



# Discussion paper

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AN EMPIRICAL INVESTIGATION***

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# Hospital competition in the Netherlands

## An empirical investigation

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### Abstract

The Dutch government introduced managed competition to the health care sector in 2006. In this regulatory framework insurers compete for enrollees and providers compete for contracts with insurers. The resulting contracts are determined by bargaining, which outcome depends on the relative position of the provider. In this paper, we compare how commonly used market power indicators predict bargaining outcomes. We combine 2013 transaction data with bilateral contract data. Our empirical models explain the relative differences in hospitals' revenues while controlling for differences in the complexity of patients. Four indicators are used: the logit competition index (LOCI), willingness-to-pay (WTP), Elzinga-Hogarty market share and a rule-of-thumb market share. We find that WTP and LOCI perform best empirically.

*Keywords:* **Hospital competition, Market power, Bargaining**

*JEL codes:* **I11, L44, L13, D22**

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<sup>6</sup>This paper reflects the personal views of the authors, which are not necessarily those of their employers. This paper is not in any way binding for the Dutch government, in particular for future decisions of the Netherlands Authority for Consumers and Markets (ACM) and the Dutch Healthcare Authority (NZA) on the topics discussed.

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## 1. Introduction

Some health care systems, such as in the U.S. and in the Netherlands, are organized around markets in which hospitals compete. Even in state run systems, such as in the U.K., competition between hospitals is important. [1] shows that competition impacts hospital mortality. There is much discussion about the effects of competition and methods to measure competition between hospitals (see e.g. [2]).

Much of the literature shows that traditional methods to assess market power do not predict market power very well. In the last two decades, new methods - most notably the logit competition index (LOCI) ([3], [4]) and the Option Demand or willingness-to-pay (WTP)([5], [6]) - have been developed. These models provide alternative indicators of market power.

In contrast to traditional methods, such as the Elzinga-Hogarty test and market definitions based on patients' travel distances, the new methods are grounded in economic theory. Both LOCI and WTP are theoretically linked to the price-cost margins. However, little validation of these models has been carried out so far. The available literature is mostly on U.S. data. Notably, [7] compares market power indicators based on pre-merger data with the actual postmerger price changes of 26 hospital mergers, providing evidence on better performance of the new methods in comparison to traditional methods for merger screening. Comparing WTP and several traditional methods, [8] argues that WTP is a consistently better predictor of prices. It is, however, useful to extend the comparison to other datasets that include additional details, allowing for the refinement of both price and control variables included in the analysis. We have a unique dataset with information about contracts and a wide array of indicators to control for the complexity of care. By using detailed patient-level data and contracts data, we study how market power indicators affect the negotiated prices between hospitals and insurers (see [9] for a study on the effects of competition in the Netherlands on quality indicators).

Our paper contributes to the literature in the following ways. First, we com-

pare four market power indicators that are commonly referred to in competition enforcement, including the more recent WTP and LOCI indicators in an SCP-type reduced-form model. We compare these recent indicators with two more traditional methods to measure market power: market share based on a common sense market definition and market share based on the Elzinga-Hogarty (EH) test. This allows us to evaluate and predict a unilateral effect of market power on hospital pricing. Data on bargaining outcomes is rarely available and we are not aware of any other paper that investigates the direct effect of market power on prices corrected for budget ceilings, renegotiations and other contracting aspects.

Second, hospital prices vary because patient complexity and corresponding costs differ across hospitals. We contribute to the literature by using machine learning to select our variables to control for differences in patient complexity.

Third, we extend the hospital competition literature with new, recent evidence on the Netherlands. Our dataset covers all hospital-insurer transactions in 2013 and allows us to control for cost and product mix differences between hospitals in a rather detailed way.

In this paper we will first review the literature and provide the institutional background on the Dutch hospital market, followed by a description of the methods to measure market power. Then we describe our data and empirical approach. Finally, we present our results followed by a discussion.

## **2. Literature**

There is a large economic literature on the effect of provider concentration in hospital markets (see [2] for an extensive literature review). In this section we provide an overview of the literature concerning the development of different techniques to assess hospital market power and its effect on prices (which partly overlaps with earlier overviews, e.g., by [3] and [10]).

Most empirical publications on the relationship between concentration and prices follow the structure – conduct – performance (SCP) tradition, using a

reduced form model in which price or price-cost margin are regressed on concentration indices (typically HHI), and cost and demand shifters. Nearly all empirical applications in this area focus on the U.S. Examples include: [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21] and [22]. The majority of these studies find a positive relationship between hospital concentration and prices: a higher concentration results in higher prices. A notable exception is [22], who do not find a significant effect of hospital market power on hospital prices.

Also in the Netherlands there is some evidence for the relationship between concentration and prices. In their study on the price effects of hospital mergers, [23] found that there are indications for positive price effects of the mergers. Furthermore, they found that a higher value for a hospital's HHI is accompanied by a higher price. Also [24] claim that the hospital market is highly concentrated and it is unclear whether the insurance companies have enough countervailing power to prevent price increases. [25] even claims in their evaluation of the Health Insurance act that there is an undesirably large power among health care providers including hospitals.

A shortcoming of the SCP modelling approach with HHIs in a pricing equation is that it can only be directly derived from a theoretical model with Cournot competitors. The assumptions of the Cournot model do not hold for managed hospital competition: products are differentiated, and prices and volumes are negotiated between hospitals and insurers. A first alternative is to use a bilateral-monopoly bargaining model, as proposed by [26] and consequently applied in [27], as described below. However, also this modelling approach is imperfect given that the hospital-insurance market is better characterized by a bilateral oligopoly. Therefore, there is still no consensus on how to model hospital competition, as explained by [22].

More recent papers take a more structural approach to model hospital competition, based on a logit model of consumer choice among hospitals, producing other measures, such as willingness-to-pay (WTP) and the logit competition index (LOCI). (See [5] and [6], for more detail on WTP; and [3], [4] and [28] for

more detail on logit demand and LOCI). The idea behind the WTP model is that prices resulting from bargaining should reflect the hospital's added value to the insurer network. Thus a higher WTP translates into a higher profit margin. In contrast, LOCI assumes a differentiated Bertrand competition model between hospitals under logit demand with insurers as price takers. This leads to an inverse relationship between the price-cost margin and LOCI.

With respect to the development of the WTP approach, [5] analyse hospital competition for inclusion in the network of an HMO, and how the HMO's valuation of a hospital's contribution to the network influences the hospital's market power and prices. [6] introduces and empirically validates an index of hospital market power measured by an aggregated consumers' willingness to pay for inclusion of a hospital in the insurer's network. These studies find that prices are increasing in hospital market power. Notable contributions to the LOCI approach are [3], [4] and [28]. [3] develop a structural model of competition under logit demand for hospital care, which provides a theoretical foundation for the LOCI competition index that was introduced by [4]. Both papers predict price increases in concentrated markets. [8] explains the shortcomings of the traditional HHI and market share measures, comparing those to the WTP measure. Based on U.S. data, the study shows that WTP is a better predictor of prices. Furthermore, comparing market power indicators based on pre-merger data with the actual postmerger price changes of 26 hospital mergers for several market power indicators, [7] argues that WTP, LOCI and diversion ratio methods perform better than traditional methods for merger screening.

In the Netherlands, [27] uses both SCP and bargaining approaches to model market power in the Dutch hospital market. The first model they estimate is an SCP model that analyses the relationship between markup and market structure. The second model is a bargaining model that analyses the relationship between (hospital) market structure and the share of bargaining gains that accrue to the hospital. Market structure can lead to market power of a hospital through two mechanisms: unilateral effect, captured by market share, and coordinated effect that arises because of (tacit) collusion, captured by market

concentration (HHI). [27] report a positive relationship between hospital market share and price in the SCP model, but they do not find this relation in the bargaining model. In the bargaining model, they find that higher insurer market shares are associated with a decrease in hospital prices.

### **3. Institutional background**

In 2006, the Dutch government introduced managed competition in the health care sector. The idea is that insurers compete for contracts with enrollees and that health care providers compete for contracts with insurers. To counteract market failures in the health care sector (see e.g. the seminal article by [29]), the Dutch government introduced regulations for basic health insurance such as mandatory insurance for all civilians, mandatory acceptance for insurers of all enrollees regardless of pre-existing medical conditions and prohibition of premium differentiation. To enable competition between insurers, insurers are compensated through a risk-adjustment model for differences in the risk profile embedded in their enrollee population. The policy objective of the reform was to increase efficiency by incentivizing the market participants to provide good-quality care for everyone at efficient cost levels. See [30] for a more detailed overview of the Dutch system.

As part of this reform, health care providers acquired more freedom to set their prices and service levels. In this regulated market, health insurers bargain with hospitals to buy health care efficiently for their enrollees. Each year, health insurers bargain with hospitals bilaterally to include them in their network. Hospitals and insurers negotiate on the prices, quantities and quality of care. An enrollee may incur (some) out-of-pocket payments if she visits an out-of-network hospital.

### **4. Market power indicators**

In our empirical estimation, we compare two new and two traditional measures of market power: the LOCI approach, the WTP-approach, a market share

based on the Elzinga-Hogarty test and a rule of thumb market share calculation.

#### 4.1. LOCI

The Logit competition index (LOCI) is an indicator for a provider's market power, see [2] and [4]. The indicator results from profit maximization with respect to price subject to logit demand under differentiated Bertrand competition. Theoretically, the higher the inverse LOCI, the higher the price-cost margin of the hospital. The calculation of LOCI (equation 6 in [4]) amounts to calculating or estimating a hospital's market share in each micromarket, taking the complement and then aggregating market shares over micromarkets using importance for a hospital's volume as weights. In our application, postal codes will be used as micromarkets. As the underlying logit demand model is based on choices made by patients between hospitals and the LOCI index is a result of profit maximization with respect to price, the formula should not include prices. Therefore, the market shares are calculated based on the number of patients (not on the value of health care that they received).<sup>7</sup>

In the following equation,  $N_{hm}$  is the number of patients of hospital  $h$  in micromarket  $m$ ,  $N_h$  is the total number of patients of hospital  $h$  (in all micromarkets) and  $N_m$  is the total number of patients (of all hospitals) in micromarket  $m$ :

$$LOCI_h = \sum_m \frac{N_{hm}}{N_h} \left( 1 - \frac{N_{hm}}{N_m} \right) \quad (1)$$

Thus, rather than delineating a geographical market, LOCI simply aggregates information from all micromarkets in which the provider is active (i.e., has positive revenue in the chosen time span). Note, that theoretically the inverse

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<sup>7</sup>When computing market power indicators in our application, we define the number of patients in a hospital as the number of health inquiries by hospital's patients. Therefore, a patient with two inquiries is counted as two patients. An inquiry is a series of claims on the same 'treatment trajectory', including both initial and follow-up claims for the patient treatment.

LOCI is related to margins and we will therefore use the inverse of the above formula in the estimation.

#### 4.2. WTP

Another measure of market power used in the health care sector stems from the willingness-to-pay framework proposed by [5] and [6]. The model assumes that while negotiating with hospitals, insurers take into account how much value each hospital brings to consumers when it is added to the network. The consumers' valuation is measured as willingness to pay for the extra hospital in the network (the relationship with consumer preferences is described below).

The relationship between the willingness-to-pay and prices or revenues is derived from the bargaining problem between the hospital and the insurer. Following e.g. [7] and denoting with  $N_{hk}$  the volume that an insurer needs, the bargaining problem between hospital  $h$  and insurer  $k$  can be characterized as:

$$\max_{p_h} \{ [WTP_h - p_h N_{hk}]^{1-\gamma} [p_h N_{hk} - c_h(N_{hk})]^\gamma \}$$

for some  $\gamma \in [0, 1]$ . In this equation,  $p_h N_{hk}$  is the amount the insurer pays the hospital for the production  $N_{hk}$  and the total costs of this production for the hospital are  $c_h(N_{hk})$ . The gains from this transaction are thus  $WTP_h - c_h(N_{hk})$  and these are divided between the hospital and the insurer. Parties negotiate with respect to the price for a unit of care and the revenue is written as price times volume. The solution of the bargaining problem yields:

$$p_h = \frac{\gamma WTP_h + (1 - \gamma)c_h(N_{hk})}{N_{hk}} \quad (2)$$

The WTP in the equations above is derived from a logit demand for hospital choice. For consumer  $i$  the willingness-to-pay for an insurance plan with hospital  $h$  in the network can be written as:

$$WTP_{hi} = \log \left[ \frac{1}{1 - s_{hi}(x_i)} \right] \quad (3)$$

where  $s_{hi}(x_i)$  is the probability of consumer  $i$  choosing hospital  $h$  given consumer characteristics  $x_i$ . The idea is that the aggregated consumers' valuations in a micromarket are translated into the insurer's willingness to pay for a contract, since the insurer is able to offer more value to those consumers if the hospital is included in the network. Summing over all patients in a micromarket yields the valuation relevant to the insurer. In our application we align the approach to the micromarket framework of LOCI and take location as the only relevant characteristic determining  $s_{hi}(x_i)$ . Furthermore, we calculate the probability directly as  $s_{hi}(x_i) = \frac{N_{hm}}{N_m}$  for all patients in micromarket  $m$ . This yields:

$$WTP_h = \sum_m N_m \log \left[ \frac{1}{1 - \frac{N_{hm}}{N_m}} \right] \quad (4)$$

Note that Equation 2 implies that WTP per patient is related to hospital pricing. Hence, we use  $\frac{WTP_h}{N_h}$  as a market power indicator in our model.

It is clear from above descriptions that the LOCI and WTP indicators have different perspectives on the role of insurers. LOCI is derived from profit maximization with respect to price and depends on how demand changes with price. Hence, an insurer does not enter the framework explicitly and can be seen as a price taker. On the other hand, the WTP indicator is derived from bargaining between a hospital and a buyer. In our application with a single WTP value per hospital we implicitly consider negotiations between a hospital and a single insurer.

The expressions for LOCI and WTP show similarities. For a given micromarket  $m$ , we have that the contribution to LOCI is  $LOCI_{hm} = \frac{N_{hm}}{N_h} \left( \frac{N_m - N_{hm}}{N_m} \right)$  and the contribution to WTP per patient equals  $WTP_{hm}/N_h = \frac{N_m}{N_h} \left( \log \frac{N_m}{N_m - N_{hm}} \right)$ . If we compare these two expressions, we can see that both can be written as a product of two terms. The second term (in brackets) is clearly negatively correlated but this is not necessarily the case for the first term. The correlation between the two measures of market power is therefore an empirical question and hinges on the correlation between  $N_m$  and  $N_{hm}$ . If a hospital serves more patients in larger micromarkets, this correlation is positive.

#### *4.3. Elzinga-Hogarty market share*

The idea behind the Elzinga-Hogarty (EH) market test is that a geographical market constitutes an area in which most people in the area go to hospitals in that area (known as Little Out From Inside, or "LOFI") and not a lot of people from outside the market seek treatments in hospitals in the area (Little In From Outside or "LIFO"). The threshold for the "import" and "export" of patients is usually set at either 90% (called a "strong" market) or 75% (called a "weak" market). Following [31], we set the threshold at 75% and we follow the implementation approach suggested by [32]. The algorithm starts with the postal code of a hospital and then adds postal codes based on the revenue of the hospital in the postal codes until the threshold is reached. This method results in most hospitals falling into a very large market (the whole of the Netherlands) and the remaining ones being practically monopolists in geographically small markets.<sup>8</sup>

#### *4.4. Rule of Thumb market share*

Finally, we compute a rule-of-thumb market share of the hospital in an area consisting of the micromarkets that together generate 90% of the hospital's total turnover. To this end, micromarkets are sorted on revenue in decreasing order and the micromarkets that cumulatively generate 90% of the hospital's revenue constitute the relevant geographical market. This approach is often used by competition authorities in their merger assessments.

### **5. Data**

We use a number of data sources. Section 5.1 describes the insurance claims database that we used to construct market power indicators. Since the billed

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<sup>8</sup>According to [32] convergence is difficult for the 90% threshold and this was also the case for our computations. Also with a 90% threshold we expect that the EH-test would indicate that most hospitals operate in a geographic market that covers the whole of the Netherlands.

amounts specified in this database are not adjusted for various contract provisions, such as budget ceilings, the total amount billed is higher than the amount actually paid to a hospital. Therefore, revenues that were actually paid have been retrieved from the bilateral contracts database, which we describe in section 5.2. Finally, section 5.3 provides data sources for control variables. Table 1 presents the descriptive statistics of the variables included in the dataset.

### *5.1. Insurance claims database*

The database of insurance claims for the year 2013 is provided by Vektis. This database consists of information submitted by health insurers to Vektis and was used for the construction of market power indices and some of the control variables. The records in Vektis show the postal code of the patient, the provider's identity, details on the provided care (product codes), the insurer, as well as the insurance claim amount. Only claims starting in 2013 were included. A number of selection and filtering steps were then taken to prepare the data for analysis. First, entities registered in the data under separate codes but who are in fact one entity were treated as the same entity, i.e. we assumed that they behaved as single price setting economic actors.<sup>9</sup> Second, we excluded providers which are not hospitals. Third, we excluded laboratory products because these products are usually outsourced to third-party contractors. Fourth, outliers in terms of prices per unit were identified and removed from the analysis according to the following procedure. At the claims level we considered unique prices that occurred in less than 10% of observations and that were set by at most one hospital. For these claims, the absolute distance of the price to the mean per claim expressed in standard deviations was calculated. If the distance was more than 3 standard deviations, the observation was removed. The outliers identified in this way amount to less than 2% of total revenue.

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<sup>9</sup>For example, recently merged hospitals with two administrative identifiers.

Table 1: Descriptive statistics

| Statistic                              | N  | Mean   | St. Dev. | Min    | Max    |
|--|----|--------|----------|--------|--------|
| <b>Price index</b>                     | 81 | 1.1    | 0.3      | 0.6    | 2.2    |
| <b>Market power</b>                    |    |        |          |        |        |
| Inverse LOCI                           | 81 | 2.87   | 1.31     | 1.01   | 9.31   |
| WTP per patient                        | 81 | 1.73   | 0.40     | 1.01   | 3.37   |
| Market share (Elzinga-Hogarty test)    | 81 | 0.1    | 0.3      | 0.002  | 1.0    |
| Market share (90% rule of thumb)       | 81 | 0.5    | 0.3      | 0.01   | 0.9    |
| <b>Revenues (mil. euro's)</b>          |    |        |          |        |        |
| Revenue                                | 81 | 228.37 | 149.71   | 25.97  | 679.50 |
| Amount claimed/billed                  | 81 | 236.20 | 156.51   | 26.50  | 693.04 |
| Number of patients (ths)               | 81 | 161.90 | 82.25    | 36.39  | 424.44 |
| <b>SiRM (% patients)</b>               |    |        |          |        |        |
| Product category C                     | 81 | 14.85  | 2.81     | 10.20  | 27.39  |
| <b>Robijn (% patients)</b>             |    |        |          |        |        |
| High intensity care                    | 81 | 1.02   | 1.11     | 0.11   | 7.31   |
| Unique care                            | 81 | 1.83   | 4.85     | 0.02   | 20.45  |
| Multiple specialists                   | 81 | 0.97   | 0.79     | 0.09   | 4.10   |
| Complex care                           | 81 | 0.53   | 0.62     | 0.05   | 2.90   |
| Rare diagnoses                         | 81 | 0.41   | 0.34     | 0.11   | 1.73   |
| Research                               | 81 | 2.09   | 6.70     | 0.00   | 33.72  |
| Comorbidity age<21                     | 81 | 1.21   | 0.80     | 0.06   | 4.60   |
| Comorbidity age<50                     | 81 | 6.37   | 2.33     | 1.87   | 14.17  |
| Expensive medication                   | 81 | 0.29   | 0.25     | 0.00   | 1.18   |
| Tertiary referrals                     | 81 | 9.35   | 5.05     | 2.55   | 25.31  |
| <b>Vektis (% turnover)</b>             |    |        |          |        |        |
| Referrals STZ/UMC                      | 81 | 6.50   | 10.98    | 0.00   | 39.45  |
| <b>Other controls</b>                  |    |        |          |        |        |
| Urbanization (1 = least, 5 = most)     | 81 | 3.04   | 0.79     | 1.55   | 4.66   |
| Average housing price (ths euro's)     | 81 | 212.83 | 31.32    | 143.07 | 302.05 |
| Average disposable income (ths euro's) | 81 | 34.93  | 2.19     | 30.18  | 40.30  |

### *5.2. Bilateral contracts*

We also use information on hospital-insurer bilateral contracts and monetary transfers in 2013. The final amounts that insurers actually pay to providers are typically not equal to the amounts in the Vektis records, due to bilaterally negotiated arrangements, e.g. a budget ceiling or lump sum, and renegotiations throughout the year. For that reason, the contracts dataset was compiled by NZa. The variable revenue in this dataset provides the final euro amount the insurer pays, net of corrections that follow from the negotiated agreements and possible subsequent renegotiations. This amount is generally not the same as the total amount of claims in the insurance claims dataset described earlier. Hence, we use two terms: the term ‘revenue’ refers to the total amount actually paid by insurers, while the billed (or claimed) amount refers to the sum of amounts billed to insurers based on produced volumes. If this amount surpasses the negotiated ceiling and no re-negotiation takes place the billed amount is higher than the actually paid amount. Descriptive statistics on both variables are shown in Table 1 at the beginning of this section, under the topic ‘Revenues’.

### *5.3. Data sources on control variables*

The market power indices described above are theoretically linked to the price-cost margins of hospitals. Thus, explaining revenues or prices is not sufficient to assess market power. To control for the differences in costs we construct a number of control variables to be used in the econometric model alongside the market power indicators. One of the major cost drivers is the complexity of offered care. A number of auxiliary datasets provide information on complexity and comorbidity of patients at either the hospital or product level. Since the definition of complexity of care is ambiguous, we use several different variables based on Robijn, SiRM and Vektis (2013) as described below.

### 5.3.1. *Robijn variables*

The Robijn variables show per hospital the share of patients receiving care which is academic in nature, i.e. highly complex care.<sup>10</sup> Project Robijn was set up by the federation of Dutch academic hospitals to make academic care transparent. The project addresses the question which types of care and which patients are considered to be ‘academic’.<sup>11</sup> To this end, all patients from all Dutch hospitals (i.e. regular and academic hospitals) have been examined and evaluated across several dimensions according to Robijn labels. Patients with the label ‘academic’ are considered to have received care that is highly complex.

Each hospital in the Netherlands is characterised by nine Robijn variables. The variables used in our analysis are simply the share of a hospital’s patient population labelled complex according to the following nine Robijn labels:<sup>12</sup>

- High treatment intensity – The more care activities a patient needs, the higher the treatment intensity. For this variable only care activities for patients with oncological and cardiovascular diseases are considered. These patients are labelled complex if:

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<sup>10</sup>Robijn is a Dutch acronym for RijksOverheid Bijdrage IJverig Nageplozen, roughly translated as “state subsidy diligently examined”. Technical details on Robijn were published by the Dutch House of Representatives on June 20th 2017 as an attachment to Kamerstuk 32864 nr. 5 as identifier “blg 810796” (<https://zoek.officielebekendmakingen.nl/blg-810796>).

<sup>11</sup>Nine Robijn labels are defined to distinguish academic from regular patients. They are still under development. If it improves their ability to capture the academic nature of care a patient needs, a label’s criteria can be adjusted. Labels use medical characteristics of individual patients from the Diagnosis treatment combination information system (DIS) database and specific criteria to determine if a patient can be labelled academic. The DIS database contains detailed medical information about all hospital patients in the Netherlands and the care they receive, which are diagnosis, diagnosis treatment combination, care products and number and type of care activities performed. For the analysis in this article DIS data on 2013 was used to construct the values of the Robijn variables.

<sup>12</sup>For the purpose of this article, definitions are taken from the master thesis ‘UMCs, a different kind - an empirical research using the Robijn labels’ by J. Arnoldus (2018) from Tilburg University in cooperation with the Dutch Healthcare Authority.

- the number of care activities in academic hospitals for these patients is at least twice as high as in other hospitals and
  - if more than 1 percent of patients with this diagnosis receive the care activity
- Research - Patients are labelled complex if in their diagnoses group the average number of scientific publications on this topic by the hospital is at least 16 over the past five years, or 10 per 10,000 patients. And the hospital treats over 1.5 times more patients for the diagnosis than expected on its theoretical market share. Only measured for academic hospitals.
  - Unique care - If more than 85 percent of total care for a combination of diagnosis, care type, medical specialisation and certain patient characteristic is supplied by academic hospitals, then all patients in this group are labelled complex.
  - Multiple specialisations - A patient is labelled complex if he receives care from more than two different types of medical specialisations in a hospital.
  - Complex surgery - A patient is labelled complex if he undergoes surgery for which the yearly prevalence in the Dutch population is less than 1 in 100,000.
  - Rare diagnoses - A patient is labelled complex if the yearly prevalence of his diagnosis in the Dutch population is less than 1 in 100,000.
  - Expensive medication - A patient who receives off-label expensive medication is labelled complex.
  - Tertiary referral - A patient is labelled complex if he is referred from another hospital within 1.5 years of the start of his initial diagnosis treatment combination.
  - Comorbidity - A patient is labelled complex if he has received care in at least four different diagnosis groups within a period of two years. There

are two different age categories for this label, namely patients under the age of 21 and patients under the age 50.

### 5.3.2. *SiRM/TG complexity categorisation*

Consultancies SiRM and Twynstra Gudde were commissioned by the Netherlands Authority for Consumers and Markets (ACM) to construct a method for categorizing products of hospital care into levels of complexity [33]. The study assigned each diagnosis treatment combination code (DBC in Dutch) to one of three levels, based on *inter alia* patients' travel patterns, using 2014 data. The more complex a treatment, the more willing the patient is to travel further or bypass nearer hospitals. We use the share of a hospital's patients in the highest category of complexity (*Category C*) as a variable in our analysis.

### 5.3.3. *Vektis*

We use the insurance claims database, which we described at the beginning, to construct a variable measuring the share of patients being referred from another hospital assuming such patients are typically complex. We allocate specialized and academic hospitals into a higher complexity hospital class (The notation STZ/UMC in table 2 refers to this class). The patient is only considered complex if the referral is to a hospital in the higher complexity class and only counts as complex for this higher complexity hospital. By doing this, we correct for likely differences between general hospitals and higher complexity hospitals. Moreover, we capture variation in complexity within the higher complexity hospital class.

### 5.3.4. *CBS Statline*

CBS Statline provides publicly available data at the postal code level. We use three variables from this source: urbanisation, housing prices and disposable income. Urbanization is measured on a scale from 1 to 5, where a higher value indicates a more urban environment. The house price data is based on the value officially imputed to dwellings in the Netherlands (WOZ in Dutch). Disposable income is approximately equal to income after tax. The data were aggregated

to the hospital level by using the postal codes of a hospital's patients. These variables are used to control for costs related to a hospital's location, e.g. real estate costs or salary costs.

## 6. Empirical model

We estimate a linear model for a hospital's prices with different market power indicators and cost shifters on a hospital level. The market power indicators we use are  $\frac{WTP_h}{N_h}$ ,  $\frac{1}{LOCI_h}$ , the market share based on the Elzinga-Hogarty test, and the rule of thumb market share. Both general and academic hospitals are included in our empirical model.

### 6.1. Model specification

We estimate the following equation:

$$P_h = \alpha + \beta \cdot mktpower_h + \delta' C_h, \quad (5)$$

where  $P_h$  is the price index of hospital  $h$ ,  $mktpower_h$  the indicator for its market power and  $C_h$  a set of control variables for hospital  $h$ . In particular, it would be important to control for relevant cost shifters such as complexity. These variables will be described below in the remainder of this section.

Other studies, such as [1], warn about possible endogeneity issues in estimating the relationship between market power and market outcomes. In our case, endogeneity issues could in theory arise due to reverse causality if patients would base their hospital choices on the prices that are bargained between hospitals and health insurers. However, we do not expect this to be the case for the following reasons. First, out-of-pocket contributions in the Netherlands are limited to small deductibles (between 350 and 850 euros in 2013). Second, prices were not transparent for patients during the study period. Thus, it is very unlikely that patients have considered prices when choosing between providers of treatments.

## 6.2. Dependent variable

Our dependent variable is a price index, which we define in two steps. First, we calculate standardized revenue by using actual hospital volumes but average prices per patient group, both based on the Vektis data.<sup>13</sup> Since more costlier products (on average) get a higher weight, the standardized revenue is higher for hospitals with a higher share of those products in their product mix.

Standardized revenue is defined as:

$$R_h = \sum_g \bar{P}_g N_{hg}, \text{ with } \bar{P}_g = \frac{\sum_h \bar{P}_{hg}}{H}, \quad (6)$$

where  $\bar{P}_{hg}$  is the average revenue per patient in hospital  $h$  in patient group  $g$ ,  $H$  is the number of hospitals and  $N_{hg}$  is the volume produced by  $h$  in product group  $g$ .

Next, we define the price index  $P_h$  as the ratio between the actual and standardized revenue  $R_h$ . The actual revenue is taken from the contracts database. We use this price index to make sure we capture variation in prices across hospitals and not a variation in product mix.

## 6.3. Market power indicators

Figure 1 depicts the distribution of the market power indicators defined in section 4. We can notice the dichotome values of the market share indicator based on the E-H test.

## 6.4. Control variables and dimensionality reduction

There are 15 candidate variables to include in the vector  $C$ . Given the number of observations and likely correlation among these candidates, we need a structural approach for reducing the dimensionality. To select control variables we use the 2-step LASSO procedure proposed by [34], [35], [36].<sup>14</sup>

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<sup>13</sup>NZa categorized hospital products into 65 patient groups based on patterns in hospital care.

<sup>14</sup>We checked the robustness of our results to an alternative dimensionality reduction method, the principal factor analysis.

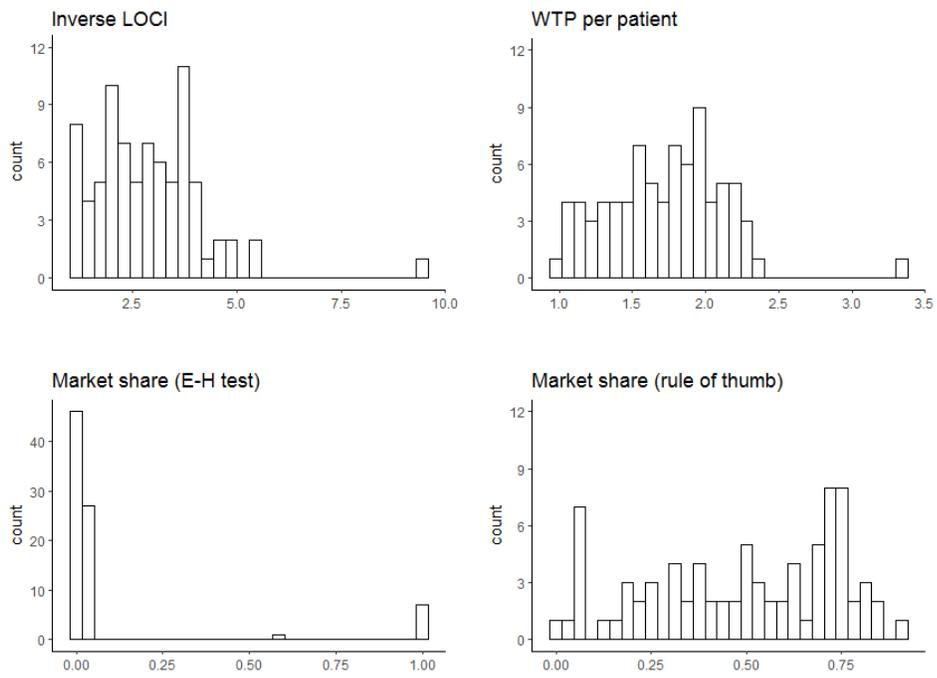


Figure 1: Histograms of calculated market power indicators

The 2-step LASSO procedure is developed to estimate a causal effect of the variable of interest. In the first step a LASSO regression ([37]) is run for the dependent variable on all the control variables, i.e. excluding market power. Hereby, the most relevant control variables are selected as coefficients for control variables with insufficient explanatory power are shrunk to zero. Another LASSO regression is run for the market power indicator on the controls. This way, we correct for potential confounding factors and mitigate omitted variable bias in the resulting model. The shrinkage parameter is determined iteratively so that theoretically, the largest covariance between the residual in the final model and any of the non-selected variables is not statistically different from zero. The union of the selected variables is included in the final post-LASSO OLS regression as control variables.

Intuitively, we are mainly interested in the single coefficient for the market power indicator. The rest of the model containing the controls is approximated by using machine learning to allow precise estimation of the structural estimand ([35]). The two steps in the LASSO procedure ensure that the controls are well approximated and all relevant predictors are included (1st step) and potential confounding factors are taken into account (2nd step).

[34], [35] and [36] show theoretically and by using simulations that the procedure leads to consistent causal/structural estimate for the variable of interest. However, as machine learning methods are used to model the controls, the individual coefficients for these controls have to be interpreted with care. The estimate of the causal effect of the variable of interest is robust to model misspecification but that does not necessarily hold for the individual coefficients of the control variables. The model also accounts for possible heteroscedasticity.

## 7. Results

Table 2 presents the results of the post-LASSO OLS estimation, i.e. the last step of the procedure with only the selected controls. The main results are:

1. All models have a good fit: nearly 90% of variation in price index is

Table 2: Estimation results

| <i>Dependent variable:</i>    | Price Index         |                     |                     |                     |
|-------------------------------|---------------------|---------------------|---------------------|---------------------|
|                               | (1)                 | (2)                 | (3)                 | (4)                 |
| Inverse LOCI                  | 0.018*<br>(0.010)   |                     |                     |                     |
| WTP per patient               |                     | 0.064*<br>(0.036)   |                     |                     |
| Market share (E-H test)       |                     |                     | 0.046<br>(0.034)    |                     |
| Market share (rule of thumb)  |                     |                     |                     | 0.045<br>(0.075)    |
| High intensity care           | 0.235<br>(3.352)    | 0.553<br>(3.209)    | 0.637<br>(3.177)    | 0.905<br>(3.299)    |
| Complex care                  | 13.977<br>(9.679)   | 13.106<br>(9.767)   | 14.863<br>(9.609)   | 14.599<br>(9.777)   |
| Research                      | 0.044<br>(0.472)    | 0.118<br>(0.446)    | 0.190<br>(0.447)    | 0.121<br>(0.463)    |
| Referrals STZ/UMC             | 1.278***<br>(0.228) | 1.243***<br>(0.213) | 1.201***<br>(0.219) | 1.257***<br>(0.240) |
| Product category C            | 1.425*<br>(0.730)   | 1.386*<br>(0.742)   | 1.350*<br>(0.739)   | 1.327*<br>(0.741)   |
| Tertiary referrals            | 0.305<br>(0.580)    | 0.396<br>(0.600)    | -0.122<br>(0.409)   | -0.001<br>(0.680)   |
| Constant                      | 0.615***<br>(0.107) | 0.556***<br>(0.141) | 0.706***<br>(0.087) | 0.677***<br>(0.105) |
| Observations                  | 81                  | 81                  | 81                  | 81                  |
| R <sup>2</sup>                | 0.889               | 0.888               | 0.887               | 0.886               |
| Adjusted R <sup>2</sup>       | 0.878               | 0.878               | 0.877               | 0.875               |
| Residual Std. Error (df = 73) | 0.095               | 0.095               | 0.095               | 0.096               |
| F Statistic (df = 7; 73)      | 98.39***            | 92.54***            | 97.70***            | 95.71***            |

Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Heteroskedasticity-robust standard errors in parentheses.

The variable Tertiary referrals was not selected by the 2-step LASSO procedure for model (3).

We include it in the model in order to make all the specifications comparable.

The results are robust to the exclusion of this variable.

explained. The complexity variables contribute by far the most to the explanatory power of the model. This can be inferred from running a model without market power indicator. We checked for overfitting by cross validation (10 folds and 3 repetitions per model). The average  $R^2$  decreased by approximately 2%. To illustrate the fit, Figure 2 shows the predicted price levels versus the observed price levels for model (2) with WTP per patient as market power indicator, with a distinction between academic and general hospitals.

2. Our results show that the theoretically grounded models of LOCI and WTP explain prices better than the traditional methods. The p-values for the respective market power indicators are 0.075, 0.080, 0.132 and 0.552. Hence, only WTP and Inverse LOCI are significant at the 10% level. Figure 3 shows that these two indicators are highly correlated.

To illustrate the economic significance of the results, we predict prices for hospitals corresponding to the first and third quartiles of composite patient complexity and market power and compare the differences in Table 3. We use the point estimate of models (1) and (2), with respectively LOCI and WTP as measures of market power. The complexity measure used is a linear combination of the selected control variables corresponding to the complexity part of each model in Table 2. Both models result in a price change of the same size. We see that moving a hospital across the interquartile range of the market power indicator leads to a price increase of 3 or 4 percent, depending on the level of complexity. For a hospital with mean revenues, this amounts to an increase in annual health care costs between 7 and 9 million euros, depending on the level of complexity and the market power indicator. The predicted increase in costs is larger when a hospital moves on the complexity measure; the interquartile range covers 15 percent price difference.

Lastly, Figure 4 shows for the LOCI model (model (1)) the contribution of the market power indicator to the predicted price. Each bar represents a hospital and hospitals are sorted on the observed value of the price index. The

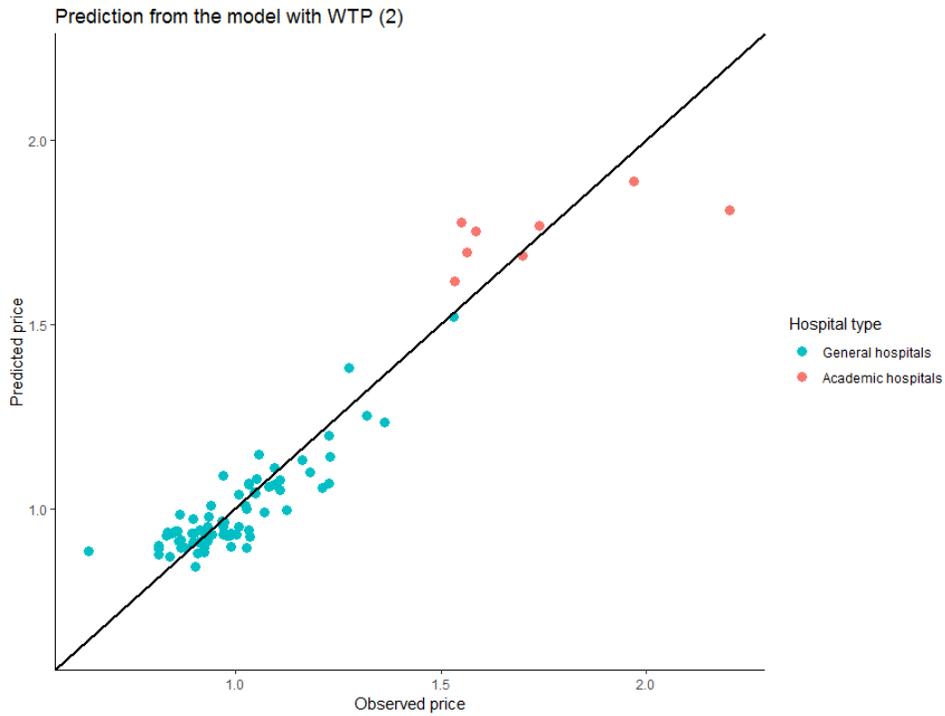


Figure 2: Scatterplot of predicted vs. observed prices

Table 3: Illustration of the size of the price effects

| Patient complexity | Market power | $\hat{P}_{LOCI}$ (1) | $\hat{P}_{WTP}$ (2) |
|--------------------|--------------|----------------------|---------------------|
| LOW                | LOW          | 0.90                 | 0.90                |
| LOW                | HIGH         | 0.93                 | 0.93                |
| HIGH               | LOW          | 1.05                 | 1.05                |
| HIGH               | HIGH         | 1.09                 | 1.09                |

Note: LOW refers to the 1st quartile, HIGH to the 3rd quartile.

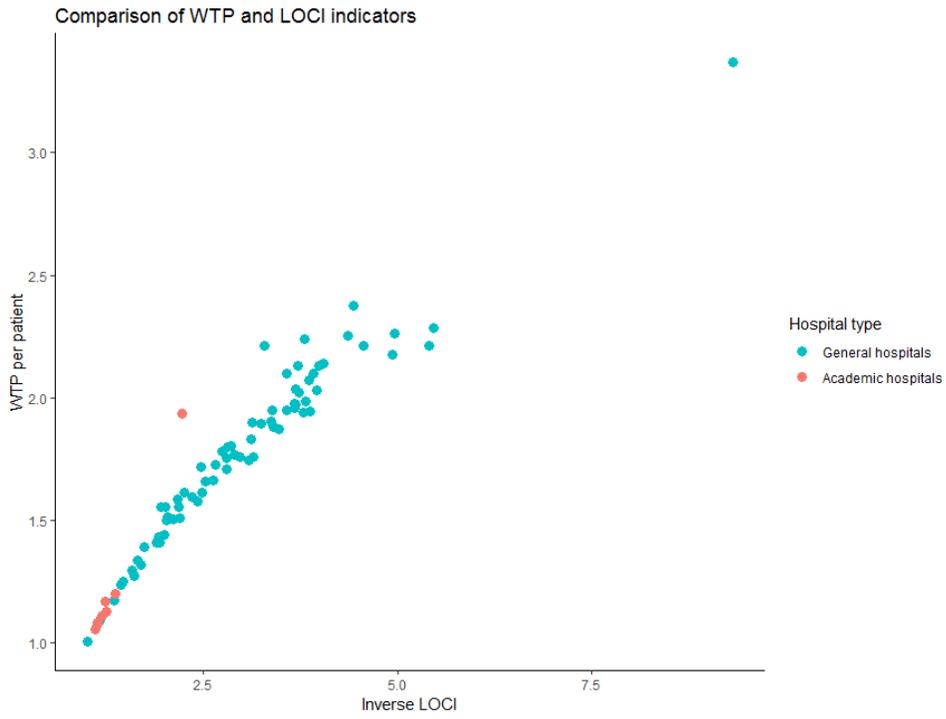


Figure 3: Scatterplot of WTP per patient vs Inverse LOCI

lower part of the bar (red) shows the contribution of the market power indicator while the upper part (blue) reflects the remaining explainers of model (1). The dot shows the observed price index. Note that we know from Figure 2 that the hospitals with the highest prices are academic hospitals. Figure 4 shows that the LOCI indicator predicts little market power for these hospitals, which is also confirmed by Figure 3 for the WTP indicator. Large catchment areas of academic hospitals explain these low values of the competition indices.

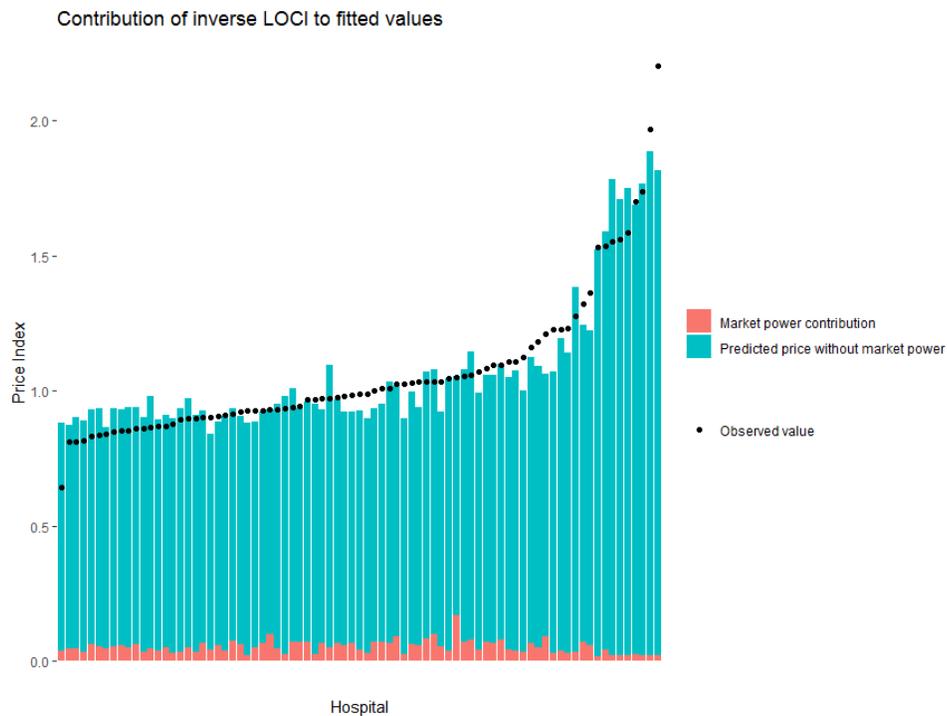


Figure 4: Contribution of market power to the price prediction

## 8. Discussion

Our empirical strategy aims at explaining variation in the price index, which is defined as the ratio of actual hospital revenue to revenue based on average

prices per patient group. The price index thus shows hospitals' abilities to secure revenues that go beyond the revenues they would obtain if their actual production volumes would be monetized with nationwide average prices. We explain nearly 90% of this variation and we believe that we capture the most important determinants. The standardized revenue captures product mix differences and thus cost differences between hospitals to some degree, but relevant cost variation in the price index remains, due to e.g. patient complexity. In our empirical setup cost variation between hospitals is modeled with patient complexity variables.

Our results show that the market power indicators explain a relatively small part of the variation. WTP per patient and LOCI are with 10% statistical significance predictors of the price index. This finding supports the theoretical notions underlying those indicators. For WTP this notion is that hospitals that negotiate in a Nash Bargaining fashion with an insurer, are able to secure a higher profit margin when consumers' revealed preferences show a higher WTP for that hospital. For LOCI, this shows that the number and size of close competitors in the differentiated Bertrand oligopoly influences prices and this notion fits the Dutch hospital market.

LOCI and WTP are both theoretically appealing since they can be derived from an economic model. Both methods can contribute to enhanced understanding of potential competitive effects from a proposed merger. Also, these measures do not require market definition, which can be seen as a major advantage given the difficulties with determining the relevant geographical region and the fact that the geographical market definition is often disputed in merger assessment cases. The market share indicators do require market definition and do not have statistically significant effects on the outcome variable. The theoretical underpinning of using market share based on a rule-of-thumb or EH test geographical market definition is weak. The results suggest that these indicators are not a suitable measure of market power when it comes to predicting hospital prices.

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