP per capita	14482.17	15503.34	12904.61	12592.56	14780.43	11090.21	13349.55	12474.30
Residents /Municipalities	9.91	9.07	8.86	9.02	9.02	8.53	9.15	8.56
Population density	5.69	5.09	5.38	5.64	5.77	4.63	5.07	4.86
Medical wages p.c.	13.04	13.11	12.87	12.86	12.94	12.91	13.02	13.00
Professional sector wages p.c.	7.88	7.97	7.23	7.31	7.68	7.31	7.60	7.34
Technical sector wages p.c.	11.27	11.32	10.86	11.18	11.22	11.29	11.40	11.20
Administrative sector wages p.c.	10.71	10.85	10.56	10.56	10.59	10.62	10.86	10.66

Table 2: averages 1997-2005 for LHA of Florence for covariates in the first column; weighted averages with SC weights for each model in the following columns.

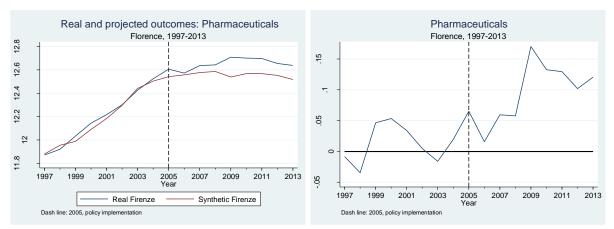


Figure 1: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Pharmaceuticals. LHA of Florence.

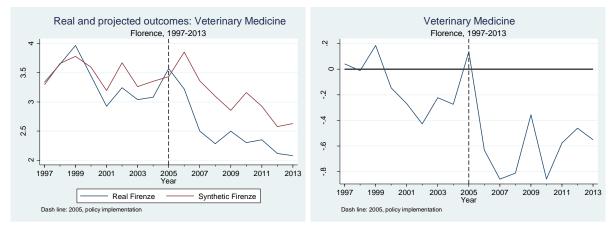


Figure 2: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Veterinary goods. LHA of Florence.

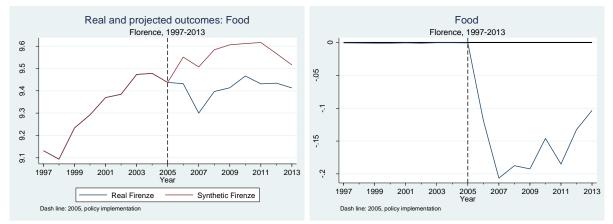


Figure 3: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Food goods and services. LHA of Florence.

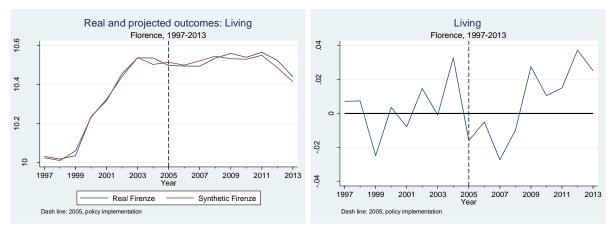


Figure 4: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Living goods and serivces. LHA of Florence.

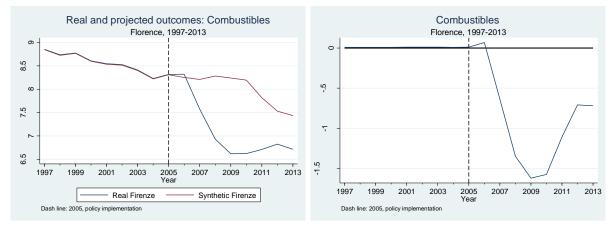


Figure 5: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Combustibles, carburant, lubricants. LHA of Florence.

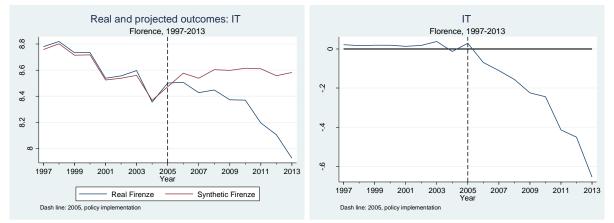


Figure 6: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: IT services and goods. LHA of Florence.

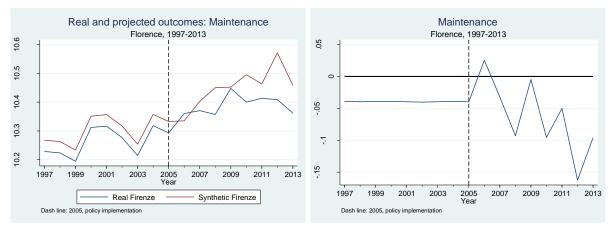


Figure 7: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Maintenance goods and services. LHA of Florence.

5.4 Synthetic Control: Pisa

As for LHA of Florence, also balance predictors for covariates for LHA of Pisa (Table 3) reveal that on average covariates are correctly balanced in estimation procedures for all models.

Figure 8 represents SC estimates for total expenditures for pharmaceuticals in the LHA of Pisa. There is no substantial effect of the policy, i.e. the real trajectory is adequately estimated by LHAs weighted average before 2005. After 2006 there is no policy effect since the differences between the two lines seem to randomly be around zero. In other words differences between real and synthetic trajectories are irrelevant before policy introduction whilst post-policy years show an effect that is opposite to cost containment.

In Figure 9 we find results for the cost variable that regards veterinary materials. Beneath a low pre-policy fit there are small evidences that the creation of ESTAV have helped LHA of Pisa to save money in this specific item. The effect is weak.

If we consider the difference between the real and the synthetic line for purchase of foodstuff goods and services (Figure 10), we can see that there is a small policy effect. Nevertheless pre-policy fit is quite good.

As for previous cost variables, SC estimates are accurate also for the purchase of living goods and services, as depicted in Figure 11. Unfortunately there is no policy effect since differences between the two lines are too small after 2006 to conclude that there is a substantial reduction in terms of cost.

In Figure 12 we find results for cost for combustibles, carburant and lubricants. The series of pre-policy intervention for LHA of Pisa is too discontinuous to find a good fit of the SC estimate. Considering that the fit of the model is weak, we although find some effect after policy introduction.

IT cost variable (Figure 13), beneath the small impact on total cost, clearly show an important reduction of expenses after policy implementation, i.e. the pre-policy trajectory is very close to the real one and post-policy values are lower than estimate of null effect.

As for IT purchase, also maintenance costs are well expressed as a linear combination of nontreated LHAs in the years before 2006, as in Figure 14. Given that differences between real and projected outcomes are not close to zero, it is clear that the policy had an effect for this specific balance item after 2006. The effect is diminishing in the last couple of years but still clear.

		Outcome:	Outcome:	Outcome:	Outcome:	Outcome:	Outcome:	Outcome:
	Pisa	Pharmaceuticals	Veterinary	Food	Living	Combustibles	IT	Maintenance
Acute admissions	19.35	18.69	18.24	17.99	18.03	18.76	17.55	17.90
Rehabilitation admissions	15.18	14.98	13.67	13.38	14.06	14.23	12.17	12.87
Long-care term admissions	11.07	13.34	11.03	9.36	10.53	11.53	10.24	11.34
Acute total days	21.20	20.49	19.95	19.83	19.84	20.46	19.44	19.74
Long-care total days	14.77	17.63	14.81	11.96	14.02	15.22	13.41	14.45
Rehabilitation total days	18.36	18.12	16.83	16.39	17.24	17.32	14.61	15.26
Prop. over 80 y.o.	5.62	5.88	4.65	5.27	5.44	3.80	5.03	4.64
Prop. over 65 y.o.	22.08	22.50	19.27	21.46	21.47	17.43	20.34	19.07
Prop. under 14 y.o.	11.56	11.74	15.22	12.86	12.16	15.80	12.67	14.22
Share of non-working people	27.06	22.59	33.12	27.56	25.17	36.88	24.48	24.89
Average stay	7.48	6.79	6.38	7.49	7.25	6.54	7.89	7.40
Performance Index	0.98	0.95	0.94	1.04	1.00	0.96	1.04	1.02
Case mix control	1.10	1.03	0.97	1.02	1.06	0.97	1.05	1.00
Share of complications	32.13	30.80	29.52	31.35	30.57	27.44	31.93	33.28
GDP per capita	13211.69	15436.17	11211.26	12208.72	13330.36	9953.40	13446.78	13168.40
Residents /Municipalities	9.39	9.08	9.60	8.36	8.92	9.37	8.30	8.00
Population density	5.27	4.96	5.52	4.82	5.30	5.48	4.70	4.19
Medical wages p.c.	13.04	13.10	12.97	13.06	12.98	12.88	12.94	13.04
Professional sector wages p.c.	8.03	7.94	7.37	7.27	7.61	7.56	7.06	7.45
Technical sector wages p.c.	11.16	11.29	11.30	11.32	11.20	11.02	11.21	11.39
Administrative sector wages p.c.	10.57	10.79	10.74	10.70	10.62	10.53	10.63	10.78

Table 3: averages 1997-2005 for LHA of Pisa for covariates in the first column; weighted averages with SC weights for each model in the following columns.

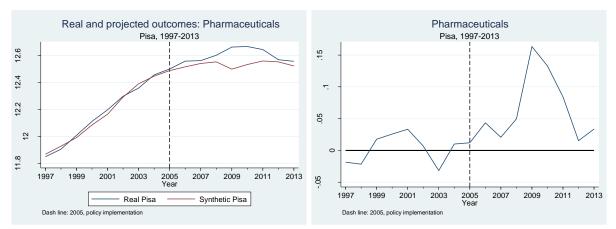


Figure 8: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Pharmaceuticals. LHA of Pisa.

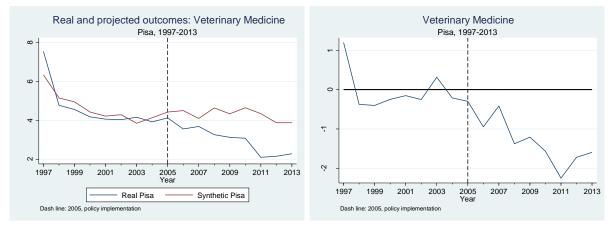


Figure 9: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Veterinary goods. LHA of Pisa.

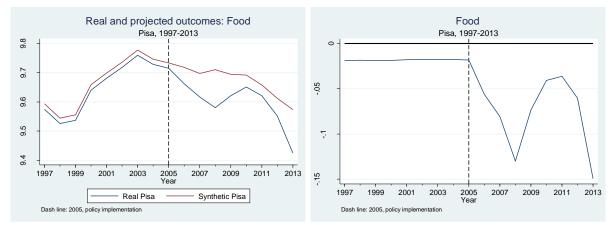


Figure 10: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Food goods and services. LHA of Pisa.

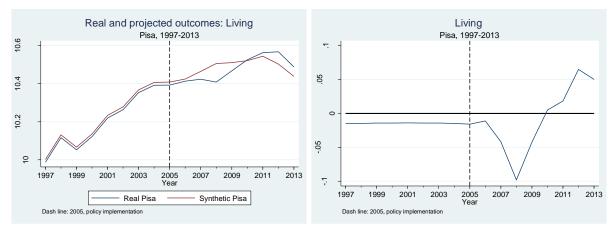


Figure 13: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Living goods and serivces. LHA of Pisa.

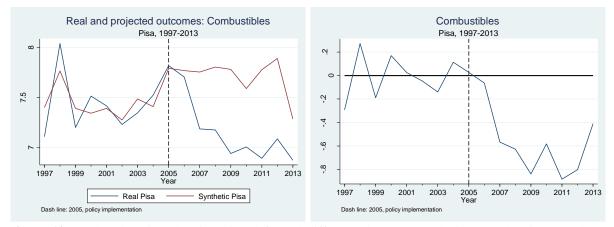


Figure 12: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Combustibles, carburant, lubricants. LHA of Pisa.

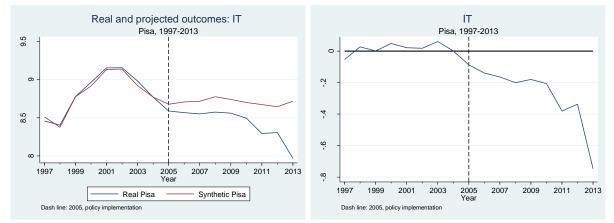


Figure 13: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: IT services and goods. LHA of Pisa.

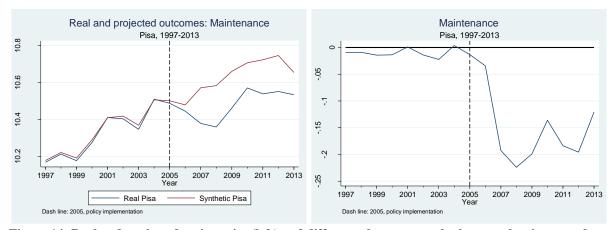


Figure 14: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Maintenance goods and services. LHA of Pisa.

5.5 Synthetic Control: Siena

In this section we report results obtained with SC procedure for the LHA of Siena. Table 4 reports predictor balance of covariates. As described in Section 5.1, in the first column we calculate averages of covariates for LHA of Siena over 1997-2005. In the remaining ones we report the average outcomes weighted with SC weights in the same 1997-2005 interval for the units included in each donor pool with assigned weights. The pre-treatment goodness of fit is on average quite good for each variable and good balance between covariates and real averages in the interval 1997-2005 reveals that SC procedure is a good choice to provide correct estimates. As for LHA of Florence and LHA of Pisa, balance predictor for covariates for LHA of Siena (Table 18) reveals that on average covariates are well weighted in estimation procedures for all models.

First of all we analyse the item regarding pharmaceuticals, which result is in Figure 15. We have to keep in mind that pharmaceuticals are the most heavy balance driver, results in pharmaceuticals are similar to the one obtained for total expenses, i.e. a dump in 2011, an overall goodness of fit and null policy effect.

As it is clear from right-hand panel of Figure 16, differences between real values and estimates obtained through SC procedure before 2006 are close to zero for veterinary per-

capita expenses. These differences do not have a clear trend after 2006 and this can mean that policy is meaningless in terms of savings for this specific item.

We can deduce the same conclusions also for foodstuff goods and services (Figure 17) but also for purchases of living goods and services (Figure 18) since differences between real values and estimates of per-capita expenses are toward zero.

As in previous cases the model which estimate per-capita expenditure for combustibles, carburant and lubricants has a good pre-policy fit (Figure 19) and show an effective impact of the policy after 2006. More precisely, in right-hand panel of Figure 19 we observe small and random differences between estimates and real values in pre-policy period together with big and almost surely non-random differences after policy implementation.

The per-capita cost for IT goods and services (Figure 20) along with per-capita cost for maintenance (Figure 21) is somehow well predicted by SC procedure. In other words, for both items, pre-policy series of per-capita expenditures show a good fit, and essentially conceal any effect of the introduction of ESTAV in balances, either in terms of savings or losses. Moreover, concerning these two last items, SC procedure deals with the same unexpected gap in year 2001 we observe for other cost variables.

		Outcome:	Outcome:	Outcome:	Outcome:	Outcome:	Outcome:	Outcome:
	Siena	Pharmaceuticals	Veterinary	Food	Living	Combustibles	IT	Maintenance
Acute admissions	18.86	18.09	17.95	18.31	18.84	17.54	17.96	17.45
Rehabilitation admissions	14.69	13.79	13.25	14.12	14.08	13.80	14.07	13.88
Long-care term admissions	10.58	11.47	9.48	11.35	12.69	11.00	10.58	9.73
Acute total days	20.71	19.92	19.67	20.04	20.57	19.35	19.73	19.24
Long-care total days	14.28	15.69	12.51	15.52	17.12	15.13	14.09	12.84
Rehabilitation total days	17.87	17.20	16.40	17.40	17.40	16.97	17.19	17.03
Prop. over 80 y.o.	6.09	5.84	4.48	4.02	4.60	5.19	4.91	5.78
Prop. over 65 y.o.	23.59	22.15	19.06	17.50	18.95	20.88	20.03	22.76
Prop. under 14 y.o.	11.49	11.72	15.32	15.66	14.11	12.96	13.02	11.57
Share of non-working people	23.59	25.01	33.90	36.26	30.60	26.83	26.16	26.62
Average stay	7.48	7.65	6.61	6.54	6.57	7.21	7.07	7.48
Performance Index	0.98	1.04	0.95	0.97	0.97	1.01	1.00	1.02
Case mix control	1.10	1.05	0.99	0.97	0.99	1.04	1.01	1.06
Share of complications	32.13	30.21	30.32	26.55	28.37	29.85	28.96	30.04
GDP per capita	13312.35	12726.98	10475.45	10440.89	12574.06	12757.70	12515.30	12536.79
Residents /Municipalities	8.96	7.97	9.20	9.02	9.33	8.84	8.85	8.08
Population density	4.22	4.60	5.11	5.80	5.49	5.15	4.93	4.60
Medical wages p.c.	13.05	13.07	12.81	12.87	12.98	13.02	12.83	12.98
Professional sector wages p.c.	8.12	7.27	6.92	7.02	7.65	7.13	7.38	7.06
Technical sector wages p.c.	11.23	11.30	11.13	11.15	11.27	11.34	11.09	11.02
Administrative sector wages p.c.	10.74	10.80	10.55	10.50	10.66	10.77	10.55	10.71

Table 4: averages 1997-2005 for LHA of Siena for covariates in the first column; weighted averages with SC weights for each model in the following columns.

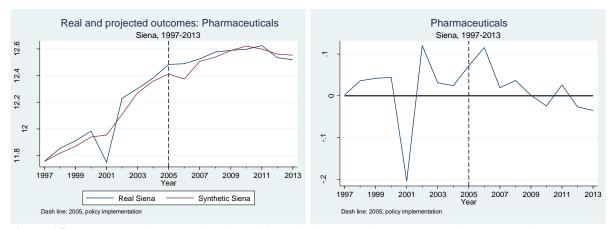


Figure 15: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Pharmaceuticals. LHA of Siena.

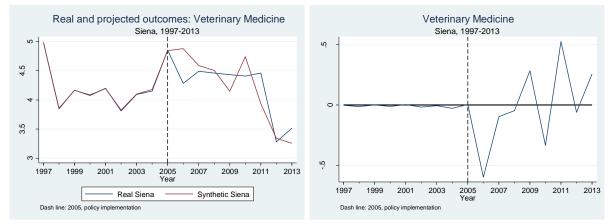


Figure 16: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Veterinary goods. LHA of Siena.

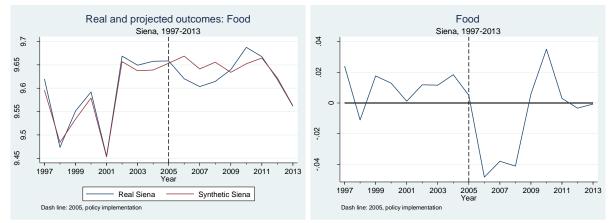


Figure 17: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Food goods and services. LHA of Siena.

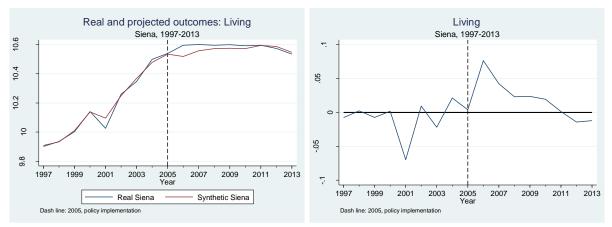


Figure 18: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Living goods and serivces. LHA of Siena.

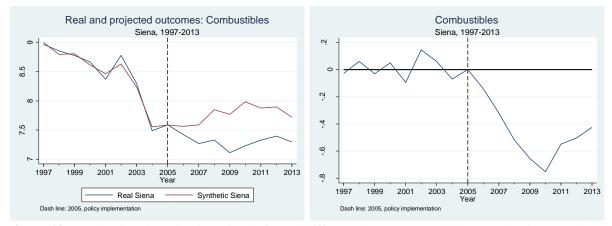


Figure 19: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Combustibles, carburant, lubricants. LHA of Siena.

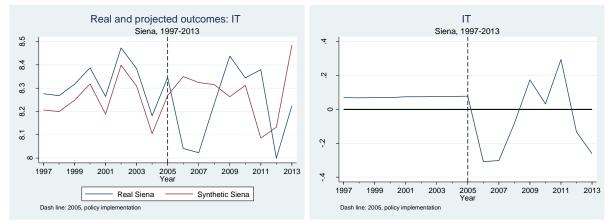


Figure 20: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: IT services and goods. LHA of Siena.

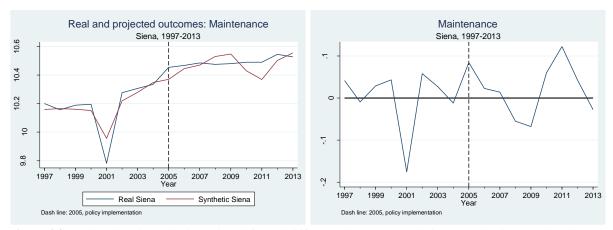


Figure 24: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right). Cost variable considered: Maintenance goods and services. LHA of Siena.

5.6 Synthetic Control for Tuscany

Our final analysis focuses on the whole Region Tuscany and compares it with all other Italian Regions. Recall that in Tuscany exist three different and independent ESTAVs, which institutional centres are located in Florence, Pisa and Siena. As before, in Table 5 we report covariates balance.

We already described in sections 5.3-5.5 the results of SC analysis conducted using as observational unit each single Tuscany L.H.A. (namely Florence, Pisa and Siena) and in this section we want to focus and measure the impact of the creation of ESTAVs in terms of savings within the Regional system, providing estimates of Tuscany as a weighted linear combination of all other regions. Results are discussed above.

If we consider projected outcomes of Synthetic Control estimates for pharmaceuticals (Figure 22), these are underestimates of real per capita costs in post ESTAV creation period, and show null differences in pre-policy implementation. The effect found for pharmaceuticals is exactly opposite to the one observed for other per capita expenditure items, i.e. all other items show significant reductions in terms of per-capita expenditure. The only exception are per-capita expenditures devoted to maintenance services and materials (Figure 28), where

beneath a good pre-policy fitting the post-policy implementation period show small and random discrepancies between real and estimated cost outcomes.

In detail, veterinary per capita expenditures are overall decreasing in real terms for Tuscany (Figure 23) and before 2006 the goodness of fit of Synthetic Control is quite good. In addition it seems that the Synthetic Control weighted average of per capita expenditures for veterinary purposes is decreasing too but with a lower rate, meaning that SC procedure cannot entirely capture the effect in terms of saving which has been caused by policy implementation.

In addition, both for food goods and services and for living expenditures we observe an overall increase in the post-policy implementation period for the Synthetic Control trajectory despite a good pre 2006 fitting, as in Figure 24 and in Figure 25. Real Tuscany per-capita expenditures are instead on average constant for foodstuff goods and services (after 2005, blue line in left-hand panel of Figure 23) or present a small increase for living goods and expenditures (blue line in left-hand panel of Figure 25). In both cases differences between Synthetic and Real trajectories are increasing, revealing an almost sure policy savings effect.

Moreover, per capita expenditures for comestibles, carburant and lubricants and per capita expenditures for IT services and goods are constant over the time span considered after the policy implementation (2006-2013, red lines in left-hand part of Figure 26 and Figure 27) if we consider the synthetic Tuscany average calculated as a linear combination of Italian Regions. Real values (blue lines in left-hand part of Figure 26 and Figure 27) are by the way significantly decreasing, we find negative – and even increasing in absolute values – differences between real and Synthetic lines, as in right-hand panel of Figures 26 and 27.

		Outcome:	Outcome:	Outcome:	Outcome:	Outcome:	Outcome:	Outcome:
	Tuscany	Pharmaceuticals	Veterinary	Food	Living	Combustibles	IT	Maintenance
Acute admissions	5.28	5.39	5.38	5.29	5.39	5.29	5.28	5.32
Rehabilitation admissions	1.11	1.48	1.60	0.77	1.05	1.27	-0.45	1.68
Long-care term admissions	-2.99	0.55	-2.64	-2.76	-4.37	-1.44	-2.10	-2.18
Acute total days	7.13	7.21	7.16	7.13	7.23	7.12	7.14	7.11
Long-care total days	0.70	5.08	0.08	0.17	-2.29	2.06	0.71	0.68
Rehabilitation total days	4.29	4.71	4.63	3.99	4.20	4.27	1.78	4.61
Prop. over 80 y.o.	5.74	5.79	4.62	5.26	5.50	5.06	4.39	5.13
Prop. over 65 y.o.	22.29	22.21	18.95	20.85	21.64	20.60	18.40	20.59
Prop. under 14 y.o.	11.66	11.52	14.64	12.95	12.64	12.52	14.07	12.95
Share of non-working people	25.27	21.10	22.64	25.99	23.91	25.23	25.70	24.34
Average stay	7.48	6.90	6.78	7.17	7.46	7.53	7.58	7.06
Performance Index	0.98	0.94	0.97	1.00	1.02	1.02	1.02	0.98
Case mix control	1.10	1.07	0.97	1.03	1.04	1.05	1.01	1.02
Share of complications	32.13	31.79	28.43	31.54	32.55	30.02	30.49	30.55
GDP per capita	13755.07	15368.52	14045.10	12498.74	13818.58	13732.89	13631.27	13532.76
Residents /Municipalities	9.44	9.39	8.60	8.56	8.62	8.67	8.50	8.65
Population density	5.03	5.18	4.37	4.82	5.04	5.01	4.67	4.72
Medical wages p.c.	13.05	13.05	13.15	13.00	13.05	12.99	13.05	13.02
Professional sector wages p.c.	8.02	7.95	7.75	7.38	7.56	7.49	7.53	7.57
Technical sector wages p.c.	11.23	11.14	11.39	11.24	11.38	11.15	11.32	11.20
Administrative sector wages p.c.	10.68	10.69	10.92	10.56	10.70	10.73	10.85	10.70

Table 5: averages 1997-2005 for Tuscany for covariates in the first column; weighted averages with SC weights for each model in the following columns.

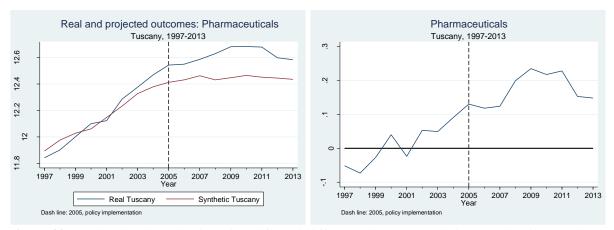


Figure 22: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right) in Tuscany. Cost variable considered: Pharmaceuticals.

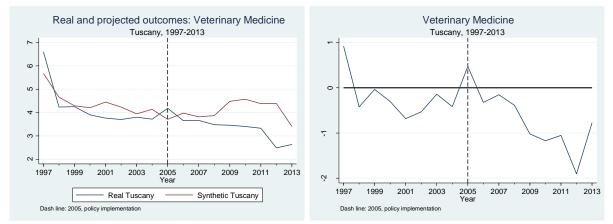


Figure 23: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right) in Tuscany. Cost variable considered: Veterinary goods.

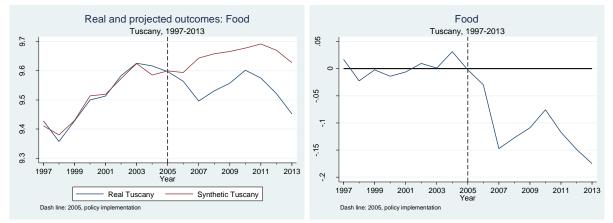


Figure 24: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right) in Tuscany. Cost variable considered: Food goods and services.

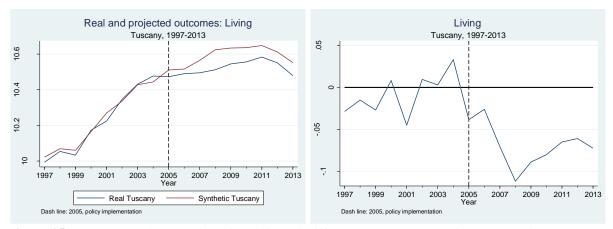


Figure 25: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right) in Tuscany. Cost variable considered: Living goods and services.

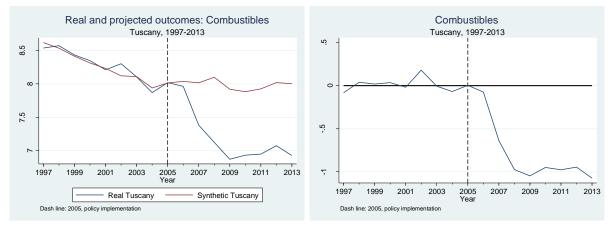


Figure 26: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right) in Tuscany. Cost variable considered: Combustibles, carburant, lubricants.

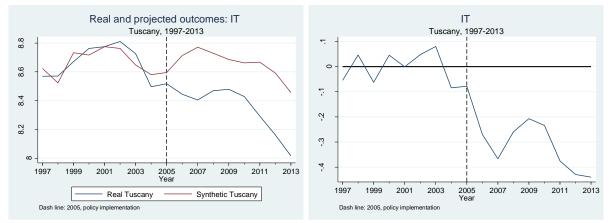


Figure 27: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right) in Tuscany. Cost variable considered: IT services and goods.

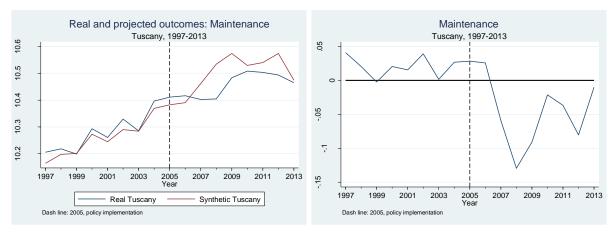


Figure 28: Real and projected trajectories (left) and difference between synthetic control estimate and real outcome (right) in Tuscany. Cost variable considered: Maintenance goods and services.

5.6 Sensitivity Analysis

For each LHA of interest (Florence, Pisa and Siena) we run 92 SC procedures randomly assigning the treatment (i.e. policy introduction) to each unit included in the donor pool. We compute for each model the Root Mean Square Prediction Error (RMSPE). As described in Section 4 we therefore estimate through SC procedure for each balance item a policy effect as the single unit had experienced the same policy implementation. We calculate the proportion of effects α_{jt} which exceed the effect α_{it} where the i-th unit of observation is represented by LHA of Florence, LHA of Pisa, LHA of Siena for LHA donor pool, and Region Tuscany for Regional set up.

Left-hand part of Tables 6, 8 and 10 report for each item and for each relevant LHA the number of effect potentially caused by the random assignment of treatment in 2005 which are above the estimated effect for LHA of Florence (Table 6), Pisa (Table 8) and Siena (Table 10). In these cases the number of LHA that have been considered as treated unit is 92 for each LHA in Tuscany. In right-hand part of the above mentioned Tables we calculate the proportion of effects that are smaller than the estimated SC effect for LHA of Florence, Pisa and Siena respectively. We can interpret this proportion as the probability of finding an effect

which is lower than the observed effect for the LHA of interest, i.e. the likelihood of finding an effect which has greater extent in terms of saving. We can thus interpret this proportion as a p-value in classical inference framework.

Tables 7, 9 and 11 respectively report for each item and for each LHA in Tuscany the number of effect potentially caused by the random assignment of treatment in 2005 which are above the estimated effect for LHA of Florence, Pisa and Siena. In these Tables we exclude from the donor pool all estimates which present a RMSPE at least 1.5 times higher the RMSPE of the real treated unit.

We also compute the proportion of meaningful differences excluding from dataset all models with RMSPE ratio higher than two, three and ten. Estimates are robust over this change even if the number of models that remain in the specification dramatically decrease.

For what concerns LHA of Florence from Tables 6 and 7 we observe that the saving effect regarding per-capita expenditures for the sum of all goods and services from 2007 is on average in the highest decile for both the whole LHA sample and for the sample with restrictions. LHA of Florence presents robust savings in particular for combustibles, carburant and lubricants. From Tables 8 and 9 we can conclude that per capita expenditures for veterinary medicine and for maintenance goods and services for LHA of Pisa are robust to random assignment of the policy. Lastly we analyse LHA of Siena, where with the only exception of per capita expenditures for combustibles and for IT services and goods in the first two year after policy implementation we do not find any effect in the first decile of the distribution, i.e. we do not find any effect which reveals us strength results.

We also compute effect randomisation considered Tuscany as a single unit, as in section 5.4. We have two possible specifications, one is the case in which only regions are in the donor pool while in the second one Tuscany is a weighted average of LHAs and in the donor pool we produce estimates for only local health authorities. For both these specifications we randomly assign treatment each time to a different unit or region and we estimate Synthetic Control model. We find that the two specifications are very similar and produce similar results. Unfortunately estimates are weak in inference framework, since in the donor pool we only have twenty regions and the possible exclusion of any single region due to RMSPE ratio higher than 1.5 give back a donor pool in which the minimum value assumed by proportion of higher effect is $\frac{1}{19} = 0.053$, which is higher. We conduct the same analysis also for average treatment effect as in Cavallo et al. (2013).

Florence	20	06	20	07	20	08	20	09	20	10	20	11	20	12	20	13				Prope	ortion			
outcome	n_e	n	n _e	n	n _e	п	n _e	n	n _e	п	n _e	п	n _e	n	n_e	п	2006	2007	2008	2009	2010	2011	2012	2013
Food	78	92	79	92	71	92	73	92	64	92	70	92	61	92	54	92	0.152	0.141	0.228	0.207	0.304	0.239	0.337	0.413
Combustibles	28	92	89	92	87	92	87	92	86	92	79	92	71	92	69	92	0.696	0.033	0.054	0.054	0.065	0.141	0.228	0.250
Pharmaceuticals	47	92	25	92	24	92	13	92	22	92	27	92	32	92	29	92	0.489	0.728	0.739	0.859	0.761	0.707	0.652	0.685
Living	47	92	59	92	53	92	45	92	49	92	49	92	44	92	45	92	0.489	0.359	0.424	0.511	0.467	0.467	0.522	0.511
IT	60	92	65	92	61	92	66	92	70	92	73	92	75	92	83	92	0.348	0.293	0.337	0.283	0.239	0.207	0.185	0.098
Maintenance	38	92	55	92	74	92	50	92	65	92	61	92	69	92	69	92	0.587	0.402	0.196	0.457	0.293	0.337	0.250	0.250
Veterinary	74	92	85	92	77	92	67	92	80	92	70	92	65	92	70	92	0.196	0.076	0.163	0.272	0.130	0.239	0.293	0.239

Table 6: for each balance item and for each year in post-policy period are reported the total number of LHA in the donor pool (n) and the number of LHA which estimated SC effect is above estimated effect for Florence (n_e). In right-hand side of the Table for each year and for each balance item, we find the proportion of effects which are under the estimated effect, i.e. the opposite of the ratio between n and n_e .

Florence	20	06	20	07	20	08	20	09	20	10	20	11	20	12	20	13				Prop	ortion			
outcome	n _e	n	n _e	n	n_e	n	n _e	n	2006	2007	2008	2009	2010	2011	2012	2013								
Food	41	43	40	43	35	43	37	43	33	43	36	43	31	43	26	43	0.047	0.070	0.186	0.140	0.233	0.163	0.279	0.395
Combustibles	0	19	17	19	16	19	16	19	15	19	13	19	11	19	11	19	1.000	0.105	0.158	0.158	0.211	0.316	0.421	0.421
Pharmaceuticals	30	62	12	62	12	62	2	62	9	62	13	62	17	62	15	62	0.516	0.806	0.806	0.968	0.855	0.790	0.726	0.758
Living	10	16	11	16	10	16	7	16	8	16	7	16	5	16	5	16	0.375	0.313	0.375	0.563	0.500	0.563	0.688	0.688
IT	12	16	10	16	9	16	11	16	12	16	12	16	13	16	14	16	0.250	0.375	0.438	0.313	0.250	0.250	0.188	0.125
Maintenance	13	40	24	40	33	40	26	40	31	40	30	40	31	40	31	40	0.675	0.400	0.175	0.350	0.225	0.250	0.225	0.225
Veterinary	45	53	50	53	45	53	39	53	47	53	39	53	35	53	41	53	0.151	0.057	0.151	0.264	0.113	0.264	0.340	0.226

Table 7: for each balance item and for each year in post-policy period are reported the total number of LHA in the donor pool (*n*) which RMSPE is less than 1.5 higher the RMSPE of Florence and the number of LHA which estimated SC effect is above estimated effect for Florence (n_e) and which RMSPE is less than 1.5 higher the RMSPE of Florence. In right-hand side of the Table for each year and for each balance item, we find the proportion of effects which are under the estimated effect, i.e. the opposite of the ratio between *n* and n_e .

Pisa	20	06	20	07	20	08	20	09	20	10	20	11	20	12	20	13				Prop	ortion			
outcome	n _e	п	n_e	n	n _e	п	2006	2007	2008	2009	2010	2011	2012	2013										
Food	67	92	57	92	63	92	54	92	50	92	50	92	54	92	64	92	0.272	0.380	0.315	0.413	0.457	0.457	0.413	0.304
Combustibles	67	92	87	92	82	92	81	92	70	92	75	92	75	92	56	92	0.272	0.054	0.109	0.120	0.239	0.185	0.185	0.391
Pharmaceuticals	23	92	41	92	28	92	14	92	21	92	34	92	45	92	45	92	0.750	0.554	0.696	0.848	0.772	0.630	0.511	0.511
Living	50	92	61	92	72	92	62	92	51	92	47	92	40	92	39	92	0.457	0.337	0.217	0.326	0.446	0.489	0.565	0.576
IT	74	92	73	92	65	92	61	92	66	92	70	92	69	92	84	92	0.196	0.207	0.293	0.337	0.283	0.239	0.250	0.087
Maintenance	62	92	84	92	88	92	79	92	70	92	75	92	73	92	71	92	0.326	0.087	0.043	0.141	0.239	0.185	0.207	0.228
Veterinary	84	92	71	92	89	92	85	92	87	92	90	92	87	92	88	92	0.087	0.228	0.033	0.076	0.054	0.022	0.054	0.043

Table 8: for each balance item and for each year in post-policy period are reported the total number of LHA in the donor pool (n) and the number of LHA which estimated SC effect is above estimated effect for Pisa (n_e). In right-hand side of the Table for each year and for each balance item, we find the proportion of effects which are under the estimated effect, i.e. the opposite of the ratio between n and n_e .

Pisa	20	06	20	07	20	08	20	09	20	10	20	11	20	12	20	13				Prop	ortion			
outcome	n _e	n	n _e	n	n_e	n	n _e	n	n _e	п	n _e	n	n _e	n	n _e	n	2006	2007	2008	2009	2010	2011	2012	2013
Food	26	31	20	31	21	31	19	31	18	31	18	31	20	31	24	31	0.161	0.355	0.323	0.387	0.419	0.419	0.355	0.226
Combustibles	61	77	73	77	68	77	67	77	58	77	63	77	64	77	48	77	0.208	0.052	0.117	0.130	0.247	0.182	0.169	0.377
Pharmaceuticals	3	51	22	51	12	51	3	51	6	51	18	51	23	51	24	51	0.941	0.569	0.765	0.941	0.882	0.647	0.549	0.529
Living	9	14	10	14	13	14	10	14	8	14	5	14	3	14	3	14	0.357	0.286	0.071	0.286	0.429	0.643	0.786	0.786
IT	42	47	39	47	33	47	32	47	33	47	37	47	37	47	44	47	0.106	0.170	0.298	0.319	0.298	0.213	0.213	0.064
Maintenance	14	18	17	18	17	18	17	18	16	18	16	18	14	18	15	18	0.222	0.056	0.056	0.056	0.111	0.111	0.222	0.167
Veterinary	67	73	57	73	70	73	69	73	70	73	71	73	71	73	70	73	0.082	0.219	0.041	0.055	0.041	0.027	0.027	0.041

Table 9: for each balance item and for each year in post-policy period are reported the total number of LHA in the donor pool (*n*) which RMSPE is less than 1.5 higher the RMSPE of Pisa and the number of LHA which estimated SC effect is above estimated effect for Pisa (n_e) and which RMSPE is less than 1.5 higher the RMSPE of Pisa. In right-hand side of the Table for each year and for each balance item, we find the proportion of effects which are under the estimated effect, i.e. the opposite of the ratio between *n* and n_e .

Siena	20	06	20	07	20	08	20	09	20	10	20	11	20	12	20	13				Prop	ortion			
outcome	n _e	п	n _e	п	n_e	n	n _e	n	n _e	n	n _e	п	n _e	n	n _e	п	2006	2007	2008	2009	2010	2011	2012	2013
Food	60	92	49	92	51	92	46	92	39	92	46	92	45	92	38	92	0.348	0.467	0.446	0.500	0.576	0.500	0.511	0.587
Combustibles	78	92	73	92	76	92	76	92	77	92	71	92	61	92	57	92	0.152	0.207	0.174	0.174	0.163	0.228	0.337	0.380
Pharmaceuticals	10	92	42	92	35	92	50	92	55	92	47	92	53	92	55	92	0.891	0.543	0.620	0.457	0.402	0.489	0.424	0.402
Living	21	92	38	92	38	92	46	92	48	92	53	92	50	92	49	92	0.772	0.587	0.587	0.500	0.478	0.424	0.457	0.467
IT	86	92	83	92	51	92	28	92	40	92	25	92	53	92	56	92	0.065	0.098	0.446	0.696	0.565	0.728	0.424	0.391
Maintenance	40	92	42	92	67	92	59	92	43	92	40	92	47	92	62	92	0.565	0.543	0.272	0.359	0.533	0.565	0.489	0.326
Veterinary	73	92	56	92	55	92	33	92	59	92	22	92	54	92	33	92	0.207	0.391	0.402	0.641	0.359	0.761	0.413	0.641

Table 10: for each balance item and for each year in post-policy period are reported the total number of LHA in the donor pool (n) and the number of LHA which estimated SC effect is above estimated effect for Siena (n_e). In right-hand side of the Table for each year and for each balance item, we find the proportion of effects which are under the estimated effect, i.e. the opposite of the ratio between n and n_e .

Siena	20	06	20	07	20	08	20	09	20	10	20	11	20	12	20	13				Propo	ortion			
outcome	n _e	n	2006	2007	2008	2009	2010	2011	2012	2013														
Food	22	31	15	31	17	31	16	31	15	31	16	31	17	31	13	31	0.290	0.516	0.452	0.484	0.516	0.484	0.452	0.581
Combustibles	71	77	64	77	63	77	63	77	65	77	59	77	51	77	49	77	0.078	0.169	0.182	0.182	0.156	0.234	0.338	0.364
Pharmaceuticals	0	51	23	51	16	51	27	51	32	51	25	51	27	51	29	51	1.000	0.549	0.686	0.471	0.373	0.510	0.471	0.431
Living	0	14	5	14	6	14	6	14	6	14	8	14	5	14	5	14	1.000	0.643	0.571	0.571	0.571	0.429	0.643	0.643
IT	46	47	45	47	26	47	13	47	22	47	12	47	28	47	28	47	0.021	0.043	0.447	0.723	0.532	0.745	0.404	0.404
Maintenance	6	18	7	18	13	18	12	18	10	18	9	18	10	18	12	18	0.667	0.611	0.278	0.333	0.444	0.500	0.444	0.333
Veterinary	59	73	42	73	44	73	22	73	48	73	17	73	41	73	22	73	0.192	0.425	0.397	0.699	0.342	0.767	0.438	0.699

Table 11: for each balance item and for each year in post-policy period are reported the total number of LHA in the donor pool (*n*) which RMSPE is less than 1.5 higher the RMSPE of Siena and the number of LHA which estimated SC effect is above estimated effect for Siena (n_e) and which RMSPE is less than 1.5 higher the RMSPE of Siena. In right-hand side of the Table for each year and for each balance item, we find the proportion of effects which are under the estimated effect, i.e. the opposite of the ratio between *n* and n_e .

6 Conclusions and Policy Implication

Governments, regions and Ministry of Health have introduced in the past 15 years measures to keep public health expenditure under control, which is likely to imply a reduction in the authorities and an increase in scale effect and corruption contrast. Tuscany opened the route to the creation of ESTAVs and purchase centralisation.

Following our previous analysis we calculate differences from real and synthetic values of expenditures and we interpret these differences as the impact of the introduction of centralised authorities responsible for the purchases of goods and supplying of services within each LHA. In addition, since the above mentioned are the differences between what is really happened to public expenditures and what would have happened to the same balance items in absence of the policy introduction, we in turn expect negative values.

The overall effect of the policy for the LHA of Florence (Table 12) is an increase by 272 million Euros in the eight years considered (2006-2013) and this is mostly driven by pharmaceuticals (+355 million Euros). The huge increase in pharmaceuticals vanishes some important savings the policy has obtained, such as 25 million Euros from food and food services, about 21 million Euros from combustibles, more than 15 million Euros from IT services and goods and 26 million Euros from maintenance goods and services. If we do not consider pharmaceuticals (last row of Table 12) the policy avoided LHA to spend about 84 million Euros in eight years, on average more than 10 millions for each year.

	2006	2007	2008	2009	2010	2011	2012	2013	Total
Food	-2305	-3695	-3679	-3877	-3041	-3814	-2672	-2029	-25112
Combustibles	401	-2553	-4332	-4535	-4315	-2504	-1426	-1323	-20586
Pharmaceuticals	6658	26121	25716	77197	61155	59858	45722	53353	355779
Living	-269	-1471	-554	1557	589	866	2047	1298	4064
IT	-520	-787	-1163	-1622	-1790	-2795	-2847	-3904	-15427
Maintenance	1159	-1550	-4544	-239	-4941	-2572	-8815	-4863	-26365
Veterinary	-32	-24	-18	-8	-20	-12	-7	-9	-132
Florence	5092	16041	11426	68473	47637	49027	32002	42523	272221
Excluding									
Dharmacouticala	1566	10001	1/200	8772	12510	10830	12720	10030	82558

Pharmaceuticals -1566 -10081 -14290 -8723 -13518 -10830 -13720 -10830 -83558 **Table 12:** Differences in thousands of Euro between real and Synthetic Control Estimates for years 2006-2013. LHA of Florence.

For what concerns LHA of Pisa (Table 13), the overall increase in terms of expenditures is reduced compared to Florence even if expenditures by item are proportional between the two LHAs. Also in this case (as for LHA of Florence) the only item that shows an increase in overall expenditure after policy introduction is *pharmaceuticals*. In fact whether we consider pharmaceuticals in the overall calculus of policy effect we obtained savings for 107 million Euros or losses for 102 million Euros. Once again pharmaceuticals represent the overall driving force with an increase higher than 209 million of Euros on a total increase of 102 million Euros have been saved, 12 million Euros for food goods and services and 10 million Euros for combustibles.

2006 2007 2008 2009 2010 2011 2012 2013 Total	
Food -1180 -1645 -2645 -1521 -861 -744 -1168 -2668 -1243	1
Combustibles -189 -1314 -1502 -1798 -1160 -1865 -1963 -657 -1044	.8
Pharmaceuticals 15665 7598 18889 63017 52476 33424 5872 12563 20950	13
Living -488 -1867 -4487 -2019 242 940 3247 2347 -208	5
IT -1025 -1207 -1552 -1367 -1491 -2467 -2164 -4296 -1556	8
Maintenance -1568 -8903 -10408 -10184 -7556 -10145 -11010 -6444 -6621	8
Veterinary -71 -27 -101 -71 -110 -92 -53 -51 -57	6
Pisa 11144 -7365 -1807 46057 41541 19051 -7239 794 10217	7
Excluding	
Pharmaceuticals -4521 -14963 -20696 -16959 -10935 -14372 -13111 -11769 -10732	7

Table 13: Differences in thousands of Euro between real and Synthetic Control Estimates for years 2006-2013.

 LHA of Pisa.

Also LHA of Siena has increased its expenditures in pharmaceuticals even at a smaller extent (+23 million Euros). This is likely due to the fact that LHA of Siena has on average half of the inhabitant with respect to Florence and Pisa and as a consequence its total savings are reduced. As in previous cases the overall effect (+22 million Euros) is mostly driven by pharmaceuticals, whilst other variables have effects closer to zero. The sum of remaining items but pharmaceuticals shows savings for about 1 million euros in the eight years considered.

	2006	2007	2008	2009	2010	2011	2012	2013	Total
Food	-601	-463	-514	73	461	40	-42	-8	-1056
Combustibles	-206	-437	-849	-940	-1289	-925	-884	-649	-6180
Pharmaceuticals	23423	4222	8573	327	-6031	6480	-6153	-8054	22787
Living	2371	1339	745	777	630	39	-465	-381	5056
IT	-904	-868	-264	609	112	923	-353	-924	-1670
Maintenance	641	398	-1642	-2067	1724	3438	1317	-865	2946
Veterinary	-48	-7	-3	17	-27	29	-1	6	-34
Siena	24677	4184	6046	-1203	-4422	10023	-6582	-10875	21848
Excluding									
Pharmaceuticals	1253	-39	-2527	-1530	1610	3543	-429	-2821	-939

Table 14: Differences in thousands of Euro between real and Synthetic Control Estimates for years 2006-2013.

 LHA of Siena.

	2006	2007	2008	2009	2010	2011	2012	2013	Total
Food	-1543	-7561	-6756	-5931	-4251	-6568	-8028	-8989	-49628
Combustibles	-801	-5116	-7418	-6503	-5945	-6336	-6820	-7273	-46212
Pharmaceuticals	112320	122059	199508	245289	230625	240190	154083	148605	1452679
Living	-3382	-9453	-15715	-12860	-11712	-9717	-8797	-9858	-81495
IT	-5129	-7079	-5104	-4036	-4407	-6665	-6887	-6182	-45490
Maintenance	3034	-7187	-16487	-12376	-2864	-5001	-11069	-1278	-53227
Veterinary	-53	-23	-55	-206	-245	-191	-253	-60	-1085
Tuscany	104447	85640	147973	203376	201201	205712	112229	114966	1175543
Excluding									
Pharmaceuticals	-7873	-36419	-51535	-41913	-29424	-34478	-41854	-33640	-277136

Table 15: Differences in thousands of Euro between real and Synthetic Control Estimates for years 2006-2013. Region Tuscany.

In Table 15 we report results for whole Tuscany and we compare the real overall expenditures with respect to other Regions. Our conclusions are exactly in line with previous

cases: Tuscany faced an increase in expenditures equal to 1 billion and 176 million Euros, pharmaceuticals experienced an increase which was quite close to 1 billion and a half, enabling us to conclude that without considering pharmaceuticals (last row of Table 15) Tuscany would have obtained savings for about 270 million Euros. This last results and all balance item results are in line with the sum of savings obtained by the three independent LHAs even if the magnitude of differences is bigger, revealing that Italian Regions are less efficient than their LHAs.

The unification of formers LHAs into AV, and the introduction of ESTAVs in Tuscany have carried with it a substantial and clear reduction in expenditures for goods and services, except for pharmaceuticals. In fact they exhibit a negative and unexpected reaction to the policy. The overall result is likely to be determined by this specific item, which account for high frequency of total expenditures for goods and services. We are not aware about policy changes that could have caused explosion in pharmaceutical items e.g. increase in reimbursement towards hospitals, undertake of new diseases, prevention campaigns.

Nevertheless some specific items as combustibles, food goods and living services show a positive and robust reaction to the policy, maybe due to economies of scale effects, confirming the goodness of the idea of the creation of specific centres for purchases. We find the most powerful results in terms of goodness-of-fit and differences between real and synthetic outcome trajectories for combustibles, carburant, lubricants, but also for IT and stationary materials.

From an economic point of view is very difficult to think that living goods and services or IT goods can be considered as substitutes of pharmaceutical goods and we use this intuition to strengthen our results. Indeed positive effects of the policy in terms of savings can have

carried the decision for Tuscany to use that money to invest in pharmaceuticals to increase quality of care. Future analysis would be appropriate to disentangle this relation.

One major limitation of this study is the fact that the time series is too short, nevertheless we are aware that this first contribution can be extended through the use of administrative data to produce more accurate estimates across LHAs. Another possible extension of the present work could consider intra-regional mobility of patients, considering incoming and exiting flows of patients to Tuscany and from Tuscany. This covariate would be meaningful to refine the standardisation by population dimension, even if we already include in our analysis volumes controls.

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Appendix A1.

List of Local Health Authorities by Region.

Regional Local Health Authorities (5): Valle D'Aosta, Autonomous Province of Trento, Autonomous Province of Bolzano, Marche, Molise.

Provincial Local Health Authorities (87): Abruzzo (4): LHAs of L'Aquila, Chieti, Pescara and Teramo; Basilicata (2): LHAs of Potenza and Matera; Calabria (5): LHAs of Catanzaro, Crotone, Cosenza, Reggio Calabria, Vibo Valentia; Campania (5): LHAs of Avellino, Benevento, Caserta, Napoli, Salerno; Emilia Romagna (9): LHAs of Bologna (province of Bologna and province of Imola), Ferrara, Forlì-Cesena, Modena, Parma, Piacenza, Ravenna, Reggio Emilia, Rimini; Friuli Venezia Giulia (4): LHAs of Gorizia, Pordenone, Trieste, Udine; Lazio (5): LHAs of Frosinone, Latina, Rieti, Roma, Viterbo; Liguria (4): LHAs of Genova, Imperia, Savona, La Spezia; Lombardia (11): LHAs of Bergamo, Brescia, Como, Cremona, Lecco, Lodi, Mantova, Milano (province of Milano and province of Monza), Pavia, Sondrio, Varese; Piemonte (8): LHAs of Alessandria, Asti, Biella, Cuneo, Novara, Torino, Verbania, Vercelli; Puglia (5): LHAs of Bari (province of Bari and province of Barletta), Brindisi, Foggia, Lecce, Taranto; Sardegna (4): LHAs of Cagliari (provinces of Cagliari, Carbonia-Iglesias, Medio-Campidano), Nuoro (provinces of Nuoro and Ogliastra), Oristano, Sassari (provinces of Olbia and Sassari); Sicilia (9); LHAs of Agrigento, Caltanissetta, Catania, Enna, Messina, Palermo, Ragusa, Siracusa, Trapani; Tuscany: LHAs of Florence (provinces of Prato, Pistoia, Florence, Empoli), Pisa (provinces of Massa Carrara, Livorno, Lucca, Pisa), Siena (provinces of Grosseto, Siena, Arezzo); Umbria (2): LHAs of Perugia and Terni; Veneto (7): LHAs of Belluno, Padova, Rovigo, Treviso, Venezia, Verona, Vicenza.

Appendix A2, Descriptive statistics, covariates.

Table A2.1: Average population.

Table A2.1a: Average population for Italian Local Health Authorities.

		Years:	Years:										
		1997-1999)	2000-2002		2003-2005	i	2006-2008	5	2009-2011		2012-2013	
	n	Mean	S.D.										
Italy	92	618442	645863	619100	645354	625004	650652	633844	660370	643317	670981	647171	680366
Florence	1	1427888	612	1429527	1807	1447038	11496	1472334	8184	1497979	6925	1514134	12668
Pisa	1	1283241	2197	1280561	361	1288724	6704	1305609	8752	1329018	4877	1334889	3152
Siena	1	781432	684	784799	1430	796414	7062	811179	6501	828895	2061	831282	1892

Note: Average population of units of observation in three-year intervals for Italian and for Tuscany LHAs. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years.

Table A2.1b: Average population for Italian Local Health Authorities.

		Years:		Years:		Years:		Years:		Years:		Years:	
		1997-1999		2000-2002		2003-2005		2006-2008	8	2009-2011		2012-2013	3
	n	Mean	S.D.										
Italy	21	2709363	2279692	2712250	2290114	2738114	2321683	2776839	2367810	2818340	2412452	2835225	2450194
Tuscany	1	3492560	2118	3494887	3595	3532176	25227	3589122	23314	3655892	13836	3680304	17712

Note: Regional average population in three-year intervals for Italian Regions and for Tuscany. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years.

Tables A2.2: Population composition and Demographical indicators.

Table A2.2a: Population composition for Italian Local Health Authorities.

		Years:	rs: Y		Years:		Years:		Years:		Years:		
		1997-1	1997-1999		2000-2002		2003-2005		008	2009-2011		2012-2013	
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Prop. over 80 y.o.	92	4.4	1.1	4.5	1.1	5.1	1.1	5.6	1.2	6.1	1.1	6.6	1.1
Prop. over 65 y.o.	92	18.5	3.2	19.3	3.1	20.1	3.0	20.8	2.9	21.1	2.8	21.6	2.6
Prop. under 14 y.o.	92	14.1	2.9	13.9	2.5	13.8	2.1	13.7	1.7	13.7	1.5	13.6	1.3
Population density	92	5.2	0.8	5.1	0.8	5.1	0.8	5.1	0.8	5.2	0.8	5.2	0.8
Resid./Municipalities	92	8.8	0.8	8.8	0.8	8.8	0.8	8.8	0.8	8.8	0.8	8.8	0.8

Note: Demographical indicators in three-year intervals for population in Italian Local Health Authorities. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Population density and the ratio between number of residents and number of municipalities are expressed in log terms.

		Years:	Years:		Years:		Years:		Years:		Years:		
		1997-19	1997-1999		2000-2002		2003-2005		2006-2008		011	2012-2013	
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Prop. over 80 y.o.	1	5.3	0.2	5.4	0.3	6.2	0.2	6.7	0.2	7.2	0.1	7.5	0.1
Prop. over 65 y.o.	1	21.1	0.2	21.8	0.2	22.4	0.2	23.1	0.1	23.2	0.0	23.7	0.2
Prop. under 14 y.o.	1	11.5	0.1	11.8	0.1	12.3	0.1	12.7	0.2	13.2	0.1	13.3	0.1
Population density	1	5.7	0.0	5.7	0.0	5.7	0.0	5.7	0.0	5.7	0.0	5.7	0.0
Resid./Municipalities	1	9.9	0.0	9.9	0.0	9.9	0.0	9.9	0.0	10.0	0.0	10.0	0.0

Table A2.2b: Population composition for Local Health Authority of Florence.

Note: Demographical indicators in three-year intervals for population in Local Health Authority of Florence. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Population density and the ratio between number of residents and number of municipalities are expressed in log terms.

		Years:	Years:		Years:		Years:		Years:		Years:		
		1997-19	1997-1999		2000-2002		2003-2005		2006-2008		011	2012-2013	
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Prop. over 80 y.o.	1	5.3	0.2	5.4	0.3	6.2	0.2	6.7	0.1	7.1	0.2	7.4	0.0
Prop. over 65 y.o.	1	21.4	0.2	22.0	0.2	22.8	0.3	23.5	0.1	23.6	0.1	24.2	0.2
Prop. under 14 y.o.	1	11.4	0.0	11.5	0.1	11.7	0.1	12.0	0.1	12.3	0.1	12.5	0.0
Population density	1	5.3	0.0	5.3	0.0	5.3	0.0	5.3	0.0	5.3	0.0	5.3	0.0
Resid./Municipalities	1	9.4	0.0	9.4	0.0	9.4	0.0	9.4	0.0	9.4	0.0	9.4	0.0

Table A2.2c: Population composition for Local Health Authority of Pisa.

Note: Demographical indicators in three-year intervals for population in Local Health Authority of Pisa. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Population density and the ratio between number of residents and number of municipalities are expressed in log terms.

		Years:	Years:											
		1997-19	1997-1999		2000-2002		2003-2005		2006-2008		2009-2011		2012-2013	
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Prop. over 80 y.o.	1	5.7	0.2	5.9	0.3	6.7	0.2	7.3	0.2	7.7	0.2	8.0	0.0	
Prop. over 65 y.o.	1	23.1	0.2	23.6	0.2	24.0	0.1	24.3	0.1	24.0	0.0	24.4	0.2	
Prop. under 14 y.o.	1	11.3	0.0	11.5	0.1	11.7	0.1	12.0	0.1	12.4	0.1	12.6	0.0	
Population density	1	4.2	0.0	4.2	0.0	4.2	0.0	4.3	0.0	4.3	0.0	4.3	0.0	
Resid./Municipalities	1	9.0	0.0	9.0	0.0	9.0	0.0	9.0	0.0	9.0	0.0	9.0	0.0	

Table A2.2d: Population composition for Local Health Authority of Pisa.

Note: Demographical indicators in three-year intervals for population in Local Health Authority of Siena. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Population density and the ratio between number of residents and number of municipalities are expressed in log terms.

		Years:	Years:		Years:		Years:		Years:		Years:		Years:	
		1997-19	1997-1999		2000-2002		2003-2005		008	2009-2011		2012-2013		
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Prop. over 80 y.o.	21	4.3	1.0	4.4	1.0	5.0	1.0	5.6	1.1	6.1	1.1	6.5	1.0	
Prop. over 65 y.o.	21	18.2	2.9	19.1	2.9	19.8	2.8	20.6	2.7	20.9	2.5	21.5	2.4	
Prop. under 14 y.o.	21	14.3	2.7	14.1	2.3	14.0	1.9	13.9	1.6	13.8	1.4	13.7	1.2	
Population density	21	4.9	0.6	4.9	0.6	4.9	0.6	5.0	0.6	5.0	0.6	5.0	0.7	
Resid./Municipalities	21	8.7	0.6	8.7	0.6	8.7	0.6	8.7	0.6	8.7	0.6	8.7	0.6	

Table A2.2e: Population composition for Italian Regions and Autonomous Provinces.

Note: Regional demographical indicators in three-year intervals for population in Italian Regions and Autonomous Provinces. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Population density and the ratio between number of residents and number of municipalities are expressed in log terms.

Table A2.2f: Population composition for Tuscany.

		Years:	Years:		Years:		Years:		Years:		Years:		Years:	
		1997-19	1997-1999		2000-2002		2003-2005		2006-2008		011	2012-2013		
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Prop. over 80 y.o.	1	5.4	0.2	5.5	0.3	6.3	0.2	6.9	0.2	7.3	0.1	7.6	0.0	
Prop. over 65 y.o.	1	21.7	0.2	22.3	0.2	22.9	0.2	23.5	0.1	23.6	0.0	24.0	0.2	
Prop. under 14 y.o.	1	11.4	0.0	11.6	0.1	11.9	0.1	12.3	0.1	12.7	0.1	12.9	0.0	
Population density	1	5.0	0.0	5.0	0.0	5.0	0.0	5.1	0.0	5.1	0.0	5.1	0.0	
Resid./Municipalities	1	9.4	0.0	9.4	0.0	9.4	0.0	9.5	0.0	9.5	0.0	9.5	0.0	

Note: Regional demographical indicators in three-year intervals for population of Tuscany. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Population density and the ratio between number of residents and number of municipalities are expressed in log terms.

Tables A2.3: Wages.

Table A2.3a: Standardised wages for employees in public health providers in Italian Local Health Authorities.

		Years:		Years:		Years:		Years:		Years:		Years:	
		1997-19	999	2000-2002		2003-20	005	2006-20	008	2009-20)11	2012-2013	
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Medical wages p.c.	92	323.61	69.2	432.51	100.2	478.83	97.1	500.84	101.2	496.50	105.9	461.94	114.1
Professional sector wages p.c.	92	1.23	0.7	1.86	0.9	2.16	1.0	2.36	1.2	2.34	1.0	2.13	1.0
Technical sector wages p.c.	92	63.53	17.0	72.77	21.8	74.85	22.5	73.33	24.0	71.72	25.7	65.51	25.8
Administrative sector wages p.c.	92	34.13	7.9	42.04	12.0	48.19	12.4	49.85	12.6	48.63	12.4	44.18	12.5

Notes: Wages for four different categories of employees working in public health providers within LHA public structures standardised by population dimension for Italian LHAs. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years.

		Years:		Years:		Years:	Years:		Years:		Years:		Years:	
		1997-19	99	2000-20	2000-2002		05	2006-20	08	2009-20	11	2012-2013		
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Medical wages p.c.	1	364.37	5.3	493.13	74.6	543.62	14.0	570.48	6.8	558.33	16.6	514.69	17.1	
Professional sector wages p.c.	1	1.72	0.1	2.87	0.5	3.75	0.4	3.94	0.1	3.68	0.1	3.41	0.2	
Technical sector wages p.c.	1	70.07	0.6	85.40	10.9	79.93	1.7	77.32	1.8	80.87	5.7	80.76	2.9	
Administrative sector wages p.c.	1	36.34	0.4	47.37	6.5	53.31	1.5	54.21	1.4	48.99	2.3	44.70	2.2	

Table A2.3b: Standardised wages for employees in public health providers in Local Health Authority of Florence.

Notes: Wages for four different categories of employees working in public health providers within LHA of Florence standardised by population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years.

Table A2.3c: Standardised wages for employees in public health providers in Local Health Authority of Pisa.

		Years:		Years:		Years:		Years:		Years:		Years:	
		1997-19	99	2000-2002		2003-20	005	2006-20	008	2009-20)11	2012-2013	
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Medical wages p.c.	1	364.31	4.4	495.80	75.7	552.45	14.0	560.56	10.9	567.14	8.0	517.52	21.2
Professional sector wages p.c.	1	2.33	0.1	3.31	0.7	3.85	0.1	4.28	0.2	3.95	0.2	3.45	0.1
Technical sector wages p.c.	1	64.24	0.9	75.95	11.1	72.78	4.1	72.49	2.5	77.51	2.4	69.86	2.2
Administrative sector wages p.c.	1	31.54	0.8	40.27	6.4	46.60	2.6	48.28	1.3	44.61	1.5	39.75	1.4

Notes: Wages for four different categories of employees working in public health providers within LHA of Pisa standardised by population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years.

		Years:		Years:		Years:	Years:		Years:		Years:		
		1997-19)99	2000-20	2000-2002		005	2006-20	008	2009-20)11	2012-2013	
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Medical wages p.c.	1	385.68	5.8	472.36	70.7	562.01	14.1	589.05	6.7	578.48	7.4	534.99	16.2
Professional sector wages p.c.	1	2.69	0.1	3.47	0.6	4.11	0.1	4.31	0.1	3.69	0.2	3.41	0.1
Technical sector wages p.c.	1	73.69	4.1	72.50	9.3	79.54	0.9	80.28	1.3	78.15	2.2	73.35	2.6
Administrative sector wages p.c.	1	40.17	0.6	46.00	5.1	53.69	1.1	53.89	1.8	48.70	2.3	43.09	1.3

Table A2.3d: Standardised wages for employees in public health providers in Local Health Authority of Siena.

Notes: Wages for four different categories of employees working in public health providers within LHA of Siena standardised by population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years.

Table A2.3e: Standardised wages for employees in public health providers in Italian Regions and Autonomous Provinces.

		Years:		Years:		Years:		Years:		Years:		Years:	
		1997-1	999	2000-2002		2003-2	2005	2006-2	2008	2009-2	2011	2012-2013	
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Medical wages p.c.	21	339.5	58	456.4	88.6	512.5	77.9	543.9	84.8	541.9	97.2	505.5	107
Professional sector wages p.c.	21	1.26	0.53	1.949	0.77	2.261	0.77	2.536	0.89	2.433	0.83	2.244	0.85
Technical sector wages p.c.	21	68.12	11.6	78.84	19.9	81.91	20.9	81.57	23.7	79.47	25.3	73.11	26.9
Administrative sector wages p.c.	21	36.02	8.66	45	14.1	52.21	13.9	53.72	14.4	52.13	14.9	47.3	16

Notes: Wages for four different categories of employees working in Italian Regions and Autonomous Provinces public health providers standardised by population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years.

Table A2.3f: Standardised	l wages for employees	s in public health	providers in Tuscany.

		Years:		Years:		Years:		Years:		Years:		Years:	
		1997-1	999	2000-2002		2003-20	005	2006-20	008	2009-20	011	2012-2013	
Variable	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Medical wages p.c.	1	373.4	3.71	492.2	67.7	551.9	13.9	572	6.07	570.1	10.2	520.3	18.4
Professional sector wages p.c.	1	2.298	0.14	3.239	0.46	3.866	0.14	4.155	0.06	3.78	0.11	3.422	0.14
Technical sector wages p.c.	1	69.15	1.03	79.39	9.01	77.37	2.11	76.37	0.94	79.51	0.97	75.14	2.53
Administrative sector wages p.c.	1	36.35	0.15	44.89	5.33	51.12	1.83	52.21	1.12	48.29	1.94	42.54	1.68

Notes: Wages for four different categories of employees working in Tuscany public health providers standardised by population dimension. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years.

Tables A2.4: Per capita Gross domestic product (GDP).

		Years:	lears:		Years:		Years:		Years:		
		2000-2002	2	2003-2005	5	2006-2008	8	2009-201	1	2012-2013	3
	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Italy	92	9994.8	2749.7	11311.5	2867.3	12564.0	3056.2	12869.5	2989.5	13004.4	3069.8
Florence	1	12685.7	481.3	13883.7	267.1	15197.6	296.6	15386.4	223.2	15645.0	92.0
Pisa	1	11092.7	555.0	12544.7	371.8	14025.2	327.2	14346.9	104.4	14467.6	110.7
Siena	1	11285.9	583.9	12706.0	347.0	14091.8	306.1	14394.5	150.7	14469.3	95.5

Table A2.4a: Standardised Gross domestic product (GDP) Italian Local Health Authority Territories.

Notes: Gross domestic product (gdp) per capita. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Unit of observation is each single LHA.

Table A2.4b: Standardised Gross domestic product (GDP) Italian Local Health Authority Territories.

		Years:		Years:		Years:		Years:		Years:	
		2000-2002	2	2003-2005	2003-2005		2006-2008		1	2012-2013	3
	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Italy	21	10253.4	2585.3	11623.6	2733.8	12914.0	2906.6	13289.5	2912.8	13426.6	3010.9
Tuscany	1	11787.7	531.2	13129.6	323.8	14521.2	309.5	14783.6	162.5	14952.4	101.3

Notes: Gross domestic product (gdp) per capita. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Unit of observation is each single Region.

Tables A2.5: Share of non-working people.

Table A2.5a: Share	of non-working peo	ople in Italian	Local Health	Authority 7	Ferritories.

		Years:		Years:	Years:		Years:		Years:		
		2000-200)2	2003-200)5	2006-200)8	2009-201	1	2012-201	3
	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Italy	92	30.9	8.9	28.9	8.2	28.7	7.7	30.0	7.1	31.4	7.0
Florence	1	24.2	1.1	23.3	0.9	24.0	0.6	25.6	0.2	26.6	0.7
Pisa	1	27.6	1.1	26.3	0.4	25.8	0.8	27.3	0.4	29.0	0.5
Siena	1	23.8	1.0	22.6	0.5	22.2	0.9	24.2	0.3	25.8	0.6

Notes: Share of non-working people. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Unit of observation is each single LHA.

Table A2.5b: Share of non-working people in Italian Regions and Autonomous Provinces.

		Years:		Years:	Years:			Years:		Years:	
		2000-2002	2	2003-200	5	2006-200	8	2009-201	1	2012-201	3
	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Italy	21	30.2	8.7	28.2	8.0	27.9	7.5	29.2	7.1	30.5	7.1
Florence	1	25.4	1.1	24.2	0.6	24.2	0.7	25.9	0.3	27.3	0.6

Notes: Share of non-working people. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Unit of observation is each single Region.

		Years: 1997-199	0	Years:		Years:		Years:		Years:		Years:	
		1997-199	99	2000-200	02	2003-200)5	2006-200)8	2009-202	11	2012-20	013
Italy	n	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Acute adm. Rehabilitation adm.	21	206.6	32.7	211.0	23.4	206.5	31.3 3.9	196.5	26.8	175.9	20.1	157.3	17.6
Rendolindation adm.	21	3.9	3.8	4.4	3.7	5.1	5.7	5.4	3.7	5.4	3.0	5.6	2.7
Long-care term adm.	21	1.2	2.2	0.9	1.8	1.7	2.0	1.8	2.0	1.9	1.8	2.1	1.9
Acute total days	21	1340.1	240.1	1259.5	158.8	1161.0	159.7	1096.8	136.1	1001.2	113.3	908.4	104.5
Long-care total days	21	35.1	53.1	43.0	60.5	50.7	62.0	56.4	61.3	56.5	57.0	55.0	53.7
Rehabilitation total days	21	86.2	73.4	98.7	74.7	116.0	80.4	126.7	84.0	131.8	72.5	132.9	60.4
Average stay	21	7.2	0.8	7.0	0.9	6.9	0.8	6.9	0.8	6.9	0.7	6.9	0.6
Tuscany													
Acute adm.	1	201.0	4.7	201.4	0.9	186.8	3.8	177.2	2.8	167.4	4.9	153.8 3.3	4.2
Rehabilitation adm.	1	3.0	0.5	2.7	0.1	3.5	0.3	3.6 0.7	0.3	3.6	0.1	5.5	0.3
Long-care term adm.	1	0.2	0.4	0.4 1270.2	0.4	0.7	0.1	0.7	0.0	0.8	0.1	0.9	0.2
Acute total days Long-care total days	1	1347.6	21.4		31.8 0.4	1139.4	28.8	1038.9	30.9	948.2	34.0	854.3	28.5
Long our total days	1	9.5	16.4	28.2	011	22.2	3.3	22.2	1.3	23.4	2.5	24.5	1.6
Rehabilitation total days	1	85.5	15.8	63.8	1.5	73.2	4.3	72.2	4.0	73.1	2.1	68.4	3.3
Average stay	1	7.5	0.2	7.4	0.1	7.5	0.1	7.3	0.1	6.5	0.1	6.4	0.0

Tables A2.6: Utilisation rates, i.e. volumes of treatment performed standardised by population dimension.

Notes: Utilisation rates for Tuscany and average of Italian Regions. Variables are divided by population dimension, multiplied by one thousand and then averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Unit of observation is each single Region.

Tables A2.7: Quality and performance indicators.

		Years:		Years:		Years:		Years:		Years:		Years:	
		1997-1	999	2000-2	2002	2003-2	2005	2006-2	2008	2009-2	2011	2012-2	013
	n	Mean	S.D.										
Italy													
Performance Index	21	1.0	0.1	1.0	0.1	1.0	0.1	1.0	0.1	1.0	0.1	1.0	0.1
Case mix control	21	0.7	0.5	1.0	0.1	1.0	0.1	1.0	0.1	1.0	0.1	1.0	0.0
Share of post-intervention	1												
complications	21	15.8	11.6	25.9	3.4	29.4	4.1	31.4	4.3	33.2	4.3	34.2	4.1
Tuscany													
Performance Index	1	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	0.9	0.0	0.9	0.0
Case mix control	1	0.7	0.6	1.1	0.0	1.1	0.0	1.1	0.0	1.1	0.0	1.1	0.0
Share of post-intervention	1												
complications	1	16.3	14.1	26.9	0.7	32.7	2.5	34.4	0.1	35.5	1.1	38.4	0.3

Notes: Quality indicators for Tuscany and average of Italian Regions. Variables are averaged over the 3-year-intervals, with the only exception of the last period, where the interval comprehends only two years. Unit of observation is each single Region.

Appendix A3, Real and Synthetic Control estimates.

Table A3.1: Local Health Authority of Florence.

	LHA: F	lorence	LHA:	Florence	LHA:	Florence	LHA: Fl	orence	LHA:	Florence	LHA:	Florence	LHA: F	lorence
	Outcom	e:	Outcon	me:	Outcon	me:	Outcome	e:	Outco	me:	Outcon	me:	Outcom	e:
	Pharma	ceuticals	Veteri	nary	Food		Living		Comb	ustibles	IT		Mainter	ance
Year	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.
1997	11.87	11.88	3.33	3.29	9.13	9.13	10.03	10.02	8.86	8.85	8.78	8.76	10.23	10.27
1998	11.92	11.95	3.65	3.66	9.09	9.09	10.02	10.01	8.74	8.73	8.82	8.80	10.22	10.26
1999	12.03	11.99	3.97	3.78	9.23	9.23	10.03	10.06	8.78	8.77	8.73	8.71	10.19	10.23
2000	12.14	12.09	3.45	3.59	9.29	9.29	10.23	10.23	8.61	8.60	8.73	8.72	10.31	10.35
2001	12.22	12.18	2.93	3.19	9.37	9.37	10.32	10.32	8.55	8.54	8.54	8.52	10.32	10.36
2002	12.30	12.30	3.24	3.67	<i>9.3</i> 8	9.39	10.46	10.44	8.53	8.52	8.56	8.54	10.28	10.32
2003	12.43	12.44	3.04	3.26	9.47	9.47	10.54	10.54	8.41	8.40	8.60	8.56	10.21	10.25
2004	12.52	12.50	3.08	3.35	9.48	9.48	10.54	10.50	8.23	8.22	8.36	8.37	10.32	10.36
2005	12.61	12.54	3.57	3.43	9.44	9.44	10.50	10.51	8.32	8.31	8.50	8.47	10.29	10.33
2006	12.57	12.56	3.22	3.85	9.43	9.55	10.49	10.50	8.32	8.25	8.51	8.58	10.36	10.34
2007	12.64	12.58	2.50	3.36	9.30	9.51	10.49	10.52	7.57	8.21	8.43	8.54	10.37	10.40
2008	12.64	12.59	2.28	3.09	9.40	9.58	10.53	10.54	6.93	8.28	8.45	8.60	10.36	10.45
2009	12.71	12.54	2.50	2.85	9.41	9.61	10.56	10.53	6.62	8.24	8.37	8.60	10.45	10.45
2010	12.70	12.57	2.30	3.16	9.47	9.61	10.54	10.53	6.62	8.20	8.37	8.61	10.40	10.50
2011	12.70	12.57	2.35	2.93	9.43	9.62	10.57	10.55	6.71	7.82	8.20	8.61	10.41	10.46
2012	12.66	12.55	2.12	2.58	9.43	9.57	10.52	10.49	6.82	7.53	8.11	8.56	10.41	10.57
2013	12.64	12.52	2.08	2.63	9.41	9.52	10.44	10.41	6.71	7.43	7.93	8.58	10.36	10.46
RMSPE	10 1	0.033		0.225		< 0.001		0.016		< 0.001		0.013		< 0.001

Note: Real and Synthetic Control estimates. In the last row Root Mean Square Prediction Error. LHA of Florence.

	LHA: Pisa		LHA: Pisa		LHA: Pisa		LHA: Pisa		LHA: Pisa		LHA: Pisa		LHA: Pisa	
	Outcom	e:	Outcon	me:	Outco	me:	Outcon	ne:	Outcon	me:	Outcor	ne:	Outcom	e:
	Pharma	ceuticals	Veteri	nary	Food		Living		Combu	istibles	IT		Mainter	
Year	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.
1997	11.85	11.87	7.54	6.35	9.57	9.59	9.99	10.00	7.11	7.40	8.46	8.51	10.17	10.18
1998	11.90	11.93	4.78	5.15	9.53	9.54	10.12	10.13	8.04	7.77	8.40	8.38	10.21	10.22
1999	12.01	11.99	4.55	4.95	9.54	9.56	10.05	10.07	7.20	7.39	8.78	8.78	10.18	10.19
2000	12.11	12.08	4.18	4.43	9.64	9.66	10.12	10.14	7.51	7.34	8.96	8.92	10.28	10.29
2001	12.20	12.16	4.06	4.21	9.68	9.70	10.22	10.23	7.42	7.39	9.16	9.13	10.41	10.41
2002	12.30	12.29	4.03	4.29	9.72	9.74	10.26	10.28	7.23	7.28	9.16	9.14	10.40	10.42
2003	12.36	12.39	4.16	3.85	9.76	9.78	10.35	10.37	7.35	7.49	8.98	8.92	10.35	10.37
2004	12.46	12.45	3.93	4.14	<i>9.73</i>	9.75	10.39	10.41	7.52	7.41	8.77	8.77	10.51	10.51
2005	12.50	12.49	4.13	4.43	9.72	9.73	10.39	10.41	7.82	7.79	8.59	8.68	10.49	10.50
2006	12.56	12.52	3.55	4.50	9.66	9.72	10.41	10.42	7.70	7.77	8.57	8.71	10.44	10.48
2007	12.56	12.54	3.68	4.10	9.62	9.70	10.42	10.46	7.19	7.75	8.55	8.72	10.38	10.57
2008	12.60	12.55	3.26	4.64	9.58	9.71	10.41	10.51	7.18	7.80	8.58	8.78	10.36	10.58
2009	12.66	12.50	3.13	4.34	9.62	9.69	10.47	10.51	6.94	7.78	8.56	8.74	10.46	10.66
2010	12.67	12.53	3.08	4.65	9.65	9.69	10.53	10.52	7.01	7.59	8.50	8.70	10.57	10.71
2011	12.64	12.56	2.10	4.35	9.62	9.66	10.56	10.54	6.89	7.78	8.29	8.67	10.54	10.72
2012	12.57	12.55	2.16	3.88	9.55	9.61	10.57	10.50	7.09	7.89	8.31	8.64	10.55	10.75
2013	12.56	12.52	2.28	3.88	9.42	9.57	10.49	10.44	6.87	7.29	7.97	8.72	10.53	10.65
RMSPE		0.022		0.485		< 0.001		< 0.001		0.170		0.045		0.008

Table A3.2: Local Health Authority of Pisa.

Note: Real and Synthetic Control estimates. In the last row Root Mean Square Prediction Error. LHA of Pisa.

	LHA: S	iena	LHA:	Siena	LHA:	Siena	LHA: S	iena	LHA:	Siena	LHA:	Siena	LHA: S	iena
	Outcom	e:	Outco	me:	Outcon	me:	Outcom	e:	Outcon	me:	Outcom	me:	Outcom	e:
	Pharma	ceuticals	Veteri	nary	Food		Living		Combu	ustibles	IT		Mainten	nance
Year	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.
1997	11.76	11.76	4.98	4.99	9.62	9.60	9.90	9.91	8.97	9.00	8.28	8.21	10.20	10.16
1998	11.85	11.82	3.85	3.86	9.47	9.48	9.94	<i>9.93</i>	8.86	8.80	8.27	8.20	10.16	10.17
1999	11.91	11.87	4.17	4.17	9.55	9.53	10.00	10.01	8.78	8.81	8.32	8.25	10.19	10.16
2000	11.98	11.94	4.07	4.09	9.59	9.58	10.14	10.14	8.67	8.62	8.39	8.32	10.19	10.15
2001	11.75	11.95	4.20	4.20	9.45	9.45	10.03	10.10	8.37	8.47	8.26	8.19	9.78	9.96
2002	12.23	12.11	3.81	3.83	9.67	9.66	10.26	10.25	8.78	8.63	8.47	8.40	10.28	10.22
2003	12.30	12.27	4.09	4.10	9.65	9.64	10.35	10.37	8.30	8.24	8.38	8.31	10.31	10.28
2004	12.38	12.36	4.15	4.18	9.66	9.64	10.50	10.48	7.49	7.56	8.18	8.10	10.34	10.35
2005	12.48	12.41	4.85	4.84	9.66	9.65	10.54	10.53	7.59	7.59	8.35	8.27	10.45	10.37
2006	12.49	12.37	4.28	4.88	9.62	9.67	10.60	10.52	7.42	7.57	8.04	8.35	10.47	10.45
2007	12.53	12.51	4.49	4.59	9.60	9.64	10.60	10.56	7.27	7.59	8.02	8.32	10.48	10.47
2008	12.58	12.54	4.46	4.51	9.61	9.66	10.60	10.57	7.33	7.85	8.23	8.32	10.47	10.53
2009	12.59	12.59	4.43	4.15	9.64	9.63	10.60	10.57	7.11	7.77	8.44	8.26	10.48	10.55
2010	12.60	12.62	4.41	4.74	9.69	9.65	10.59	10.57	7.23	7.99	8.34	8.31	10.49	10.43
2011	12.63	12.60	4.46	3.94	9.67	9.66	10.60	10.59	7.33	7.88	8.38	8.09	10.49	10.37
2012	12.54	12.56	3.28	3.34	9.62	9.62	10.57	10.59	7.40	7.90	8.00	8.13	10.55	10.50
2013	12.52	12.55	3.51	3.26	9.56	9.56	10.53	10.55	7.30	7.72	8.22	8.49	10.53	10.56
RMSPE		0.085		0.011		0.010		0.025		0.071		< 0.001		0.072

Table A3.3: Local Health Authority of Siena.

Note: Real and Synthetic Control estimates. In the last row Root Mean Square Prediction Error. LHA of Siena

	Tuscany	/	Tuscar	ny	Tuscar	ıy	Tuscany	/	Tuscar	пу	Tuscar	ıy	Tuscany	/
	Outcom	e:	Outcon	me:	Outcor	me:	Outcom	e:	Outcon	me:	Outcor	me:	Outcom	e:
	Pharma	ceuticals	Veteri	nary	Food		Living		Combu	ustibles	IT		Mainter	nance
Year	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.	Tr.	Sy.
1997	11.84	11.89	6.60	5.68	9.43	9.41	9.99	10.02	8.54	8.62	8.57	8.62	10.21	10.16
1998	11.90	11.97	4.24	4.66	9.36	<i>9.38</i>	10.05	10.07	8.57	8.53	8.57	8.52	10.22	10.20
1999	12.00	12.03	4.25	4.29	9.43	9.43	10.03	10.06	8.43	8.41	8.67	8.73	10.20	10.20
2000	12.10	12.06	3.90	4.20	9.50	9.51	10.17	10.16	8.35	8.31	8.76	8.72	10.29	10.27
2001	12.12	12.15	3.77	4.45	9.51	9.52	10.22	10.27	8.21	8.23	8.77	8.77	10.26	10.24
2002	12.29	12.23	3.71	4.24	9.58	9.57	10.35	10.34	8.30	8.12	8.81	8.76	10.33	10.29
2003	12.38	12.33	3.80	3.95	9.63	9.62	10.43	10.43	8.11	8.11	8.73	8.65	10.29	10.28
2004	12.47	12.38	3.72	4.14	9.62	9.59	10.48	10.44	7.87	7.94	8.50	8.58	10.40	10.37
2005	12.54	12.41	4.18	3.71	9.60	9.60	10.47	10.51	8.02	8.01	8.52	8.60	10.41	10.38
2006	12.55	12.43	3.66	3.98	9.56	9.59	10.49	10.52	7.96	8.04	8.44	8.71	10.42	10.39
2007	12.59	12.46	3.66	3.82	9.50	9.64	10.49	10.57	7.38	8.02	8.40	8.77	10.40	10.46
2008	12.63	12.43	3.48	3.87	9.53	9.66	10.51	10.62	7.13	8.10	8.47	8.73	10.40	10.53
2009	12.68	12.45	3.46	4.48	9.56	9.67	10.55	10.63	6.87	7.92	8.48	8.69	10.48	10.57
2010	12.68	12.47	3.40	4.57	9.60	9.68	10.56	10.64	6.93	7.88	8.43	8.66	10.51	10.53
2011	12.68	12.45	3.33	4.38	9.57	9.69	10.58	10.65	6.95	7.93	8.29	8.67	10.50	10.54
2012	12.60	12.44	2.49	4.39	9.52	9.67	10.55	10.61	7.07	8.02	8.16	8.59	10.49	10.57
2013	12.58	12.43	2.63	3.40	9.45	9.63	10.48	10.55	6.93	8.00	8.02	8.46	10.46	10.47
RMSPE		0.068		0.505		0.015		0.025		0.072		0.060		0.014

Table A3.4: Tuscany.

Note: Real and Synthetic Control estimates for Tuscany. In the last row Root Mean Square Prediction Error.

The Effect of Waiting Times on Demand and Supply for Elective Surgery: Evidence from Italy

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Abstract

Waiting times are a major policy concern in publicly-funded health systems across OECD countries. Economists have argued that, in the presence of excess demand, waiting times act as non-monetary prices to bring demand for and supply of health care in equilibrium. Using administrative data disaggregated by region and surgical procedure over 2010-2014 in Italy, we estimate demand and supply elasticities with respect to waiting times. We employ linear regression models with first-differences and instrumental variables to deal with endogeneity of waiting times. We find that demand is inelastic to waiting times while supply is more elastic. Estimates of demand elasticity are between -0.15 to -0.24. Our results have implications on the effectiveness of policies aimed at increasing supply and their ability to reduce waiting times.

Keywords: Waiting times; Elective surgery; Demand; Supply.

JEL: I10

1. Introduction

Waiting times in health care sector are a major health policy concern across many OECD countries (Siciliani, Borowitz and Moran, 2013). Waiting times for elective surgeries can last several months (Siciliani, Moran and Borowitz, 2014) and generate dissatisfaction to patients and the general public. Patients' disutility from waiting includes postponed health benefits, potential worsening of health status while waiting, and uncertainty about receipt of treatment.

In many publicly funded systems, the combination of capacity constraints and limited or no user charges generates an excess demand. Patients are added to a waiting list and are asked to wait. Economists have argued that in the absence of price rationing, waiting times act as a form of non-price rationing which brings together the demand for and the supply of health care (see seminal papers by Lindsay and Feigenbaum, 1984, and Martin and Smith, 1999). On the demand side, a longer wait will induce some patients to go private at a fee (or a reduced fee if they hold private health insurance) or to seek a less intensive drug treatment, therefore reducing the demand for public surgery. On the supply side, waiting times may induce hospitals to work harder and provide more treatments if doctors are altruistic (i.e. they feel bad about the patients waiting excessively) or if penalties are in place for hospitals exceeding maximum waiting time guarantees (see Martin and Smith, 1999, for a theoretical model, and Propper et al, 2008, on penalties).

From a policy perspective, it is critical to establish the extent to which demand and supply respond to waiting time. For example, if demand is highly elastic, an exogenous increase in supply will only have minimal effect in reducing waiting times. In turn, this will make policymakers more reluctant to fund additional resources. Similarly, if supply is elastic, an exogenous increase in demand (e.g. due to ageing population or technology) will imply that waiting time will increase only to a small extent.

There is extensive empirical evidence on demand and supply elasticities from the United Kingdom. Lindsay and Feigenbaum (1984) and Martin and Smith (1999) find that the elasticity of demand is generally low. The finding is also confirmed by more recent studies (Gravelle, Dusheiko and Sutton, 2002; Gravelle, Smith and Xavier, 2003, and Martin, Jacobs, Rice and Smith, 2007). In most studies, demand elasticity is below -0.2. Estimates of supply elasticity are less stable and vary depending on methods, sample and time period considered (see Siciliani and Iversen, 2012 for a more detailed discussion of the literature).

We know however very little about demand and supply elasticities from other OECD countries. These are likely to differ based on differ institutional arrangements (gatekeeping system, use of user charges, payment arrangements) and funding levels. Administrative data on waiting times have been collected within the English NHS since its inception, but only in the last years in other countries (Siciliani, Moran and Borowitz, 2014).

We advance the literature by filling this gap in knowledge, and study demand and supply elasticities within the Italian context. Using administrative data in 2010-2014, we employ linear regression models exploiting variability in waiting times by region, surgical procedure and time. We first estimated pooled cross-section models using ordinary least squares (OLS). Second, we use an instrumental variables (IV) approach to deal with the endogeneity of waiting time due to simultaneity of demand and supply. Finally, we use a first-difference estimation procedure to address the remaining endogeneity of waiting time due to its possible correlation with time-invariant unobserved factors (e.g. regional factors). Differently from fixed-effect modes, which require strict exogeneity (i.e. the error term is uncorrelated to past, present as well as future values of the control variables), first-difference models only require a weak-exogeneity assumption (i.e. there is no feedback from the idiosyncratic shock today to a covariate tomorrow). This is a considerably weaker assumption as it permits future values of the regressors to be correlated with the error, which is particularly important for the use of past values of regressors as controls or as instruments.

Our key finding is that demand is inelastic to waiting times and in the range of -0.15 and - 0.24. This result is important for policy. It implies that an increase in publicly-funded supply will reduce waiting times to a great extent since reductions in waiting are only offset by a small increase in demand. Conversely, governments under financial pressure who withdraw resources from the public system will experience large increases in waiting times.

As far as the authors are aware, this is the first study which uses administrative data to estimate demand and supply elasticities within the Italian context. We are only aware of another study which estimates demand elasticity for Italy (Fabbri and Monfardini, 2009). This study focuses on specialist consultations as opposed to elective surgeries. It makes use of survey in 2000 rather than recent administrative data. The methodology and period covered is different. We are also not aware of studies estimating demand and supply elasticities from other OECD countries (in addition to the UK) except for one study from Australia, which finds that demand of public hospitals is elastic to waiting times and equal to -1.7 (Stavrunova and Yerokhin, 2011). This may be explained by the large private sector which generates a more extensive margin between public and private provision compared to England. It also confirms that demand estimates can vary significantly across countries.

The paper is structured as follows. In Section 2 we set out the theoretical framework for the estimation of demand for and supply of elective surgeries in the Italian NHS. In Section 3 we briefly describe the institutional background and sources of data. Sections 4 and 5 describe empirical implementation and provide descriptive statistics. Section 6 contains empirical results. Section 7 concludes and discusses policy implications.

2. Theoretical Framework

We adopt the theoretical framework outlined by Martin and Smith (1999, 2003). We assume that waiting times act as a non-monetary price, which brings the demand for and the supply of elective surgery in equilibrium in a National Health System. The demand for publicly-funded elective surgery is described by the following function and we include (in parentheses) the expected direction of each of the effects:

$$D = f(waiting time(-), need(+), quality(+), private availability(-))$$
(1)

Demand for publicly-funded surgery is assumed to decrease in waiting times. Longer waiting times may induce some patients at the margin to look for treatment in the private sector by paying out of pocket (or if they hold private health insurance) and therefore to opt out of the public system (i.e. the NHS). In addition, longer waits may induce some patients to substitute surgery with a pharmaceutical treatment therefore reducing demand for publicly-funded surgery.

Demand for public treatment will be higher in areas with higher need, e.g. areas with an older and sicker population, and in areas where the quality of healthcare is higher making hospital services more attractive to patients (though quality is potentially endogenous if low demand reduces quality due to learning-by-doing effects). Similarly, private hospital availability is assumed to reduce demand for public treatment: smaller access costs to the private sector will induce some patients to switch from the public to the private sector (Martin and Smith, 2003; Martin et al., 2007).

The supply of (publicly-funded) elective surgery is assumed to be determined by waiting time and local resources:

$$S = g(waiting time(+), capacity(+))$$
(2)

We assume that long waits induce the provider to increase the supply, for given level of inputs, for both altruistic and non-altruistic motivations. Doctors may be willing to work harder when waiting times are longer since they care about the patients. Waiting times are regularly used as performance indicators or targets for public providers (and for private providers treating publicly-funded patients). When waiting times are longer hospitals with a higher proportion of patients waiting longer than expected may be under tighter scrutiny from the regulator (Linsday and Feigenbaum,1984; Propper et al., 2008; Siciliani and Iversen, 2012). Longer waits may also reduce idle capacity due to random patient arrivals, and therefore increase efficiency and the number of patients treated, though this effect is likely to be modest when waiting times are generally long (Iversen, 1997; Siciliani, Stanciole and Jacobs, 2009). Finally, the supply of care in a region is a function of its inputs, such as the number of available beds in publicly-funded hospitals and their personnel, which determine the overall capacity.

3. Institutional background and data

The Italian healthcare system is publicly funded with hospitals reimbursed by DRG according to volumes performed. The system is decentralised: Italy is divided in 19 regions and two autonomous provinces (Trento and Bolzano). The Italian National Health System was founded in 1978, provides full coverage to every citizen and is funded through national and regional taxation. In 2001 the Constitutional reform gave regions the freedom to choose the type of healthcare model, generating great variability in institutional arrangements across regions.

Every region can decide its own organisational and regulatory scheme for public and private sector, how to allocate resources, define prevention and budgetary policies, strategic plans

(e.g. building new hospitals) and elective admission rules. To avoid excessive territorial disparities, the Italian Ministry of Health sets the Essential Levels of Assistance, which are minimum healthcare requirements that regions have to provide, whose compliance is annually verified by the national government. Heterogeneity in regional policies has emerged in relation to waiting times (Fattore et al., 2013) driven by differences in co-payment schemes, unified booking centres and promotion of private health insurance, providing a fragmented framework with regional disparities.

There are similarities but also differences between the Italian and the English National Health Service. In England, to which most of the empirical literature refers to, hospitals are also paid by a DRG-type payment system (known as Healthcare Resources Groups, HRGs) and patients have choice of hospital. Patients are also heavily insured with no co-payments for surgery or specialist visits, and some co-payments for drugs. In both countries there are exemptions for persons with disabilities or chronic conditions, pregnant women, elderly and children (Paris et al., 2010). There are more pronounced differences between England and other health systems in the UK (e.g. Scotland and Wales) but arrangements vary less across different regions within England. In this respect, Italy has much more pronounced differences across regions in organisational arrangements and regulatory schemes.

The proportion of private health expenditure is similar for both countries. The share of public health expenditure out of total health expenditure (at the beginning of our period of observation) was about 76.5% for Italy and 81.7% for the UK. Although the public-private mix is similar on the funding side, this is not the case on the hospital provision one. 96% of acute care beds in the UK is provided by public hospitals, while this is only 81.5% in Italy where 16.7% of the total number of acute beds is provided by not-for-profit private hospitals (Paris et al., 2010).

In this paper we use information on waiting times provided by the Italian Ministry of Health's Statistical Office.¹⁰ Waiting times are available for 19 regions and the two autonomous provinces for several procedures during the period 2010-2014. Waiting times are calculated for elective publicly-funded patients who receive treatment in a public or private hospital. They are published annually in the Hospital Discharges Report (HDR) by the Ministry of Health.

Waiting times are defined as the number of days elapsed between the time the patient has been added to a hospital waiting list for elective surgery and the day the patient is admitted to the hospital to receive the treatment. From the same source and for each year, region and procedure we collect data on hospital utilisation, i.e. the total number of elective and emergency discharges. Hospital utilisation rates are computed for each procedure as the ratio of the total number of discharges to the regional population in a given year. Hospital utilisation also refers to publicly-funded patients regardless of the type of provider (public or private) in which they receive treatment. The annual report for Hospital Discharges refers to patients treated in public hospitals and from the same source of data we calculate within each combination of region and year the overall share of patients treated in public hospitals paying with their own resources. The share is small and on average only about 2%, which is in line with findings as in Vittadini et al. (2012).

We use data on waiting time for elective surgical (as opposed to medical) treatments since only these are available from administrative sources and are used as hospital targets. The ten procedures included in the HDR are: prostatectomy, breast cancer, colon cancer, uterus cancer and lung cancer surgeries, coronary bypass, percutaneous transluminal coronary

¹⁰ Data are publicly available on the Italian Ministry of Health website (<u>www.salute.gov.it</u>) under Section "Temi e professioni" (Figures), subsections "Assistenza, ospedale e territorio" (Assistance, hospitals and local areas), "Ricoveri Ospedalieri" (Hospital discharges) and it is possible to select and download annual reports and data: <u>www.salute.gov.it/portale/temi/p2_6.jsp?lingua=italiano&id=1237&area=ricoveriOspedalieri&menu=vuoto</u> We use the original data and no data cleaning was performed apart for the exclusions mentioned in this section.

angioplasty, carotid endarterectomy, hip replacement and tonsillectomy.¹¹ We exclude tonsillectomy since regions show heterogeneous clinical attitudes and protocols which in turn reduce comparability across regions (Materia et al., 2005; see also national guidelines provided by the Italian Institute of Health for this clinical area¹²). We also compute the proportion of emergency discharges as the ratio between the number of emergency discharges and the total number of discharges by procedure, region and year. In summary, the HDR data used in this analysis vary along three dimensions: surgical procedure, region and year.

Control variables are obtained from demographic indicators available from ISTAT (the Italian National Institute of Statistics), which vary only by year and region, not by procedure. They include number of residents, age distribution in the regional population and age and sex adjusted mortality rates. From the age distribution of residents, we calculate the proportion of population over 60 years old. We use risk-adjusted mortality rates and proportion of the elderly as a need indicators.

As measure of local resources in the supply equation, we measure the capacity of private and public providers within each region. These are measured as (i) the total number of acute care beds in *public* and *private* hospitals (standardised by the number of residents); and (ii) the ratio between beds in private hospitals and total number of beds within each region. Private hospitals treat both publicly and privately-funded patients and our data do not allow to make a distinction whether the treatment is paid by the NHS or privately. Since regulatory policies vary across regions in relation to reimbursements to private providers, it is not possible to identify the number – or the proportion – of publicly-funded patients who are treated by the private sector. Therefore private hospitals contribute to the capacity available to publicly-funded patients. Variable (ii) measures the public-private mix in provision in each region.

¹¹ Other six procedures have been added in 2011 but there are consistency issues across regions, which prevented their use here. ¹² http://www.snlg-iss.it/pubblico tonsillectomia adenoidectomia

On the demand equation, we use control variables from the annual National Survey on Householders' Lifestyles, and compute the proportion of regional population smoking more than 11 cigarettes per day on the total number of smokers as a proxy of unhealthy behaviour. We use the C-section rate as a proxy of poor appropriateness of care, which is a form of quality. This is computed as the total number of C-section deliveries to the total number of births within each region, which is provided in the HDR by the Italian Ministry of Health. C-section rates have been used by international organisations (OECD, 2015; WHO, 2015) as markers of appropriateness of care in health system performance. High C-section rates (on total births) are positively associated with complications and maternal and infant morbidity. According to the OECD, Italy has a surprisingly high C-section rate compared to other OECD countries although there are marked differences across regions, which we exploit in our analysis.

To measure the availability of private supply to privately-funded patients, which could potentially reduce demand for public services, we measure the number of acute care beds in *private* hospitals (standardised by the number of residents).¹³ Ideally, we would have liked to measure the number of private hospital beds available to privately-funded patients, therefore excluding beds available to publicly-funded patients. Information on private beds is however available only at hospital level, and is not split between publicly- and privately-funded patients.

We do not have information on the fraction of patients who die on the waiting list. However, the proportion of patients who are likely to die while on the waiting list is negligible for most of the elective procedures (e.g. hip replacement). Even for most of the more serious

¹³ Beds refer to the number of beds available in each Region on the 1st of January of each year. We only considered beds for elective patients, thus excluding beds for day cases and day surgeries. Source: Ministero della Salute - Dipartimento della programmazione e dell'ordinamento del Servizio sanitario nazionale - Direzione generale del sistema informativo e statistico sanitario;

conditions (e.g. cancer) elective patients experiencing a worsening of their health status are treated quickly or as emergencies.

4. Econometric Specification

We use linear models to estimate the impact of waiting times on the demand for and supply of surgical treatments. We estimate separate models for demand and supply. We assume that the system is in equilibrium and that demand y_{irt}^d in equation (1) equates supply y_{irt}^s in equation (2), so that $y_{irt}^d = y_{irt}^s = y_{irt}$.

The empirical specification of the *demand* equation is:

$$y_{irt} = \alpha + w'_{irt}\beta + x'_{irt}\gamma + z'_{rt}\delta + h_t + h_i + \varepsilon_{irt},$$
(3)

where subscript *i* indicates the type of elective surgery (e.g. hip replacement, surgeries for breast cancer etc., with, i = 1, ..., I), *r* the region (with r = 1, ..., R), *t* the year (with t = 2010, ..., 2014). Utilisation rate (y_{irt}) and waiting time (w_{irt}) are log-transformed so that the key coefficient of interest (β) can be interpreted as the elasticity of demand with respect to waiting time. Utilisation rates are the total number of discharges for a given surgical procedure in a region and year standardised by population (the total number of residents, in thousands) of the region in the same year.

The vector x_{irt} includes control variables that vary over time, procedures and regions, such as the proportion of emergency discharges. The vector z_{rt} includes variables which vary only over time and region and, in the demand equation, it includes the proportion of residents over 60, smoking prevalence, age and sex adjusted mortality rates at time t - 1, the number of private beds per capita and the C-section rate as indicator of poor quality. The empirical model also includes time dummies h_t to capture common time trends and surgical procedure dummies h_i to control for differences in waiting times by procedure which amongst other factors reflect different degree of urgencies (e.g. cancer patients waiting less than hip replacement patients). We therefore exploit variations of waiting times *across* regions pooled across several years, controlling for the type of procedure, to identify the effect of waiting on demand. ε_{irt} is the error term.

The empirical specification of the *supply* of elective surgery (y_{irt}) is analogous to equation (3) but uses a different set of controls (x_{irt}, z_{rt}) . x_{irt} includes the proportion of emergency discharges. z_{rt} includes the per capita number of acute beds in public and private hospitals and the proportion of beds in private hospitals on the total amount of available beds within each region.

Since average waiting times in Italy are relatively short (about one month), we model demand for elective care as contemporaneously responding to waiting time, given the yearly frequency of the data used in the empirical analysis. We model the relation between supply and waiting time also as simultaneous since providers can quickly react to waiting time which they observe with no time lag, and are also aware that waiting time are annually assessed by the Ministry of Health.

The ordinary least square estimation of equation (3), which again is estimated separately for the demand and supply equation, might produce a biased and inconsistent estimate of the coefficient of interest β . As mentioned above, longer waiting times may reduce demand for public treatment (because some patients opt for swifter private treatment) and also increase the supply of public treatments (due to targets or altruistic motives): therefore, waiting times are endogenous and have a simultaneous effect on both demand for and supply of treatment. Following previous literature (e.g. Martin and Smith, 1999, 2003), we instrument waiting time in the supply equation with a selection of exogenous demand shifters and we instrument waiting time in the demand equation with a selection of exogenous supply shifters. As the latter proved to be weak instruments, we also used the lag of waiting time as an instrument in demand models.¹⁴

To eliminate the remaining time-invariant unobservable factors, e.g. at regional level, that might simultaneously affect the dependent variable as well as the controls in the regression, we also estimated first-difference models. This specification will for example control for any time-invariant regional factor (e.g. proportion of individuals holding private insurance, which is unlikely to vary quickly over time). We prefer the first-difference models over the (region) fixed-effect models, since the latter require the strong exogeneity assumption,¹⁵ which is violated when we use the lag of waiting time as an instrument. Although the first-difference models are less efficient of fixed-effects ones they only require weak exogeneity (i.e. that there is no feedback from the idiosyncratic shocks today to a covariate or an instrument tomorrow). The first difference version of the previous model is:

$$\Delta y_{ir\,t,t-1} = \beta_1 \cdot \Delta w_{ir\,t,t-1} + \Delta x'_{ir\,t,t-1} \gamma + \Delta z'_{r\,t,t-1} \delta + h_t - h_{t-1} + \Delta \varepsilon_{ir\,t,t-1}, \tag{4}$$

We estimate an analogous model for the supply (i.e. $\Delta y_{ir t,t-1}^s$).

To control for endogeneity caused in the demand model by the presence of waiting time, we instrument $\Delta w_{ir\,t,t-1}$ with $\Delta w_{ir\,t-2,t-3}$. This is a valid instrument since

$$Cov(\Delta\varepsilon_{irt,t-1},\Delta\varepsilon_{irt-2,t-3}) = Cov((\varepsilon_{irt} - \varepsilon_{irt-1}), (\varepsilon_{irt-2} - \varepsilon_{irt-3})) = 0$$

¹⁴ This instrument is used also in Martin and Smith (2003). Admittedly, this is not an ideal instrument because persistency of waiting time over the years can cause the error term in the base equation to remain correlated, to some extent, with the instrument.

¹⁵ The within transformation of error term $(\varepsilon_{it} - \overline{\varepsilon_i})$ and of the log of waiting times $(w_{it} - \overline{w_i})$ are correlated through their means.

To check the validity of the instruments we use the F-statistic on the excluded instruments, both for robust and cluster standard errors, under the null of weak instruments. Following Stock, Wright and Yogo (2002), we conclude that instruments are valid if the F-statistic is larger than 10.

5. Descriptive Statistics

We use data from nineteen Italian regions and two autonomous provinces for five years and nine surgical procedures. Table 1 reports some descriptive statistics for variables entering the supply and demand equations, respectively. Due to the presence of lagged variables in estimation procedure we report descriptive statistics for four years of observation (732 units – left hand side of Table 1) and for the last two years (366 units – right hand side of Table 1), which are respectively the maximum and minimum sample size used, depending on whether the lagged values of waiting time is used as instrument in the first-difference estimation.

On average the per capita utilisation is of about 0.6 procedures per thousand residents, of which about 22% is emergency discharges. Waiting time is about 31 days across all procedures. The number of total beds for acute care per thousand residents is about 2.84 whereas the availability of private beds per thousand residents is 0.48. The proportion of population over 60 years old is about 28% and the proportion of smokers who smoke more than 11 cigarettes per day is close to 40%. C-section rates are on average around 35% and adjusted mortality rate per thousand residents at time t - 1 is about 1%. The summary statistics are similar across the two samples used in the analysis.

Figure 1 shows the average waiting time and utilisation rate for different procedures, at the beginning and at the end of the study period. It suggests that there is larger variability across

treatments than over time, with hip replacement procedures (Hip) having the longest wait. Lung and Uterus cancer surgeries, PTCA exhibit the shortest wait. Figure 2 shows that waiting times and utilisation rates exhibit high variability across regions both at the beginning and at the end of the period.

		2011-201	4	2013-2014				
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.		
Utilisation rate (per 1000 residents)	732	0.60	0.65	366	0.61	0.67		
Waiting time (days)	732	31.33	0.55	366	30.87	0.53		
Demand shifters								
Emergency discharges (%)	732	21.64	22.44	366	22.86	22.95		
C-section rates (%)	732	35.09	9.45	366	34.77	9.24		
Heavy smokers (%)	732	39.59	4.59	366	38.46	4.62		
Population over 60 years old (%)	732	27.75	2.66	366	28.00	2.60		
Private beds (per 1000 residents)	732	0.48	0.28	366	0.46	0.27		
Mortality rate (per 1000 residents, at $t - 1$)	732	10.29	1.26	366	10.21	1.23		
Supply shifters	700	01.64	22.44	244	22 0.4	22.05		
Emergency discharges (%)	732	21.64	22.44	366	22.86	22.95		
Beds (public and private, per 1000 residents)	732	2.84	0.29	366	2.73	0.28		
Private beds (%)	732	0.17	0.10	366	0.17	0.10		

Table 1: Descriptive statistics

Source: Our calculations using ISTAT and HDR data.

6. Empirical results

In Table 2 we report the results for the demand equation. We first estimated the model in equation (3) using ordinary least squares (OLS) over the period 2011-14. The model includes year- and procedure-fixed effects and is reported in the first column. In line with previous literature (e.g. Martin and Smith, 2003) we first considered a cross-sectional specification, exploiting variability across procedures, regions and years. Given the likely endogeneity of waiting times, we estimate the same model with instrumental variables (IV), using as instrument the lagged value of waiting times. The model is reported in the second column. Because of the inclusion of the one-year lagged value of waiting time among controls of the demand model, we lose the first year of observations. Hence, we omit the first year from all estimation samples to maintain data consistency.

Estimation results for the cross-sectional analysis show a negative and significant at 10% level coefficient for waiting time. The OLS estimation suggests an elasticity of demand to waiting time of -0.1, which increases (in absolute value) to -0.15 once waiting time is instrumented. In the third and fourth column of Table 2, we estimate the same models but restrict the sample to the last two years, to compare the results with those obtained in the first-difference (FD) specification (see model (4) above). In this restricted, hence less informative sample, the elasticity of waiting time coefficient loses statistical significance, but the magnitude of the coefficient remains similar. In the last two columns of Table 2, which uses FD estimation, we test whether the results for the demand equation are robust once controlling for time-invariant characteristics in the error term, which might be an additional source of endogeneity. The results show that the elasticity is equal to -0.04 using OLS and increases (in absolute value) to -0.24 with an IV estimation, which uses the 2-years-lagged difference in waiting times as an instrument, albeit statistical evidence is weak.

In relation to the control variables, we find that lower hospital quality (i.e. higher C-section rates) reduces demand. A higher proportion of emergency discharges and of heavy smokers (unhealthy lifestyle), both reduce the demand. Since the FD models control for time-invariant characteristics, the statistical significance of some control variables reduces. This is not the case for the emergency admission rate, which remains highly statistically significant.

The F-statistics for the instrument used in the first stage regression show that the instrument is valid, even when FD models are used. In A1, Table A1 we report first-stage regressions, which show positive associations of waiting time over years, and of waiting time with population over 60, whereas the associations between waiting time and share of emergency discharges and C-section rate tend to be negative. In the first-difference model (Appendix 1, Table A1, third column) we find a negative coefficient of lagged waiting times, which is negative by construction as the autocorrelation coefficient for the change of waiting time is positive.¹⁶

Table 3 contains results for the supply equation. Again, it presents first the OLS and then the IV estimation for each model. In the first two columns we present the pooled cross-sectional specification over the period 2011-14. Estimates show an elastic supply of elective surgery to waiting time only when waiting time is instrumented. Here, we use as instrument the proportion of population over 60 years old, which is a key driver of demand and exogenous to supply. The following two columns show that results are qualitatively similar when only observations in 2013-14 are used. In all pooled cross-sectional models the number of beds in public and private hospitals, measuring local endowments, has a positive and significant

¹⁶ This follows from computing the correlation coefficient of $(\Delta w_{t,t-1}, \Delta w_{t-2,t-3})$, which has opposite sign with respect to the correlation coefficient of $(w_{t,}, w_{t-1})$. Intuitively, assuming for simplicity a simple autoregressive model for our first stage regression, the sign of the autocorrelation coefficient, $\rho(\Delta w_{t,t-1}, \Delta w_{t-2,t-3})$ is given by the covariance $C(\Delta w_{t,t-1}, \Delta w_{t-2,t-3})$. Under weak stationarity $C(w_t, w_{t-h}) =$ q for all integer values of t,h and $C(\Delta w_{t,t-1}, \Delta w_{t-2,t-3}) = -q(q-1)^2$. This implies that for a positive autocorrelation coefficient q > 0, from which follows that the sign of $\rho(\Delta w_{t,t-1}, \Delta w_{t-2,t-3})$ is negative. Relevant proof is in Appendix 3.

coefficient, suggesting that the higher capacity increases supply. A higher rate of emergency discharges reduces the supply for elective interventions, since emergency discharges require more stand-by capacity. The results are robust to the use of alternative instruments, including C-section rates. All instruments are valid in the cross-sectional models and first-stage results are presented in Appendix 1, Table A2.

In the last four columns of Table 3 we report estimation results for first-difference estimates, which controls for time-invariant characteristics. The waiting time coefficients are still positive but smaller and not statistically significant. Given the aggregate nature of our data, the lack of statistical significance might be due to the loss of information caused by the first difference transformation. Moreover, all instruments used are weak and vary only by region and year.

Other factors should ideally be included in the demand equation, such as (average) distance to the hospital or co-payments, which are likely to deter some patients and reduce demand. A variable capturing the average distance would require detailed access to patient level data and geographical coordinates between patients' residence and hospital address. We conjecture the bias caused by the omission of these variables is likely to be negligible in our first-difference model which controls for time-invariant factors including regional effects. The average distance to hospital is unlikely to have changed significantly over time.

We check the robustness of our findings on the demand side excluding the variable that is related to smoking prevalence. Coefficients and significance levels are similar to the one presented in base model at the cost of losing estimate precision in the waiting time coefficient for the pooled IV cross-section (see Appendix 1, Table A3).

As a robustness check of the supply equation estimation, we also measure the per capita cost of medical staff (wages) in public hospitals as an additional input in the production function of publicly-funded treatments. The results are very similar in terms of magnitude and significance of coefficients (see Appendix 1, Table A4), though the power of the instruments is marginally reduced due to the high correlation between wages and beds (equal to 0.9).

The small sample size does not allow us to perform sensitivity analysis by intervention type. Nonetheless we test the robustness of our results by excluding from the sample procedures with more than 40% of emergency discharges (i.e. percutaneous transluminal coronary angioplasty whose fraction of emergency discharges is 67%), and we found similar pointwise estimates, though with some precision loss. Results are in tables A5 and A6 of Appendix 1.

Table 2: Demand estimates	Table	2: Demand	estimates
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		oss-section – 14		oss-section 3 – 14	First-difference 2013 – 14		
Variables	OLS	IV	OLS	IV	OLS	IV	
Waiting time (log)	-0.102*	-0.149*	-0.045	-0.128	-0.04*	-0.238*	
	(0.060)	(0.086)	(0.067)	(0.105)	(0.023)	(0.142)	
Emergency discharges (%)	-0.011***	-0.012***	-0.016***	-0.016***	-0.002**	-0.004**	
	(0.003)	(0.003)	(0.005)	(0.005)	(0.001)	(0.001)	
C-section rates (%)	-0.018***	-0.018***	-0.015***	-0.016***	-0.006	-0.016	
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.051)	
Proportion of over 60 years old (%)	0.018	0.021	-0.004	0.003	0.004	-0.012	
	(0.034)	(0.035)	(0.039)	(0.041)	(0.045)	(0.057)	
Proportion of heavy smokers (%)	-0.018***	-0.018***	-0.014***	-0.015***	0.000	0.002	
	(0.005)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	
Private beds (per 1000 residents)	0.047	0.050	0.041	0.047	0.054	0.05	
	(0.033)	(0.032)	(0.036)	(0.035)	(0.056)	(0.061)	
Mortality rate (per 1000	0.029	0.024	0.057	0.049	-0.01	-0.028	
residents, at $t - 1$)	(0.064)	(0.064)	(0.069)	(0.069)	(0.019)	(0.024)	
Constant	6.078***	6.175***	6.002***	6.147***	-0.009	-0.002	
	(0.509)	(0.513)	(0.576)	(0.561)	(0.013)	(0.0159)	
Observations	732	732	366	366	366	366	
R-squared	0.902		0.9		0.025		
First stage F-stat		196.7		116.3		11.15	

The dependent variable is utilisation rate and standard errors are given in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. In cross-sectional specifications we also include year and procedure dummy variables, whose estimated coefficients are omitted here. The instrument used in pooled cross-section models is the 1-year-lagged waiting time; in the first difference specification it includes 2-years-lagged values of first differences. Standard errors are robust and clustered

Table 3: Supply estimates

	Pooled cro	oss-section	Pooled cro	oss-section	First-di	fference	First-dif	ference
	2011	- 14	2013	- 14 2		- 14	2013	- 14
Variables	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Waiting time (log)	0.010	1.069***	0.079	0.718***	0.025	0.627*	-0.036	0.176
	(0.057)	(0.354)	(0.057)	(0.237)	(0.045)	(0.360)	(0.022)	(0.206)
Emergency discharges (%)	-0.010***	-0.001	-0.018***	-0.016**	0.001	0.003	-0.002**	-0.000
	(0.003)	(0.006)	(0.006)	(0.007)	(0.002)	(0.003)	(0.001)	(0.002)
Beds (public and private, per 1000 residents)	1.567***	1.313***	1.408***	1.124***	0.018	0.382	-0.085	0.009
	(0.314)	(0.416)	(0.352)	(0.386)	(0.220)	(0.373)	(0.193)	(0.233)
Private beds (%)	-0.399*	-0.203	-0.116	0.092	0.100	-0.379	0.367	0.591
	(0.237)	(0.362)	(0.213)	(0.287)	(0.696)	(1.130)	(0.461)	(0.556)
Constant	-7.041***	-8.416**	-5.902**	-5.732*	0.006	0.002	-0.013	-0.011
	(2.537)	(3.323)	(2.811)	(2.981)	(0.025)	(0.013)	(0.010)	(0.011)
Observations	732	732	366	366	732	732	366	366
R-squared	0.887		0.896		0.001		0.021	
First stage F-stat		14.04		18.90		4.439		2.622

The dependent variable is utilisation rate and standard errors are given in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. In cross-section specifications we also include year and procedure dummy variables, whose estimated coefficients are omitted here. The instrument set in pooled cross-section models includes proportion of population over 60 years old; in the first-difference specifications it also includes C-section rates. Robust and clustered standard errors computed.

7. Conclusions and policy implications

We have used administrative data on waiting times and volume of elective surgeries across different procedures and regions in Italy over the period 2010-2014. Our key finding suggests that the demand for elective surgery is inelastic to waiting times, and the elasticity is in the range of -0.15 and -0.24. This is in line with the literature in England (Martin and Smith, 1999, 2003; Martin et al. 2007), which provides a comparable demand elasticity of -0.2. The statistical significance of our results is however weaker and this is likely to be due to our use of aggregated data at regional level as opposed to electoral ward and a shorter time series used in the English context (Martin and Smith, 2003, 2007).

The similar elasticity between Italy and the UK could be the result of the similarities between health systems (both with a National Health Service, similar public-private funding mix, and financial arrangements for hospitals). But there are also differences (such as the differences in public-private mix in hospital provision) and a priori elasticities could have been different. The importance of different institutional arrangements across health systems is indeed confirmed by the different demand elasticity for Australia, which has been estimated at -1.7 (Stavrunova and Yerokhin, 2011). This is because, in Australia, the public-private mix is very different on the funding side, with more than half of the population holding private health insurance and therefore more susceptible to switch from the public to the private sector when waiting times are longer.

Although our study suggests a weak effect of waiting times on demand, the results have important policy implications in relation to the effectiveness of policy initiatives that encourage an expansion in supply to reduce waiting times (through more funding, an extension of working hours, revision of contracts, contracting out to existing private providers etc.). Some policymakers have argued that such supply-side policy initiatives can be ineffective since an increase in supply can be offset by large increases in demand (Hurst and Siciliani, 2005). Whether there are merits to this argument depends critically on the demand elasticity to waiting times. Our results show that within the Italian institutional context the demand is inelastic. Therefore, policies aimed at increasing supply would be effective in reducing waiting times.

At times of great financial pressure following the economic crisis, governments have introduced or are introducing measures to keep health expenditure under control, which is likely to imply a reduction or a slower growth in supply. Driven by the ageing population and technology, the gap between demand and supply may increase and, based on our findings, so will waiting times and waiting lists. Governments therefore need to consider policy interventions which act on the demand, for example by reducing unnecessary referrals through better coordination between GPs and specialists (Mariotti et al., 2014) or improving the prioritisation of the list to minimise the impact of delays (Siciliani, Borowitz and Moran, 2013).

Health systems differ to a great extent across the OECD countries on funding, provision and organisational arrangements. As data on waiting times become increasingly available, future work could replicate our analysis in other health systems to inform the policy debate on supply-side initiatives aimed at reducing waiting times.

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Appendix 1: Additional results.

Table A1. First Stage Estimates; Demand Equation.

	Pooled	Pooled	First-
	cross-section	cross-section	difference
Variables	2011 - 14	2013 - 14	2013 - 14
Waiting time (log) at t-1	0.653***	0.610***	
(atom (10g) at t 1	(0.047)	(0.057)	
Waiting time (log) at t-2			-0.181***
			(0.054)
Emergency discharges (%)	-0.005***	0.002	-0.007***
	(0.002)	(0.003)	(0.002)
C-section rate (%)	0.001	-0.005**	-0.025*
	(0.002)	(0.002)	(0.014)
Proportion of heavy smokers (%)	-0.000	0.004	0.008**
	(0.002)	(0.003)	(0.004)
Proportion of over 60 years old (%)	0.040***	0.052***	-0.075
	(0.013)	(0.017)	(0.103)
Private beds (per 1000 residents)	0.012	0.039**	-0.042
*	(0.015)	(0.018)	(0.129)
Mortality rate (per 1000 residents, at $t - 1$)	-0.047*	-0.063**	-0.076*
• • •	(0.024)	(0.027)	(0.044)
Constant	0.447*	0.228	0.036
	(0.250)	(0.329)	(0.030)
Observations	732	366	366
R-squared	0.798	0.824	0.109

The dependent variable is waiting time and standard errors are given in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. In all specifications we also include year and procedure dummy variables, whose estimated coefficients are omitted here. Robust and clustered standard errors computed.

Table A2. First Stage Estimates; Supply Equation.

	Pooled	Pooled	First-	First-
	cross-section	cross-section	difference	difference
	2011 - 14	2013 - 14	2011 - 14	2013 - 14
Proportion of over 60 years old (%)	0.040***	0.050***	0.050	-0.045
•	(0.011)	(0.011)	(0.059)	(0.106)
C-section rate (%)			-0.028***	-0.033**
			(0.011)	(0.015)
Emergency discharges (%)	-0.010***	-0.003	-0.005	-0.008***
	(0.003)	(0.003)	(0.003)	(0.002)
Beds (public and private, per 1000 residents)	-0.040	0.148	-0.586	-0.243
	(0.243)	(0.222)	(0.503)	(0.463)
Private beds (%)	0.171	0.138	1.471	0.030
	(0.254)	(0.258)	(1.038)	(1.245)
Constant	2.399	0.626	-0.024	0.002
	(1.881)	(1.674)	(0.035)	(0.035)
Observations	732	366	732	366
R-squared	0.590	0.637	0.037	0.062

The dependent variable is waiting time and standard errors are given in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. In all specifications we also include year and procedure dummy variables, whose estimated coefficients are omitted here. The instrument set in pooled cross-section models includes proportion of over 60 years old in the population, in first-difference specifications it also includes low hospital quality measured by C-section rate. Robust and clustered standard errors computed.

	Estimatio	oss-section on period: 1 – 14	Estimatio	oss-section on period: – 14	First-difference Estimation period: 2013 – 14		
Variables	OLS	IV	OLS	IV	OLS	IV	
Waiting time (log)	-0.077	-0.101	-0.028	-0.07	-0.040*	-0.243*	
	(0.059)	(0.085)	(0.067)	(0.103)	(0.023)	(0.146)	
Emergency discharges (%)	-0.012***	-0.012***	-0.017***	-0.017***	-0.002**	-0.004**	
	(0.003)	(0.003)	(0.005)	(0.005)	(0.001)	(0.001)	
C-section rates (%)	-0.015***	-0.015***	-0.013***	-0.014***	-0.006	-0.012	
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.008)	
Proportion of over 60 years old (%)	0.051	0.054	0.021	0.026	0.005	-0.008	
	(0.040)	(0.040)	(0.043)	(0.044)	(0.044)	(0.049)	
Private beds (per 1000 residents)	0.047	0.049	0.050	0.053	0.054	0.051	
	(0.034)	(0.033)	(0.035)	(0.035)	(0.056)	(0.061)	
Mortality rate (per 1000	-0.024	-0.027	0.022	0.017	-0.010	-0.028	
residents, at $t - 1$)	(0.072)	(0.072)	(0.075)	(0.075)	(0.019)	(0.025)	
Constant	4.776***	4.807***	4.926***	4.980***	-0.010	-0.006	
	(0.516)	(0.510)	(0.587)	(0.571)	(0.012)	(0.014)	
Observations	732	732	366	366	366	366	
R-squared	0.898		0.897		0.024		
First stage F-stat		196.6		109.9		10.62	

Table A3. Robustness check: Demand estimates without fraction oh heavy smokers among Demand controls.

The dependent variable is utilisation rate and standard errors are given in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. In cross-sectional specifications we also include year and procedure dummy variables, whose estimated coefficients are omitted here. The instrument used in pooled cross-section models is the 1-year-lagged waiting time; in the first difference specification it includes 2-years-lagged values of first differences. Standard errors are robust and clustered.

	Pooled cross-section Estimation period: 2011 – 14		Pooled cross-section Estimation period: 2013 – 14		First-difference Estimation period: 2011 – 14		First-difference Estimation period: 2013 – 14	
Variables	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Waiting time (log)	-0.016	1.126**	0.063	0.739***	0.022	0.596*	-0.038*	0.160
	(0.056)	(0.443)	(0.057)	(0.269)	(0.045)	(0.356)	(0.022)	(0.193)
Emergency discharges (%)	-0.011***	-0.000	-0.018***	-0.016**	0.001	0.003	-0.002**	-0.001
	(0.003)	(0.007)	(0.006)	(0.007)	(0.002)	(0.003)	(0.001)	(0.002)
Beds (public and private, per 1000 residents)	1.778***	1.238**	1.503***	1.092**	-0.061	0.324	-0.107	-0.005
	(0.333)	(0.489)	(0.370)	(0.430)	(0.235)	(0.398)	(0.194)	(0.235)
Private beds (%)	-0.465**	-0.174	-0.165	0.110	0.416	-0.195	0.558	0.636
	(0.233)	(0.394)	(0.207)	(0.300)	(0.711)	(1.181)	(0.491)	(0.543)
Wages (log)	-0.064***	0.019	-0.037	0.010	0.706**	0.361	0.356	0.115
	(0.022)	(0.048)	(0.026)	(0.035)	(0.328)	(0.517)	(0.316)	(0.418)
Constant	-8.290***	-8.105**	-6.400**	-5.599*	0.005	0.002	-0.012	-0.011
	(2.617)	(3.491)	(2.887)	(3.115)	(0.007)	(0.013)	(0.010)	(0.011)
Observations	732	732	366	366	732	732	366	366
R-squared	0.890		0.897		0.005	-0.492	0.024	-0.189
First stage F-stat		9.310		14.31		4.106		2.904

Table A4. Robustness check: Supply estimates including wages per capita.

The dependent variable is utilisation rate and standard errors are given in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. In cross-section specifications we also include year and procedure dummy variables, whose estimated coefficients are omitted here. The instrument set in pooled cross-section models includes proportion of population over 60 years old; in the first-difference specifications it also includes C-section rates. Standard errors are robust and clustered.

	Estimatio	on period: - 14	Estimatio	oss-section on period: 5 – 14	First-difference Estimation period: 2013 – 14		
Variables	OLS	IV	OLS	IV	OLS	IV	
Waiting time (log)	-0.086	-0.160*	-0.031	-0.120	-0.021	-0.255	
	(0.065)	(0.093)	(0.075)	(0.111)	(0.026)	(0.332)	
Emergency admissions (%)	-0.012***	-0.012***	-0.016**	-0.017***	-0.003**	-0.003**	
	(0.004)	(0.004)	(0.006)	(0.006)	(0.001)	(0.002)	
C-section rates (%)	-0.019***	-0.019***	-0.016***	-0.017***	-0.007	-0.011	
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.009)	
Proportion of over 60 years old (%)	-0.018***	-0.019***	-0.015***	-0.016***	0.000	0.002	
	(0.006)	(0.006)	(0.005)	(0.005)	(0.002)	(0.003)	
Proportion of heavy smokers (%)	0.021	0.026	-0.001	0.006	-0.008	-0.024	
	(0.038)	(0.038)	(0.044)	(0.044)	(0.049)	(0.059)	
Private beds (per 1000 residents)	0.043	0.047	0.039	0.045	0.066	0.058	
	(0.037)	(0.035)	(0.039)	(0.039)	(0.062)	(0.069)	
Mortality rate (per 1000	0.025	0.021	0.053	0.046	-0.014	-0.036	
residents, at $t - 1$)	(0.070)	(0.070)	(0.076)	(0.076)	(0.021)	(0.038)	
Constant	6.081***	6.238***	5.996***	6.154***	-0.010	-0.001	
	(0.553)	(0.556)	(0.636)	(0.615)	(0.014)	(0.020)	
Observations	650	650	325	325	325	325	
R-squared	0.870	0.870	0.865	0.864	0.026	-0.214	
First stage F-stat		190		112		2.469	

Table A5. Robustness check: Demand estimates excluding PTCA.

The dependent variable is utilisation rate and standard errors are given in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. In cross-sectional specifications we also include year and procedure dummy variables, whose estimated coefficients are omitted here. The instrument used in pooled cross-section models is the 1-year-lagged waiting time; in the first difference specification it includes 2-years-lagged values of first differences. Standard errors are robust and clustered

Table A6. Robustness check: Supply estimates excluding PT	CA.
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	Pooled cross-section Estimation period: 2011 – 14		Pooled cross-section Estimation period: 2013 – 14		First-difference Estimation period: 2011 – 14		First-difference Estimation period: 2013 – 14	
Variables	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Waiting time (log)	0.038	1.088***	0.098	0.758***	-0.004	0.617	-0.015	0.427
	(0.059)	(0.376)	(0.063)	(0.258)	(0.036)	(0.394)	(0.026)	(0.462)
Emergency discharges (%)	-0.012***	-0.005	-0.019***	-0.017**	-0.002	-0.001	-0.003**	-0.001
	(0.005)	(0.007)	(0.007)	(0.008)	(0.002)	(0.003)	(0.001)	(0.002)
Beds (public and private, per 1000 residents)	1.673***	1.439***	1.521***	1.262***	0.145	0.492	-0.075	0.087
	(0.347)	(0.447)	(0.390)	(0.425)	(0.206)	(0.365)	(0.213)	(0.336)
Private beds (%)	-0.466*	-0.284	-0.149	0.042	0.294	0.009	0.374	1.038
	(0.258)	(0.394)	(0.236)	(0.316)	(0.740)	(1.125)	(0.508)	(0.980)
Constant	-7.952***	-9.447***	-6.846**	-6.941**	0.002	-0.003	-0.016	-0.015
	(2.793)	(3.562)	(3.119)	(3.289)	(0.007)	(0.014)	(0.011)	(0.015)
Observations	650	650	325	325	650	650	325	325
R-squared	0.851	0.699	0.861	0.808	0.010	-1.611	0.021	-0.861
First stage F-stat		12.64		16.67		2.779		0.956

The dependent variable is utilisation rate and standard errors are given in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. In cross-section specifications we also include year and procedure dummy variables, whose estimated coefficients are omitted here. The instrument set in pooled cross-section models includes proportion of population over 60 years old; in the first-difference specifications it also includes C-section rates. Robust and clustered standard errors computed.

Appendix 2. Data sources.

We download from Italian Ministry of Health website Annual report on Hospital Discharges for years 2010-2014. Data are free and the Ministry of Health does not require any special permission for access. Data are available in xls format.

For year 2014 the relevant file is:

"C_17_pubblicazioni_2396_ulterioriallegati_ulterioreallegato_0_alleg" and data on waiting times are in tables 3.10 - 3.10(5). We use the total number of discharges ("Totale dimisisoni") and the relative average of waited time (in days, "Attesa media in giorni").

For year 2013 the relevant file is:

"C_17_tavole_18_allegati_iitemAllegati_0_fileAllegati_itemFile_1_file" and data on waiting times are in tables 3.10 - 3.10(5). We use the total number of discharges ("Totale dimisisoni") and the relative average of waited time (in days, "Attesa media in giorni").

For year 2012 the relevant file is:

"C_17_tavole_16_allegati_iitemAllegati_0_fileAllegati_itemFile_1_file" and data on waiting times are in tables 3.10 - 3.10(5). We use the total number of discharges ("Totale dimisisoni") and the relative average of waited time (in days, "Attesa media in giorni").

For year 2011 the relevant file is:

"C_17_tavole_1_allegati_iitemAllegati_0_fileAllegati_itemFile_11_file" and data on waiting times are in tables 3.10 - 3.10(5). We use the total number of discharges ("Totale dimisisoni") and the relative average of waited time (in days, "Attesa media in giorni").

For year 2010 the relevant file is:

"C_17_pubblicazioni_1690_ulterioriallegati_ulterioreallegato_0_alleg" and data on waiting times are in tables 3.10 - 3.10(5). We use the total number of discharges ("Totale dimisisoni") and the relative average of waited time (in days, "Attesa media in giorni").

Appendix 3.

Proof:

$$Corr((wt_{t} - wt_{t-1}); (wt_{t-2} - wt_{t-3})) = E((wt_{t} - wt_{t-1}) * (wt_{t-2} - wt_{t-3})) + E(wt_{t} - wt_{t-1}) * E(wt_{t-2} - wt_{t-3}) = \diamond$$

where
$$E((wt_t - wt_{t-1}) * (wt_{t-2} - wt_{t-3})) =$$

= $E(wt_twt_{t-2} - wt_twt_{t-3} - wt_{t-1}wt_{t-2} + wt_{t-1}wt_{t-3}) =$
= $E(wt_twt_{t-2}) - E(wt_twt_{t-3}) - E(wt_{t-1}wt_{t-2}) + E(wt_{t-1}wt_{t-3})$

and
$$E(wt_t - wt_{t-1}) * E(wt_{t-2} - wt_{t-3}) =$$

= $(E(wt_t) - E(wt_{t-1})) * (E(wt_{t-2}) - E(wt_{t-3})) =$
= $E(wt_t)E(wt_{t-2}) - E(wt_t)E(wt_{t-3}) - E(wt_{t-1})E(wt_{t-2})$
+ $E(wt_{t-1})E(wt_{t-3})$

$$\begin{split} & \Leftrightarrow = E(wt_twt_{t-2}) - E(wt_twt_{t-3}) - E(wt_{t-1}wt_{t-2}) + E(wt_{t-1}wt_{t-3}) - E(wt_t)E(wt_{t-2}) \\ & + E(wt_t)E(wt_{t-3}) + E(wt_{t-1})E(wt_{t-2}) - E(wt_{t-1})E(wt_{t-3}) \\ & = E(wt_twt_{t-2}) - E(wt_t)E(wt_{t-2}) - E(wt_twt_{t-3}) + E(wt_t)E(wt_{t-3}) \\ & - E(wt_{t-1}wt_{t-2}) + E(wt_{t-1})E(wt_{t-2}) + E(wt_{t-1}wt_{t-3}) \\ & - E(wt_{t-1})E(wt_{t-3}) \end{split}$$

 $Corr((wt_t - wt_{t-1}); (wt_{t-2} - wt_{t-3})) = \rho_{t(t-1),(t-2)(t-3)}$ $= \rho_{t,t-2} - \rho_{t,t-3} - \rho_{t-1,t-2} + \rho_{t-1,t-3}$

If

$$\label{eq:rho} \begin{split} \rho_{t,t-1} &= \rho_{t-1,t-2} \;, \\ \rho_{t,t-2} &= \rho_{t-1,t-3} = \rho_{t,t-1}^2, \end{split}$$

$$\rho_{t,t-3} = \rho_{t,t-1}^3$$

 $Corr((wt_t - wt_{t-1}); (wt_{t-2} - wt_{t-3})) = \rho_{t,t-1}^2 - \rho_{t,t-1}^3 - \rho_{t,t-1} + \rho_{t,t-1}^2$

Substituting $\rho_{t,t-1} = r$ we obtain

$$Corr((wt_t - wt_{t-1}); (wt_{t-2} - wt_{t-3})) = r^2 - r^3 - r + r^2 = -r(r^2 - 2r + 1)$$
$$= -r(r-1)^2$$

Given that $(r-1)^2 \ge 0 \forall r$ (and $(r-1)^2 = 0 \Leftrightarrow r = \pm 1$) the sign of the correlation is given by -r

Recall that $r = \rho_{t,t-1}$

$$Corr((wt_t - wt_{t-1}); (wt_{t-2} - wt_{t-3})) = \begin{cases} > 0 \ if \ \rho_{t,t-1} < 0 \\ < 0 \ if \ \rho_{t,t-1} > 0 \end{cases}$$

q.e.d.

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In manibus nostris codices, in oculis facta

(Agostino d'Ippona)