Back to the Future:

Predictive Power of the Option Demand Method in the Dutch Hospital Industry

With Anne-Fleur Roos

ACKNOWLEDGEMENTS

We are very grateful to Erik Schut, Marco Varkevisser, Danny Hughes, Misja Mikkers and Rein Halbersma for their valuable comments to the paper.

ABSTRACT

Antitrust authorities need new approaches to predict the effects of healthcare mergers. Merger simulation models are promising alternatives to highly debated traditional approaches, but they have only been validated to a limited extent. This paper evaluates the predictive power of the Option Demand method, a merger simulation model developed specifically for the US hospital market. We contrast the predictions of the merger simulation model to the estimated price effects of a consummated merger between two Dutch hospitals. We find that the Option Demand method could be a valuable addition to the antitrust agencies' toolkit, but that more research is necessary.

INTRODUCTION

In competitive markets, the aim of preventive merger control is to prohibit anticompetitive consolidation. To determine whether a merger between two (or more) firms will result in anticompetitive price increases (and/or quality decreases), antitrust authorities need to carry out an *ex ante* (prospective) review. Unfortunately, the approaches that are commonly used to prospectively review mergers are problematic. Generally, these methods first define the relevant market for the industry being studied and then use market shares to infer how the merger could affect competition in that market (Shapiro 2010; Werden and Froeb 2006). However, in order to delineate the relevant market, they typically rely on disputed methodologies and the conclusions drawn from the resulting analysis will depend heavily on how that market is defined. Moreover, these measurements are imperfect indicators of market power and so they do not necessarily reveal the actual exercise of market power. Merger reviews in the healthcare sector are subject to an additional difficulty because there are unique factors that render the most commonly used tests for measuring geographic markets less reliable in healthcare than in other sectors (Elzinga and Swisher 2011). Antitrust authorities therefore struggle to delineate the healthcare market effectively (Gaynor and Town 2012; Varkevisser and Schut 2012; Capps et al. 2002).

The most promising alternatives to these traditional approaches to review mergers are Merger Simulation Models (MSMs). The use of MSMs has clear advantages over the traditional approaches. MSMs use structural models to represent specific industries. By calibrating these models to the specifics of the market being studied, they can be used to predict the price effects of a merger directly (Werden 2005). Merger simulations take into account more than just market shares and concentration levels; they provide direct evidence and do not require or depend upon arbitrary market definitions (Argue and Shin 2009). For all these reasons, interest in MSMs is growing, both in the US and the EU (see e.g. Budzinski and Ruhmer 2009; Argue and Shin 2009; Walker 2005; Kalbfleisch 2005). However, the important question of whether MSMs are able to predict anticompetitive price increases accurately has not yet been answered conclusively. So far, MSMs have only been validated to a limited extent; they are always used in combination with traditional approaches and have rarely been subject to public scrutiny (Budzinski and Ruhmer 2009). Only merger simulation models that can produce reliable predictions are useful for merger policies, and the key issue with any merger simulation is its predictive capacity.

This paper contributes to the small, but growing, body of literature relating to the evaluation of merger simulation methods by evaluating the predictive powers of a reduced-form MSM that was developed specifically for hospital markets. The reduced-form MSM that we tested is referred to by its developers as the Option Demand method

(OD method). In the literature, this model is also referred to as the Capps, Dranove and Satterthwaite (CDS) or Willingness-to-Pay (WTP) model. The OD method is designed specifically to model markets in which managed care organizations or health insurers (selectively) contract with hospitals (Capps, Dranove, and Satterthwaite 2003; Town and Vistnes 2001). Recently, this model has been generalized by Gowrisankaran, Nevo and Town (2015)[43].

In this paper, we use the OD method to predict the price effects of a hospital merger between a general acute care hospital (hospital M1) and a neighboring general acute care hospital that also provides tertiary hospital care (hospital M2) that took place in the Dutch hospital market[44]. From the viewpoint of the Option Demand method, the current Dutch healthcare system bears evident similarities with the US healthcare system. We explicitly take the multiproduct nature of hospitals into account by examining the price effects of the hospital merger for different hospital products. We also allow for potential differences in bargaining outcomes between neighboring locations by predicting the merger effects for each location. We use an instrumental variable approach to control for potential endogeneity issues. The actual price effects of the merger that we study are determined through a difference-in-difference (DiD) technique (Roos et al. 2017). By contrasting the simulated price effects with the actual price effects of the merger, we are able to evaluate the predictive power of the Option Demand method for hospital mergers in the Dutch context.

This paper is structured as follows. In section 1, we discuss how to identify unilateral effects after a horizontal merger and we consider the small number of available studies that evaluate the accuracy of merger simulation models. Section 2 describes the Option Demand model and discusses the applicability of the Option Demand method to the Dutch healthcare industry. Section 3 focuses on the modeling details of the Option Demand method and in section 4 we focus on the details of the estimation that we carried out. Section 5 describes the data that were used and section 4 presents the results. In section 7 we briefly discuss the findings of the retrospective study and compare the simulation results with the effects of the actual merger. In section 8 we present our conclusions on the predictive power of the reduced-form merger simulation model that we have applied.

43 For an extensive review of the literature on modeling hospital competition, see Gaynor, Ho and Town (2015).

44 For reasons of confidentiality, we anonymize the merged hospitals' and health insurers' names. For the same reason, the merger year is reported as *t* (*t* lies in the period 2005 – 2012).

1. MERGER SIMULATION MODELS

A. Identifying unilateral effects after a horizontal merger

According to most national and supranational antitrust laws, mergers must be reported to an antitrust authority prior to being consummated[45]. After notification, the antitrust authorities carry out a review of the proposed merger, in which they make inferences regarding the expected anticompetitive effects of a merger in the relevant market. In general, horizontal mergers may give rise to two types of anticompetitive effects: (i) unilateral and (ii) coordinated effects. Both unilateral and coordinated effects may lead to higher post-merger prices, but prospective merger analyses focus predominantly on predicting the unilateral effects that a merger may cause (Baker 2003). In this paper, we also focus on the potential for unilateral effects.

Two methods are available to determine unilateral effects quantitatively: (i) a market definition approach and (ii) methods to predict unilateral effects directly. The market definition approach first defines the market and then hypothesizes on the merger-effect in that market. However, the market definition approach has several shortcomings, particularly when applied to the hospital industry (Dranove and Ody 2016; Elzinga and Swisher 2011; Gaynor, Kleiner, and Vogt 2011; Kaplow 2011; Shapiro 2010; Varkevisser, Capps, and Schut 2008; Capps et al. 2002). For example, the approach assumes that a product is either inside or outside the market. The products in the market are assumed to be subject to equal competitive pressure, while the products outside the market are not taken into account. However, in a market with differentiated products - which is typically the case for hospital markets - the degree of competition between two products depends on their substitutability and it is often difficult to draw meaningful boundaries between markets (Werden and Froeb 2006). Furthermore, it is only when very specific assumptions are made (e.g. homogeneous goods) that market shares can be translated into unilateral price effects (Kaplow 2011). The Elzinga-Hogarty test, in particular, has also been criticized because of its limited applicability to the hospital industry, mainly because of what has become known as the silent majority fallacy (e.g. Elzinga and Swisher 2011; Capps et al. 2001).

Given the drawbacks of the market definition approach, alternatives such as MSM that screen or predict anticompetitive effects directly and that circumvent the need for market delineation are promising alternatives.

45 See 15 USC §18A for the US and the competition laws of the EU Member States or EC:2004 for the European Union's rules on prior merger notification.

B. Merger Simulation Models

An MSM builds a structural model of the industry being studied. Typically, a structural model consists of (i) a demand model, which models the consumers' decision-making process and (ii) a model of competition, which models the supply-side of the market on the basis of the firm's behavior, the actions of its rivals and the consumer demand model. Having defined the competition model that best fits the industry being studied, the demand model can be estimated and the model of competition should be calibrated with pre-merger data. Next, a merger can be simulated by changing the ownership structure, for example by modeling that the number of competitors in a market decreases from 4 to 3 after merger (Budzinski and Ruhmer 2009).

A major issue with merger simulations is their predictive power and, thus, their credibility as a technique in the prospective merger review process (Budzinski and Ruhmer 2009). Only MSMs that are able to predict the actual effects of mergers accurately are useful for merger policy. Weinberg and Hosken (2013) stipulate that there are two methods for testing structural models: (i) the marginal costs approach, in which the actual (observed) marginal costs are contrasted with the marginal costs calculated by the calibrated simulation model; and (ii) the market structure approach, in which actual (observed) changes in price and/or quality following a merger are contrasted with the changes in price and/or quality simulated by the structural model. Budzinski and Ruhmer (2009), Werden and Froeb (2006) and Davis and Garcés (2010; chapter 8) describe both these methods in detail. Our study employs the second approach. Hence, we use past changes in market structure and the resulting price effects to test the accuracy of a (reduced-form) merger simulation model.

There are a handful of studies that have used the market structure approach to test merger simulation models. In addition to the three studies reviewed by Budzinski and Ruhmer (2009) (i.e. Pinkse and Slade 2004; Peters 2006 and Weinberg and Hosken 2013[46]), Weinberg (2011), Friberg and Romahn (2015), Greenfield, Kreisle and Williams (2015) and Björnerstedt and Verboven (2016) also apply this approach. The studies differ in their efficacy (i.e. whether they are able to accurately predict price effects). In terms of methodology, they most often use a Bertrand model to model market competition. The studies use different demand functions to reflect the differences in industries and data and they also differ in the methodology that they employ to compare the simulated price changes to the actual price changes induced by the merger. Also, none of the previous studies have focused on hospital merger cases, although the problems that arise from using the more traditional market definition approaches are particularly strik-

46 Budzinski and Ruhmer (2009) review an earlier version (working paper: Weinberg. Matthew C. and Daniel Hosken. 2008. 'Using Mergers to Test a Model of Oligopoly'. *Working paper.* University of Georgia) of Weinberg and Hosken (2013).

ing in this sector (e.g. Elzinga and Swisher 2011). A notable exception is a recent FTC working paper (Garmon 2016) that reflects on the accuracy of hospital merger screening methods. The study concludes that the market definition approach is less accurate at predicting post-merger price effects than more recently developed models, including the Option Demand method (Garmon 2016). In contrast to Garmon (2016), we do not focus on contrasting the results of traditional approaches versus MSMs but rather on the predictive powers of one reduced-form MSM that is tailor-made for the healthcare industry: the Option Demand model.

2. THE OPTION DEMAND METHOD AND ITS APPLICABILITY TO THE DUTCH HEALTHCARE SYSTEM

A. What are Option Demand markets?

The Option Demand model that we evaluate in this paper was developed by Town and Vistnes (2001) and further refined by Capps, Dranove, and Satterthwaite (2003) and Gowrisankaran et al. (2015). The papers developed a framework for analyzing bargaining relationships between hospitals and insurers under selective contracting. Under such a healthcare system, consumers buy health insurance from health insurers. The consumers decide on a specific health insurance policy on the basis of the network of hospitals that the insurance contract offers and the premium. Each hospital renegotiates the terms of its contracts with health insurers on a regular basis. The idea is that the (threat of) selective contracting of hospitals may enable insurers to negotiate lower prices and/or higher quality, which may lower premiums (Ho 2009).

The OD method builds on this two-layer model of the hospital industry; that is, it models that (i) consumers buy health insurance from health insurers before fully knowing their medical needs and (ii) health insurers bargain and contract with healthcare providers (here: hospitals) on behalf of their insured. Following Dranove and White (1996), Capps, Dranove, and Satterthwaite (2003) refer to markets that exhibit these two layers as 'Option Demand' markets (or OD markets), since the consumer commits to a possibly restricted network of hospitals when he buys health insurance prior to knowing his future healthcare needs and when he is in need of specific care, he has the option of visiting any of the contracted hospitals. The value that a consumer then places on health insurance depends on his expected demand for healthcare and the expected utility that a particular hospital from this network will provide him. This value can be expressed as Willingness-To-Pay (WTP). The notion of WTP gives an estimate of how much consumers are willing to pay *ex ante* to retain access to this hospital in the network. The WTP is therefore a proxy of the hospital's market power: a hospital with a high WTP score will be better able to secure higher prices from the health insurer than a hospital with a low WTP score (Capps, Dranove, and Satterthwaite 2003:738).

B. The applicability of the Option Demand method to the Dutch healthcare sector

To date, the OD method has been applied by Capps, Dranove, and Satterthwaite (2003), by Dranove and Sfekas (2009) and by Dranove and Ody (2016) who find a positive relationship between hospital profits and WTP. Garmon (2016) finds an imprecise relationship between prices and WTP. The OD method has also been applied by the US Federal Trade Commission (Dranove and Ody 2016; Garmon 2016).

From the viewpoint of the Option Demand method, the current Dutch healthcare system bears similarities with the US healthcare system. In recent decades, the Dutch healthcare system has moved away from strict governmental supply-side regulation and towards regulated (or 'managed') competition (Van de Ven and Schut 2008; Schut and Van de Ven 2005). Of particular importance to this paper is the gradual introduction of hospital-insurer bargaining since 2005. In 2005, a product classification system for hospital and medical specialist care was introduced. Each activity and/or hospital service associated with a patient's demand for care, including outpatient care, is referred to as a Diagnosis and Treatment Combination (or DTC)[47]. Following the introduction of the DTC system, the room for free negotiations between hospitals and health insurers on prices, volume and quality was gradually increased from 10% of hospitals' revenue in 2005, to 20% in 2008, to 34% in 2009 and to 70% in 2012. The remainder of hospital prices is regulated by the Dutch Healthcare Authority. For those services in the free-pricing segment, each hospital typically renegotiates the terms of its contracts with health insurers on an annual basis. Health insurers are allowed to contract selectively with healthcare providers.

The two-layer model that underlies the OD method seems to reflect the Dutch healthcare system accurately; consumers buy health insurance from health insurers and health insurers bargain and contract with hospitals on behalf of their enrollees. In the early years of the reform selective contracting was limitedly used. However, over the years, the number of health insurers offering contracts with restricted provider networks has increased. Furthermore, the introduction of a new Health Insurance Act has led to strong price competition between health insurers, and health insurers have put increasing pressure on hospitals to charge lower prices (Schut and Van de Ven 2011). The threat of selective contracting, rather than its actual use, may already have had an impact on

47 The DTC system is based on the concept of DRGs (Diagnosis-Related Groups) but constitutes a newly developed classification system.

hospital-insurer bargaining. We therefore consider the OD method applicable to the free-pricing segment of the Dutch hospital industry.

3. THE OPTION DEMAND METHOD: THE MODELING DETAILS

In this section, we describe how to estimate the demand model and Willingness-To-Pay (WTP) (section 3A), how to estimate the supply side and the competition model (section 3B) and how to simulate a merger with the WTP (section 3C). Our paper makes two modifications to the model by Capps, Dranove, and Satterthwaite (2003).

First, we explicitly take into account the multiproduct nature of hospitals by examining the price effects of the hospital merger for different hospital products. Typically, antitrust agencies use a cluster approach to define hospital product markets, assuming that 'acute care, in-patient services' can be considered as a single and thus homogenous hospital product. Most empirical studies follow this approach and examine the aggregated price effects of hospital mergers. However, the hospital market is highly complex due to the multiplicity of services provided and the heterogeneity of consumers, which is in turn caused by differences in medical treatment needs and third-party payer coverage. Sacher and Silvia (1998) show that using the standard in-patient cluster may mask considerable variability in the concentration statistics across the in-patient categories that make up a whole cluster. They show that disaggregation can provide a fuller understanding of the potential competitive effects of a merger in a variety of market configurations. Roos et al. (2017) also find evidence of heterogeneous price effects across products in their retrospective case study. They studied the same merger case as the one simulated in this paper. We therefore also disaggregate the effect of the merger by product markets. We estimate the impact of the merger in three separate product markets that jointly represent 47.5 per cent of the merged hospital's turnover in the segment for which Dutch insurers and hospitals at the time of the merger were allowed to freely negotiate prices. The products included in this study are hip replacements, knee replacements and cataract surgery.

Second, our study allows for potential differences in bargaining outcomes between neighboring locations of merged hospitals by predicting the merger effects for each location. Hitherto, most studies have aggregated the merger effect, thereby disregarding the fact that post-merger differences in market power for each location may lead to opportunities to differentiate pricing strategies. In the case of multiple locations, price differentiation across locations may be a profitable strategy for the merged hospital. In retrospectives studies, Roos et al. (2017) and Tenn (2011) find evidence of differential pricing strategies in hospital mergers. However, most previous studies on mergers have not controlled for this potential source of heterogeneity. We disaggregate the predicted price change for each hospital location. In sections 2C and 4, we will explain in more detail how we handled the modification of the model by Capps, Dranove, and Satterthwaite (2003) in our paper. We also discuss the relationship with the extension of the OD model by Gowrisankaran et al. (2015).

A. Step 1: demand model and Willingness-To-Pay (WTP)

Under the OD method, a consumer's demand for hospital treatment is modeled using a conditional logit demand function (see McFadden 1974). Under this model, patient *i* seeks treatment after falling ill. His health insurance gives him access to network *G* of hospitals (all the available hospitals in the market). The expected utility of patient *i* for receiving treatment at hospital *j* is given by: $U_{ij} = U(H_j, X_i, \lambda_i) + \varepsilon_{ij}$ where H_j is a vector of hospital *j* characteristics. X_i is a vector which combines the characteristics and clinical attributes of patient *i*. The patient's travel time (λ_i) is determined by the distance between the patient's location (e.g. zip code) and the hospital *j*. Under the conditional logit demand function, we assume that the residuals (ε) are i.i.d. with the double standard exponential distribution (see McFadden 1974)[48].

Using a logit demand model, the probability that patient *i* chooses hospital *j* is given by: $s_j(H_j, X_i, \lambda_i) = \frac{exp[U(H_j, X_i, \lambda_i)]}{\Sigma_{g \in G}\, exp[U(H_g, X_i, \lambda_i)]}$.

Denote the utility of patient *i* for access to network *G* as $V^{UI}(G, X_i, \lambda_i)$. The WTP of patient *i* for hospital *j*, denoted by $\Delta V_{ij}^{UI}(G, X_i, \lambda_i)$, is the reduction in V^{UI} due to the exclusion of hospital *j* from network *G*. Hence, $\Delta V_{ij}^{UI}(G, X_i, \lambda_i) = V_{ij}^{UI}(G, X_i, \lambda_i) - V_{ij}^{UI}(G/j, X_i, \lambda_i)$, where *G/j* is the network of hospitals *G* excluding hospital *j*. Capps et al. (2003) show that it follows from the logit demand that for the WTP of patient *i* for hospital *j* that:

$$\Delta V_{ij}^{UI}(G, X_i, \lambda_i) = ln\left[\frac{1}{1 - s_j(H_j, X_i, \lambda_i)}\right].$$

The *ex ante* WTP for the entire population (with *N* ill consumers) of hospital *j* is the weighted sum of the patients' WTPs (Capps, Dranove, and Satterthwaite 2003:743):

$$W_j = N \int_{X,\lambda} \tfrac{1}{\gamma} ln\left[\tfrac{1}{1 - s_j(H_j, X_i, \lambda_i)}\right] f(X_i, \lambda_i)\, dX_i\, d\lambda_i,$$

48 To avoid the IIA property that underlies the conditional logit functions, some studies use the mixed logit model to analyze patient hospital choice (see e.g. Pope 2009; Varkevisser, van der Geest, and Schut 2012). Farrell et al. (2011) find that there is almost no difference in the estimated hospital-level diversions in the patient-level mixed logit compared to the standard patient-level conditional logit model. Recent studies on hospital choice use the conditional logit model (e.g. Chandra et al. 2016; Gaynor, Propper, and Seiler 2016; Gutacker et al. 2016; Frank et al. 2015; Chou et al. 2014; Ho, and Pakes 2014).

where the population density distribution of all ill consumers is given by $f(X_i, \lambda_i)$ and constant γ convert utils into monetary terms. Since we do not observe constant γ, we use WTP up to the unidentified scale factor. For our application this is sufficient, since we are not interested in the exact value of the WTP.

We apply the discrete equivalent of the above equation to calculate the WTP of each hospital (see also Garmon 2016; Balan and Brand 2015; Farrell et al. 2011). Further, following Farrell et al. (2011), we rescale the WTP according to the hospital's expected number of patients. The rescaled discrete WTP equation for hospital j is[49]:

$$w_j = \frac{\sum_{i=1}^{N} ln\left[\frac{1}{1 - s_j(H_j, X_i, \lambda_i)}\right]}{\sum_{i=1}^{N} s_j(H_j, X_i, \lambda_i)}.$$

B. Step 2: supply side and competition model

Under the OD method, the idea is that if a hospital adds a high value to the health insurance network, it will be able to extract more profits from its negotiations and vice versa. Hospitals and insurers thus bargain according to the total value that hospital j adds to the health insurance network, i.e. w_j. Following Capps, Dranove, and Satterthwaite (2003), we model this negotiation with a reduced-form bargaining model:

$$p_j - c_j = \alpha \cdot w_j, \tag{2}$$

where p_j is the revenue per patient and c_j is the variable cost per patient. This equation thus gives the relationship between the margin of hospital j, i.e. the per-patient revenue minus the variable cost per patient, and the WTP per patient for hospital j. The per-patient gain of including hospital j in the network is split between the hospital and the insurer. Parameter α is the proportion that each hospital captures ($0 \leq \alpha \leq 1$). Parameter α is fixed and depends on the parties' relative bargaining abilities (Farrell et al. 2011).

Gowrisankaran et al. (2015) present a structural bargaining model that is more general than the Capps et al. (2003) model that we present here. Gowrisankaran et al. (2015) show that the Capps et al. (2003) model is a special case of their structural bargaining model. An important extension in the model of Gowrisankaran et al. (2015) is that patients face coinsurances. The Capps et al. (2003) model assumes that there is no coinsurance, which simplifies the bargaining model. In the Dutch market, there is no coinsurance. There is a yearly mandatory deductible that the patient pays when he starts using healthcare. However, the deductible is limited to a relatively small fixed amount (220 euro per year

49 The unscaled WTP employed by Capps, Dranove, and Satterthwaite (2003) also increases with the number of patients that a hospital treats. This is undesirable. The rescaled WTP is high only if a hospital does not have close substitutes.

in 2012). Since most hospital prices are higher than this amount, each patient receiving treatment at any hospital would generally pay the same deductible. Hence, deductibles are expected to hardly affect patient hospital choice, which implies that the no out-of-pocket payment assumption is also justifiable in our application of the model. Another extension of Gowrisankaran et al. (2015) is that they take health insurers' costs into account in the bargaining model. However, following Capps et al. (2003) and as is often done in practice (Gaynor, Ho and Town 2015), we regress WTP measures on price, and add marginal cost controls to the regression in our reduced-form merger simulation[50].

C. Step 3: merger simulation with WTP

In a merger review, antitrust authorities need to make an *ex ante* review to find out whether the merger between two (or more) hospitals will result in anticompetitive price increases. In our model, this means that we are interested in the increase in the post-merger prices of entity j+k compared to the pre-merger prices of hospitals j and k. If we know the demand, WTP and bargaining model, we can calculate the post-merger WTP of the new entity and the post-merger price increase of the merged entity by estimating α (Capps, Dranove, and Satterthwaite 2003).

This works as follows. Let us assume that we want to predict the increase in prices due to a merger between hospitals j and k. With equation (1), we can calculate the pre-merger WTP of hospitals j and k, which we will denote with w_j^{pre} and w_k^{pre}. Post-merger, hospitals j and k form one entity. The weighted joint pre-merger WTP of hospitals j and m is: $w_{j+m}^{pre} := S_j w_j^{pre} + S_k w_k^{pre}$ where S_j is the post-merger revenue share of hospital j in the merged hospital and S_k is the post-merger share of hospital k in the merged hospital. We assume that the merged firm will bargain on an all-or-nothing basis (i.e. the merged hospitals are either in or out of the insurer's network and reimbursement for patients visiting that hospital is therefore either 100% or 0%[51]). Thus, post-merger, the WTP of entity j+k is:

$$w_{j+k}^{post} = \frac{\sum_{i=1}^{N} ln\left[\frac{1}{1 - s_j(H_j, Y_i, Z_i, \lambda_i) - s_k(H_k, Y_i, Z_i, \lambda_i)}\right]}{\sum_{i=1}^{N}\left(s_j(H_j, Y_i, Z_i, \lambda_i) + s_k(H_k, Y_i, Z_i, \lambda_i)\right)}.$$

The increase in WTP due to the merger for the combined entity is then $w_{j+k}^{post} - w_{j+k}^{pre}$.

Given bargaining model (2), we can calculate the increase in the j+k entities' margin with: $\left(p_{j+k}^{post} - c_{j+k}^{post}\right) - \left(p_{j+k}^{pre} - c_{j+k}^{pre}\right) = \alpha \cdot \left(w_{j+k}^{post} - w_{j+k}^{pre}\right)$. Using equation (2) the α can be estimat-

50 In a Monte Carlo setting, Balan and Brand (2015) compared the true price effects of more general bargaining models with WTP-based merger simulation methods. They conclude that generally the WTP-based merger simulation methods perform well.

51 In practice, this is the most common negotiating strategy of hospitals. The assumption can, however, be relaxed by adapting WTP to separate bargaining scenarios (Brand and Garmon 2014).

ed and post-merger prices can be predicted. Capps, Dranove, and Satterthwaite (2003) estimate α with an OLS regression of total hospital profits on the unscaled WTP and use the above equation to predict the increase in total profits due to the merger. However, we are interested in the predicted price changes due to the merger. As is common in the MSM literature, we assume that the variable costs per patient do not change due to the merger (i.e. $c_{j+k}^{post} = c_{j+k}^{pre}$) and we can therefore rewrite the latter equation as:

$$(3) \qquad \left(p_{j+k}^{post} - p_{j+k}^{pre}\right) = \alpha \cdot \left(w_{j+k}^{post} - w_{j+k}^{pre}\right)$$

Following Balan and Brand (2013), we divide the merged entity's increase in WTP into a per-hospital WTP increase. To this end, we have to determine the post-merger WTP of hospital j and k: w_j^{post} and w_k^{post}. We do this by using two assumptions. The first assumption stipulates that the increase in the joint WTP is divided between the two hospitals according to their revenue share in the merged entity: $w_{j+k}^{post} - w_{j+k}^{pre} = S_j\left(w_j^{post} - w_j^{pre}\right) + S_k\left(w_k^{post} - w_k^{pre}\right)$. But this equation does not yet identify a unique pair (w_j^{post}, w_k^{post}), since there is an infinite number of combinations that satisfies this assumption. The second assumption therefore stipulates that the increase in the hospitals' WTP is divided in proportion to their diversion ratios:

$$\left(w_j^{post} - w_j^{pre}\right) = \tfrac{D_{jk}}{D_{kj}}\left(w_k^{post} - w_k^{pre}\right),$$

where diversion ratio D_{jk} is the share of patients from hospital j that would go to hospital k if hospital j were no longer accessible to them[52]. From the IIA property of the conditional logit model it follows that if patient i can no longer visit hospital j, the diversion of hospital j to hospital k for patient i is equal to $\frac{s_k(H_k, X_i, \lambda_i)}{1 - s_j(H_j, X_i, \lambda_i)}$ (see for example Conlon and Mortimer 2013). We calculated the weighted average diversion of hospital j to hospital k (D_{jk}) by summing over all patients and weighting each patient with their predicted share in hospital j:

$$D_{jk} = \sum_i^N \left(\frac{s_j(H_j, X_i, \lambda_i)}{\sum_i^N s_j(H_j, X_i, \lambda_i)} \frac{s_k(H_k, X_i, \lambda_i)}{1 - s_j(H_j, X_i, \lambda_i)} \right).$$

Similarly, diversion ratio D_{kj} is the share of patients from hospital k that would go to hospital j if hospital k were no longer accessible to them. Together, the above assumptions can identify the unique pair (w_j^{post}, w_k^{post}) of hospital specific post-merger WTPs. The hospital-specific increase in WTP for hospitals j and k are $\left(w_j^{post} - w_j^{pre}\right)$ and $\left(w_k^{post} - w_k^{pre}\right)$ respectively.

52 The intuition behind this assumption is that the hospital for which the diversion ratio is relatively high, can profit more from the merger.

Following equation (3), the hospital-specific price increase for hospital *j* is then given by:

(4) $\left(p_j^{post} - p_j^{pre}\right) = \alpha \cdot \left(w_j^{post} - w_j^{pre}\right).$

Similarly, the hospital-specific price increase for hospital *k* is given by:

(5) $\left(p_k^{post} - p_k^{pre}\right) = \alpha \cdot \left(w_k^{post} - w_k^{pre}\right).$

In the following, we will use equations (4) and (5) to predict the price increases resulting from the merger that we examined in this paper.

4. ESTIMATION

A. Specification of our choice model

Following Capps, Dranove, and Satterthwaite (2003), we first estimated a conditional logit model (see section 3A). Unlike Capps, Dranove, and Satterthwaite (2003), however, we ran the model for each of the products separately (rather than aggregating all the products for each hospital). We used the following specification for patient utility:

(6) $U_{ij} = \sum_j^{J-1} \alpha_j \cdot D_j + \beta_1 \cdot TRAVELTIME + \beta_2 \cdot TRAVELTIME \cdot D_{AGE} + \beta_3 \cdot TRAVELTIME \cdot D_{FEMALE} + \beta_4 \cdot TRAVELTIME \cdot SESSCORE + \varepsilon_{ij}$

where *TRAVELTIME* was the travel time in minutes from the patient's home (zip code) to the hospitals, D_{AGE} was a dummy indicating whether the patient is older or younger than 65, D_{FEMALE} was a dummy for the patient's gender and *SESSCORE* was a socio-economic status (SES) score for the patient's zip code. We estimated a fixed-effects conditional logit model. Given that there were *J* hospitals, the dummy variables in this model would pick up *J* different sets of undefined attributes (e.g. Farrell et al. 2011; Train 2009). In our data we observed that 99% of the patients will not travel more than 100 minutes for a hip or a knee replacement or cataract surgery. We therefore restricted the choice set of each patient to the hospitals reachable within 100 minutes[53]. For cataract surgery, we only estimated the conditional logit model for the patient's *first* cataract surgery. Out of all patients, 30% received more than one treatment at the same hospital. It is likely that a patient who received more than one cataract treatment at the same hospital was

53 As a robustness check several alternative patient choice sets were used. Our results are robust to these other assumptions. The results are available from the authors upon request.

treated for both the left and right eyes. In the estimation of the choice model (and the calculation of the WTP), we excluded such repeat choices by the same patient.

B. Specification of our WTP regression

For each product, we used the predicted probabilities that followed from the conditional logit estimation to calculate the WTP for the inclusion of each of the hospitals in the network using equation (1). From the estimated conditional logit (equation (6)), we calculated the per-patient probability for choosing a certain hospital. Patient type *i* chooses hospital *j* with probability:

$$\hat{s}_j(H_j, X_i, \lambda_i) = \frac{exp\left[\hat{U}(H_j, X_i, \lambda_i)\right]}{\sum_{g \in G} exp\left[\hat{U}(H_g, X_i, \lambda_i)\right]}$$

We use these probabilities and equation (1) to calculate the WTP for each hospital: $\widehat{w}_j = \frac{\sum_{i=1}^{N} ln\left[\frac{1}{1-\hat{s}_j(H_j, X_i, \lambda_i)}\right]}{\sum_{i=1}^{N} \hat{s}_j(H_j, X_i, \lambda_i)}$. The calculations were performed in R with the package MergerAnalysis (Halbersma 2013).

The next step was to regress the predicted WTPs on the prices negotiated between hospitals and insurers for hip and knee replacements and cataract surgery. We estimated the following model[54]:

$$(7) \qquad PRICE_j = c + \alpha \cdot WTP_j + \beta_1 \cdot INSURER.HHI_j + \beta_2 \cdot SESSCORE_j + \beta_3 \cdot AGE_j + \beta_4 \cdot HOUSEPRICE_j + \beta_5 \cdot HOSPITAL.TYPE_j + \beta_6 \cdot HOSPITAL.SIZE_j + \beta_7 \cdot LIBERALIZED_j + \varepsilon_j$$

where *PRICE* was the average pre-merger price (per hospital per product), *WTP* was the WTP following from equation (1) and based on the probabilities from the fixed-effects conditional logit model (equation (6)) (i.e.$\widehat{w}_j$), *INSURER.HHI* is the insurer's Herfindahl-Hirschmann Index (*HHI*) for each hospital (based on the insurer's market shares of the total revenue of the hospital, per product). To control for potential differences in hospital costs, we included the average SES-score of the patients (*SESSCORE)* and the average age of the patients (*AGE*) as proxies for hospitals' casemix differences, the average house price of the hospital's zip code (divided by 100.000) as a proxy for location-specific costs *(HOUSEPRICE)*, the hospital type (academic or general hospital[55]) (*HOSPITAL.TYPE)*, and the hospitals' size, measured in terms of the total number of beds (*HOSPITAL.SIZE)* to account for potential (dis)economies of scale. Further, we control for the per hospital frac-

54 We examined the robustness of the model by estimating the Huber M-estimator (Huber 1964) and the least trimmed squares (lts) regression (Rousseeuw and Van Driessen 1999). Both methods produced similar results. The results are available from the authors upon request.

55 Due to their low number, we did not distinguish Independent Treatment Centres (ITCs – see also footnote 24) or specialty hospitals separately in this analysis. They were treated as general hospitals.

tion of the liberalized segment (defined by the revenue of the total liberalized segment divided by the total revenue of the hospital) (*LIBERALIZED*). We report the MacKinnon and White (1985) Heteroskedasticity-Consistent standard errors.

C. Instrumental variable approach

It is possible that our predicted WTP is endogenous. There are two important sources of endogeneity. First, performance may feed back into structure, causing a simultaneous equation bias (e.g. lower prices may induce patients to go to a cheaper hospital, which in turn increases the (predicted) WTP of the hospital as derived from observed patient choices). Second, there are attributes that influence both price and patients' choice of a hospital (e.g. quality of care). These are picked up by the conditional logit model's fixed effects, causing an omitted variables bias (see also Evans, Froeb, and Werden 1993).

The common solution to these problems is to use an instrumental variables (IV) approach. Kessler and McClellan (2000), Cooper et al. (2011) and Gaynor, Morena-Serra, and Propper (2013) solve the endogeneity problem by using the predicted patient flows generated from models of patient choice. These only use observable, exogenous characteristics of patients and hospitals (Kessler and McClellan 2000). In our paper, we estimate a WTP instrument (*TRAVELTIME-WTP*) which is based on the predicted probabilities of a conditional logit model that only includes patients' travel times ($U_{ij} = \beta_1 \cdot TRAVELTIME + \varepsilon_{ij}$). Following Kessler and McClellan (2000) and Gaynor, Morena-Serra, and Propper (2013), we explicitly omit hospital-level fixed effects to prevent predicted choice being based on unobserved attributes of prices.

After determining the *TRAVELTIME-WTP*, we carried out a two-stage least square (2SLS) model where the instrument list consisted of *TRAVELTIME-WTP* (instrument for WTP), *INSURER.HHI*, *SESSCORE*, *AGE*, *HOUSEPRICE*, *HOSPITAL.TYPE*, *HOSPITAL.SIZE,* and *LIBERALIZED* (see section 5 for details on these variables).

5. Data

In this paper, we analyze the price effects of a merger between a general acute care hospital (hospital M1) and a neighboring general acute care hospital that also provides tertiary hospital care (hospital M2). The merger was consummated in the Netherlands in year *t*. We used pre-merger data (*t*-1 data) to establish what price increases the Option Demand method would have predicted if an antitrust authority had used the model in their review after being notified of the merger. We contrast the predictions obtained using the OD method with the actual price effects of the merger. The latter are determined through a difference-in-difference technique (Roos et al. 2017). In section 3 we explained that we focus on three products for which prices are freely negotiable: hip replacements, knee replacements and cataract surgery. In year *t*-1 these product markets jointly represent 47.5 percent of the merged hospital's turnover in the segment for which Dutch health insurers and hospitals were allowed to freely negotiate prices.

We use a nationwide patient-level dataset that contains all inpatient and outpatient visits for all hospital locations and Independent Treatment Centers (ITCs)[56]. For each visit, the patient's zip code, age (year of birth), gender, health insurer, diagnosis and treatment were observed, as well as the price negotiated for each hospital location-insurer-product combination in year *t*-1. The patient-level data that we used came from the insurers' claims administration and hospital registries and was provided by the Dutch Healthcare Authority.

For the choice model (see section 4A), we calculated each patient's travel time (in minutes) to the hospitals using a travel time matrix for year *t*-1. Some hospitals have multiple treatment locations, but the data does not reflect which location the patient actually went to. For hospitals with more than one treatment location, we calculated the patient's travel time (in minutes) to the closest hospital location[57]. Additionally, we obtained socio-economics status (SES) scores from the Netherlands Institute for Social Research (SCP). A higher SES score means a higher socio-economic status in the zip code area.

In the WTP regression (see section 4B), we included the average SES score and the average age. Additionally, we included the average house price for the zip code area of the hospital and the hospital types as proxies for location-specific costs. The data on house prices was obtained from Statistics Netherlands (CBS). We differentiated between academic and general hospitals (taking general hospitals as the reference group). ITCs and specialty hospitals were treated as general hospitals. The insurer's HHI was based on the insurer's market shares per product (of the total revenue of the hospital) and ranged from zero to one. Thus, the insurer's HHI for hospital *j* and product *k* was calculated as: $INSURER.HHI_{jk} = \sum_{l=1}^{n}\left(\frac{REV_{jkl}}{\sum_{l=1}^{n} REV_{jkl}}\right)^2$, where REV_{jkl} is the revenue of insurer *l* (*l*=1,..,n) in hospital *j* for product *k*. We also included the per-hospital fraction of the liberalized segment (*LIBERALIZED*), which was defined by the revenue of the whole liberalized segment divided by the total revenue of a hospital (i.e. the regulated and liberalized segments together).

56 ITCs are comparable to the freestanding Ambulatory Surgery Centers (ASCs) that operate in the US and UK healthcare markets.

57 25 hospitals had multiple locations for hip replacements and cataract surgeries. For knee replacements 27 hospitals had multiple locations. As a sensitivity check we also estimated the choice model using the patient's travel time (in minutes) to the main hospital location. This did not affect our WTP estimations. The results are available from the authors upon request.

6. RESULTS

A. Choice model

Table 1 presents summary statistics on the main variables that were included in the conditional logit model of patients' choice of hospital for hip and knee replacement and cataract surgery (panels A).

Table 2 presents the results of our estimation. We estimated two models for each product (hip, knee and cataract). Model 2 is the conditional logit model that includes patients' travel time only (see section 4C), while model 1 is the full fixed effects conditional logit model that also includes other covariates (see section 4A). The results of model 2 clearly show that, as expected, patients dislike travel time. Model 1 also takes patient heterogeneity into account by adding interaction terms. The results show that travel time interacts with age, gender and SES score, indicating that older patients prefer hospitals closer to home than younger patients and that females are less willing to travel further than men, while the higher the SES score, the greater the patients' willingness to travel. All coefficients have the expected sign and correspond with findings from other studies on patient choice in the Netherlands (e.g. Beukers, Kemp, and Varkevisser 2014; Varkevisser, Van der Geest, and Schut 2012; Varkevisser, Van der Geest, and Schut 2010). Furthermore, the goodness of fit measures that are also presented in table 2 show that our models perform well.

B. WTP regression

As discussed in section 4B, we used the estimated coefficients from the conditional logit models to calculate the Willingness-To-Pay for the inclusion of each of the hospitals in the network. We then regressed the predicted WTPs on the observed prices. Equation (7) is an OLS regression model that we estimated with and without instrumental variables (see sections 4B and 4C). Table 1 presents summary statistics on the main variables that were included in the OLS regressions (panels B).

The results of the estimation can be found in table 3. The first model is a simple ordinary least squares model with the WTP and the insurers market power vis-á-vis each individual hospital (measured by the HHI) regressed on price; model 2 adds control variables to model 1; and model 3 is a 2SLS approach with control and instrumental variables. As discussed in section 4C, we use *TRAVELTIME-WTP* as an instrument for the WTP. To determine the relevance of the instrument, we tested its correlation with the possibly endogenous regressor WTP by determining the first-stage F-statistic (Stock and Yogo 2005; Staiger and Stock 1997). Our first-stage F-statistic was 62.617 (p-value = 0.00) for hip replacement, 39.549 (p-value = 0.00) for knee replacement and 181.51 (p-value = 0.00) for cataract surgery. This indicates that our instrument (*TRAVELTIME-WTP*) is strongly correlated with the WTP. The Wu-Hausman statistic was 0.16 (p-value = 0.68) for

Table 1. Descriptive statistics

Variable	Mean	Standard deviation	Minimum	Maximum	Observations
Hip replacements					
Panel A. Patient characteristics					
Age	69.2	10.5	16	99	*N* = 20846
Age Dummy (>65)	0.66	-	0	1	*N* = 20846
Gender (female)	0.68	-	0	1	*N* = 20846
SES score in the zip code area	-0.002	1.000	-5.437	3.813	*N* = 20846
Travel time (in minutes)	12.60	13.15	0.00	99.96	*N* = 20846
Panel B. Hospital characteristics					
Patients' average age	69.0	2.7	55.1	0.6	*n* = 82
Patients' average SES score	-0.023	0.361	-0.909	0.639	*n* = 82
Price hip replacement (in €)	9092.00	293.29	8527.00	10408.00	*n* = 82
Willingness-To-Pay	1.813	0.885	1.024	7.234	*n* = 82
Instrument Willingness-To-Pay (TRAVELTIME-WTP)	1.666	0.676	1.056	5.177	*n* = 82
Academic hospital	0.09	-	0	1	*n* = 82
ITC	0	-	0	1	*n* = 82
Insurers' HHI	0.391	0.134	0.163	0.795	*n* = 82
Housing price in the zip code area (€1000)	193.9	32.9	134.0	266.0	*n* = 82
Hospital size (number of beds)	512.7	275.0	138.0	1575.0	*n* = 82
The hospital's share of the liberalized segment (LIBERALIZED)	0.11	0.04	0.02	0.23	*n* = 82
Knee replacements					
Panel A. Patient characteristics					
Age	69.0	9.9	20	97	*N* = 17558
Age Dummy (>65)	0.65	-	0	1	*N* = 17558
Gender (female)	0.69	-	0	1	*N* = 17558
SES score in the zip code area	-0.002	1.001	-5.148	2.772	*N* = 17558
Travel time (in minutes)	13.25	14.15	0	99.71	*N* = 17558
Panel B. Hospital characteristics					
Patients' average age	69.0	2.0	64.1	74.6	*n* = 85
Patients' average SES score	0.009	0.357	-0.869	0.791	*n* = 85
Price knee replacement (in €)	11493.00	390.69	9756.00	10689.00	*n* = 85
Willingness-To-Pay	1.712	0.795	1.019	6.628	*n* = 85
Instrument Willingness-To-Pay (TRAVELTIME-WTP)	1.579	0.589	1.045	4.576	*n* = 85
Academic hospital	0.09	-	0	1	*n* = 85
ITC					*n* = 85
Insurers' HHI	0.408	0.127	0.618	0.783	*n* = 85
Housing price in the zip code area (€1000)	194.1	32.2	134.0	266.0	*n* = 85
Hospital size (number of beds)	509.3	272.3	140.0	1575.0	*n* = 85

Variable	Mean	Standard deviation	Minimum	Maximum	Observations
The hospital's share of the liberalized segment (LIBERALIZED)	0.11	0.03	0.02	0.23	$n = 85$
Cataract surgery					
Panel A. Patient characteristics					
Age	73.5	10.4	0.0	110.0	$N = 103750$
Age Dummy (>65)	0.81	-	0	1	$N = 103750$
Gender (female)	0.61	-	0	1	$N = 103750$
SES score in the zip code area	0.000	1.000	-6.171	2.809	$N = 103750$
Travel time (in minutes)	11.30	11.35	0.00	99.99	$N = 103750$
Panel B. Hospital characteristics					
Patients' average age	73.3	2.3	63.5	77.0	$n = 86$
Patients' average SES score	-0.031	0.385	-1.148	0.627	$n = 86$
Price cataract surgery (in €)	1365.00	83.80	1046.00	1547.00	$n = 86$
Willingness-To-Pay	1.875	0.846	1.018	5.795	$n = 86$
Instrument Willingness-To-Pay (TRAVELTIME-WTP)	1.782	0.805	1.056	5.766	$n = 86$
Academic hospital	0.08	-	0	1	$n = 86$
Insurers' HHI	0.421	0.128	0.210	0.694	$n = 86$
Housing price in the zip code area (€1000)	192.5	33.4	134.0	284.0	$n = 86$
Hospital size (number of beds)	488.3	289.35	0.0	1575.0	$n = 86$
The hospital's share of the liberalized segment (LIBERALIZED)	0.12	0.06	0.02	0.44	$n = 86$

Notes: Summary statistics refer to t-1, where t is the merger year. N = total number of patients that underwent hip or knee replacements or cataract surgeries. The total number of patients that underwent cataract surgery only includes the patient's first cataract surgery. n = total number of hospitals in the sample. We calculated the patient's travel time (in minutes) to the closest hospital location.

hip replacement, 2.39 (p-value = 0.13) for knee replacement and 0.24 (p-value = 0.63) for cataract surgery. This indicates that the variable WTP is not endogenous.

The average price for hip replacements is €9,092 (table 1). Table 3 indicates that a one-unit increase in WTP will increase prices for hip replacements by €88.69 (model 2). Following Capps, Dranove, and Satterthwaite (2003), we show how to interpret the magnitude of this estimate by considering the hospital with the highest *WTP* (i.e. *WTP*: 7.234 –table 1) and the hospital with the lowest *WTP* (i.e. *WTP*: 1.024 –table 1). Using the results of model 2, the WTP difference of 6.210 translates into a difference in the price of a hip replacement of €550.76.

For knee replacements and cataract surgeries, the WTP is not significantly related to price. Apparently, in our regression model, WTP does not explain the variation in prices for knee replacement and cataract surgeries. This means that in the market for knee

Table 2. Conditional logit model of patient hospital choice for hip and knee replacements and cataract surgery[a]

	Hip replacements		Knee replacements		Cataract surgery	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Time	-0.1266***	-0.1488***	-0.1248***	-0.1504***	-0.1343***	-0.1668***
	(0.0018)	(0.0010)	(0.0018)	(0.0011)	(0.0010)	(0.0005)
Time * Age	-0.0590***		-0.0460***		-0.0551***	
	(0.0020)		(0.0019)		(0.0011)	
Time * Female	-0.0031		-0.0025		-0.0088***	
	(0.0020)		(0.0020)		(0.0010)	
Time * SES-score	0.0085***		0.0104***		0.0072***	
	(0.0011)		(0.0011)		(0.0006)	
Observations	20846	20846	17558	17558	103750	103750
McFadden's R^2	0.68	0.64	0.65	0.61	0.72	0.67
Hit-and-miss	0.70	0.69	0.67	0.66	0.70	0.68

Notes: Models estimated by conditional logit model with standard errors in parentheses under coefficients. Model 2 is the conditional logit model that only includes patients' travel time (see section 4C), while model 1 includes a full set of hospital dummies (not reported here) and other covariates (see section 4A). The conditional logit models are estimated on data from *t*-1, where *t* is the merger year. We restricted the patients' choice sets to the hospitals reachable within 100 minutes.

[a] For clarity reasons, we do not report the hospital dummies (fixed effects) here. The results are available from the authors upon request.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

replacements and cataract surgeries using the WTP for the WTP-based merger simulation is less meaningful than in the market for hip replacements.

7. USING THE WTP FOR ANTITRUST PURPOSES

In this section, we contrast the *ex ante* predicted price effects with the actual *ex post* price effects of a merger between a general acute care hospital (hospital M1) and a neighboring general acute care hospital that also provides some types of tertiary hospital care (hospital M2).

The actual price effects were determined through a difference-in-differences technique (Roos et al. 2017). For a detailed discussion of the method, data and results of the difference-in-differences technique, we refer to Roos et al. (2017). In sum, Roos et al. (2017) use data on hospital-insurer negotiated contract prices in the Netherlands for each of the three hospital products considered, to investigate whether the merger between hospitals M1 and M2 has led to price changes. They first estimate an aggregated difference-in-differences model ($\ln p_{ht} = \alpha + \sum_{j=1}^{N-1} \beta_j D_j + \lambda \cdot D_{t+1} + \delta \cdot D_{t+1} \cdot D_{merged} + \varepsilon_{ht}$)

Table 3. Willingness-To-Pay models for hip and knee replacements and cataract surgery

	Model 1	Model 2	Model 3
Hip replacements			
(intercept)	9238.21*** (100.09)	8075.17*** (1515.84)	8027.90*** (1519.47)
WTP	76.21** (33.28)	88.69** (40.00)	94.40** (42.44)
INSURER.HHI	-727.75** (294.38)	-894.08*** (324.63)	-909.52*** (335.73)
SESSCORE		-91.61 (101.93)	-95.51 (104.86)
AGE		16.81 (20.00)	17.30 (20.11)
HOUSEPRICE		-0.24 (0.98)	-0.18 (0.98)
HOSPITAL.TYPE		151.25 (220.69)	154.75 (220.79)
HOSPITAL.SIZE		0.09 (0.19)	0.09 (0.19)
LIBERALIZED		279.38 (2298.29)	256.06 (2295.96)
IV	NO	NO	YES: TRAVELTIME-WTP
Observations	82	82	82
R-Squared	0.10	0.13	0.13
Adjusted R-Squared	0.08	0.04	0.04
Knee replacements			
(intercept)	10857.12*** (170.90)	10805.00*** (1947.40)	10619.25*** (1917.42)
WTP	14.38 (105.15)	3.00 (125.09)	37.90 (122.47)
INSURER.HHI	-473.89 (433.23)	-5381.80 (450.97)	-613.11 (447.91)
SESSCORE		21.99 (136.89)	-3.59 (138.74)
AGE		8.25 (26.70)	9.88 (26.27)
HOUSEPRICE		-2.12 (1.63)	-1.76 (1.62)
HOSPITAL.TYPE		153.74 (277.65)	156.39 (282.73)
HOSPITAL.SIZE		-0.06 (0.21)	-0.06 (0.21)
LIBERALIZED		-394.23 (2938.10)	-605.29 (2903.94)
IV	NO	NO	YES: TRAVELTIME-WTP
Observations	85	85	85
R-Squared	0.02	0.06	0.06
Adjusted R-Squared	-0.00	-0.04	-0.04
Cataract surgery			
(intercept)	1319.70*** (35.50)	803.25 (899.40)	295.27 (899.51)
WTP	1.26 (9.70)	-2.17 (10.79)	-5.94 (10.77)
INSURER.HHI	100.78 (71.39)	33.65 (89.72)	47.49 (89.22)
SESSCORE		-19.57 (32.78)	-17.03 (33.09)
AGE		10.12 (11.09)	10.30 (11.09)
HOUSEPRICE		-0.34 (0.36)	-0.36 (0.36)
HOSPITAL.TYPE		74.51 (83.95)	75.24 (83.43)
HOSPITAL.SIZE		-0.07 (0.05)	-0.07 (0.05)
LIBERALIZED		-828.47 (331.48)	-822.98** (338.05)

	Model 1	Model 2	Model 3
IV	NO	NO	YES: TRAVELTIME-WTP
Observations	86	86	86
R-Squared	0.03	0.41	0.41
Adjusted R-Squared	0.00	0.35	0.35

Notes: Per product we report three models. The first model is a simple OLS model with the WTP and the insurers' market power vis-á-vis each individual hospital regressed on price. Model 2 adds control variables to model 1 and model 3 is a 2SLS model that adds control and instrumental variables. We report the MacKinnon and White (1985) Heteroskedasticity-Consistent standard errors (in parentheses under coefficients). We used data from *t*-1, where *t* is the merger year. Note that the R^2 for cataract surgeries is much higher than the R^2 for hip and knee replacements. This is due to a higher number of ITCs in the market for cataract surgeries.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

and then, to show the effect of aggregating over products, locations and insurers, they remove the aggregations stepwise. The pre-merger price was based on data from the year preceding the merger (*t*-1) and the post-merger price was based on data from the year after the merger (*t*+1). Table 4 summarizes the estimated merger effects on prices of hip replacement, knee replacement and cataract surgery for hospitals M1 and M2 in comparison with the average price change pre- and post-merger in a control group. Roos et al. (2017) find evidence of heterogeneous price effects for a merger between neighboring hospitals across hospital products and hospital locations. Their result is robust for different control groups and different model specifications.

The *ex ante* predictions for merger-induced price increases were calculated using the Option Demand method as described in section 3C. Table 5 displays the predicted WTP increases. To see how a merger affects WTP, we looked at the change in the predicted WTPs. In the case of hip replacements, the WTP for hospital M1 increased by 25.7%, and the WTP for hospital M2 increased by 11.7%. Both of these increases were substantial. In general, patients are more willing to pay for the inclusion of hospital M1 than hospital M2. This is not surprising because the merger also had a differential impact on the structure of the market in which the hospitals were competing. Hospital M1 is located in an isolated geographical area and hospital M2 was the largest competitor to hospital M1 pre-merger. Hospital M2, in contrast, is subject to notable competitive pressure from (at least) five other hospitals in the three submarkets studied in this paper. Note that table 4 suggests that the price increases are higher for hospital M1 than for hospital M2, a finding which is only statistically significant for hip replacements.

Next, the increase in the hospital specific prices due to merger can be determined using equations (4) and (5). From equations (4) and (5) it follows that we were able to calculate the predicted increase in prices for hospital *j* as:

Table 4. Merger effect on prices of hip and knee replacements and cataract surgery for hospitals M1 and M2 in comparison to average price changes pre- and post-merger in a control group (retrospective analysis)

	Merger effect on price (DiD coefficient)
Panel A. Hospital M1	
Hip replacements	0.090* (0.053)
Knee replacements	0.021 (0.062)
Cataract surgery	0.027 (0.057)
Panel B. Hospital M2	
Hip replacements	-0.035 (0.053)
Knee replacements	-0.064 (0.062)
Cataract surgery	-0.049 (0.057)

Notes: Time period is *t*-2 and *t*+2, where *t* is the merger. Models estimated by OLS with standard errors in parentheses under coefficients. Null hypothesis: difference-in-difference estimator is equal to zero.
Source: Roos et al. 2017.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

$$(8) \qquad \frac{\hat{a}(w_j^{post} - w_j^{pre})}{\widehat{PRICE}_j},$$

where $\widehat{PRICE}_j$ is the fitted pre-merger price of hospital *j* and $\hat{a}$ is the estimated coefficient of the WTP that is obtained by equation (7). As discussed above, we only estimate the predicted price increases for hip replacements. Table 6 compares the results with the *ex post* estimates.

We constructed 90% and 95% confidence intervals for the predicted and estimated price increases using the student *t* distribution of $\hat{a}$ and treatment effect, respectively. Care should be taken in interpreting the results as the *ex post* estimates have large confidence intervals.

The merger simulation showed that the prices for hip replacements in hospitals M1 and M2 were likely to increase significantly, although at a different magnitude. The confidence intervals of the predicted price increases are all nested within the confidence intervals of the actual price increases. Given that the confidence intervals of the *ex post* estimates are quite large, however, we should be cautious in interpreting this result as evidence that the OD method is able to accurately predict price increases after merger. If we were to ignore this for a moment, because Roos et al. (2017) showed that the *ex post* estimation was robust for different control groups and different model specifications, table 6 suggest that OD method overestimates the price effects for hospital M2 and underestimates the price effects for hospital M1.

Table 5. Hospital specific change in WTP after merger for hip and knee replacements and cataract surgery

	Pre-merger price (mean in €)	Pre-merger WTP	Absolute increase in WTP after merger
Panel A. Hospital M1			
Hip replacements	9135.66	4.668	1.199
Knee replacements	10693.64	4.706	0.994
Cataract surgery	1393.25	3.655	1.530
Panel B. Hospital M2			
Hip replacements	9064.99	2.296	0.268
Knee replacements	10645.73	2.021	0.322
Cataract surgery	1358.92	2.500	0.157

Notes: For the pre-merger WTP, we used data from *t*-1, where *t* is the merger year (WTP estimation using the results from table 3, model 2). For the change in WTP after merger, we used data from *t*-1 and *t*+1, where *t* is the merger year (change in WTP using the results from table 3, model 2).

Table 6. Predicted and estimated price increases for hip replacements due to merger

	Ex ante predictions (by the Option Demand Method)			*Ex post* estimates (by the difference-in-differences estimates)		
	% price increases	95% CI	90% CI	% price increase	95% CI	90% CI
Panel A. Hospital M1						
Hip replacements	1.16	[0.12 –2.21]	[0.29 – 2.04]	9.00	[-1.63 – 19.63]	[0.13 – 17.87]
Panel B. Hospital M2						
Hip replacements	0.26	[0.03 – 0.50]	[0.07 – 0.46]	-3.50	[-14.13 – 7.13]	[-12.37 – 5.37]

Notes: The increases in the hospital specific prices due to merger are determined using equations 4 and 5. The *ex post* estimates are obtained using a difference-in-differences technique, which is reported in Roos et al. (2017).

8. CONCLUSION

The aim of this paper is to examine the predictive power of the option demand (OD) method for hospital mergers. Like other merger simulation models (MSMs), the OD method has clear advantages over more traditional market definition approaches because it provides antitrust agencies with direct evidence about the expected effects of the merger and does not require questionable assumptions to be made on the relevant (geographic) market. Also, studies that contrasted the predictions by the OD method and several traditional measures concluded that the OD model outperforms ad hoc measures in predicting prices (Garmon 2016; Dranove & Ody 2016).

Antitrust agencies should aim to use MSMs that are able to explain outcomes in the relevant market reasonable well, for example by demonstrating that the model accurately predicts the effects of mergers in the same industry (Budzinsky and Ruhmer 2009; Werden, Froeb, and Scheffman 2004). We have contrasted the findings of this prospective method of analysis with the findings of a retrospective study involving a consummated Dutch hospital merger (Roos et al. 2017). Our results indicate that there is a relationship between WTP and prices for hip replacements. We were not able to establish a relationship between WTP and prices for knee replacements and cataract surgeries. We therefore only estimated a reduced-form merger simulation for hip replacements. The comparison between the reduced-form merger simulation and *ex post* estimates suggest that the OD method overestimates the price effects for hospital M2 and underestimates the price effects for hospital M1. Yet, the overestimation is not statistically significant.

Garmon (2016) also finds mixed results for the performance of the reduced-form merger simulation in the US. Hence, we conclude that although the OD method could be a valuable addition to the antitrust agencies' toolkit in signaling potentially anticompetitive merger effects, our findings also indicate that more research is necessary. For example, the explanatory power of our regression models is quite low. This may either indicate that the model needs to be reconsidered to find factors that have higher explanatory power or that the model does not (yet) fit the Dutch healthcare market well enough. With respect to the latter, we concluded in section 2B that the OD method is applicable to the free-pricing segment of the Dutch hospital industry. However, the industry is in transition and the number of health insurers offering contracts with restricted provider networks has increased over the years. As the OD method depends upon the bargaining relationship between health insurers and hospitals, we expect that the relationship between WTP and price will get stronger as the threat of selective contracting becomes more credible.

REFERENCES

Argue, David A., and Richard T. Shin. 2009. "An Innovative Approach to an Old Problem: Hospital Merger Simulation" *Antitrus*t 24 (1): 49-54.

Baker, Jonathan B. 2003. "Why did the antitrust agencies embrace unilateral effects?" *George Mason Law Review* 12 (1): 31-37.

Balan, David J., and Keith Brand. 2013. "Simulating hospital merger simulations". *Working paper.*

Balan, David J., and Keith Brand. 2015. "Simulating hospital merger simulations". *Unpublished Draft.* Available at https://works.bepress.com/david_balan/7/

Brand, Keith, and Christopher Garmon. 2014. *Hospital Merger Simulation*. Member Briefing Antitrust Practice Group: American Health Lawyers Association.

Beukers, Puck D.C., Ron G.M. Kemp, and Marco Varkevisser. 2014. "Patient hospital choice for hip replacement: empirical evidence from the Netherlands" *European Journal of Health Economics* 15(9): 927-936.

Björnerstedt, Jonas, and Frank Verboven. 2016. "Does merger simulation work? Evidence from the Swedish analgesics market" *American Economic Journal: Applied Economics* 8 (3): 125-164.

Budzinski, Oliver, and Isabel Ruhmer. 2009. "Merger Simulation in Competition Policy: a Survey" *Journal of Competition Law and Economics* 6 (2): 277-319.

Capps, Cory, David Dranove, and Mark Satterthwaite. 2003. "Competition and market power in option demand markets" *The RAND journal of economics* 34 (4): 737-763.

Capps, Cory, David Dranove, Shane Greenstein, and Mark Satterthwaite. 2002. "Antitrust policy and hospital mergers: recommendations for a new approach" *The Antirust Bulletin* 47: 677-714.

Capps, Cory, David Dranove, Shane Greenstein, and Mark Satterthwaite. 2001. *The silent majority fallacy of the Elzinga-Hogarty criteria: a critique and new approach to analyzing hospital mergers*. "NBER Working Paper 8216". Cambridge: National Bureau of Economic Research.

Chandra, Amitabh, Amy Finkelstein, Adam Sacarny, and Chad Syverson. 2016. "Health Care Exceptionalism? Performance and Allocation in the US Health Care Sector" *American Economic Review* 106 (8): 2110-2144.

Chou, Shin-Yi, Mary .E. Deily, Suhui. Li, and Yi Lu. 2014. "Competition and the impact of online hospital report cards" *Journal of Health Economics* 34 (1): 42-58.

Cooper, Zack, Stephen Gibbons, Simon Jones, and Alistair McGuire. 2011. "Does hospital competition save lives? Evidence from the English NHS patient choice reforms" *The Economic Journal* 121: 228-260.

Conlon, Christopher, and Julie Mortimer. 2013. *An Experimental Approach to Merger Evaluation*. "NBER working paper 19703". Cambridge: National Bureau of Economic Research.

Davis, Peter J., and Eliana Garcés. 2010. *Chapter 8: Merger Simulation*. In: "Quantitative techniques for competition and antitrust analysis". (eds. Davis. P.J. & E. Garcés). Princeton: Princeton University Press. 382-434.

Dranove, David, and Christopher Ody. 2016. "Evolving measures of provider market power" *American Journal of Health Economics* 2 (2): 145-160.

Dranove, David, and Andrew Sfekas. 2009. "The Revolution in Health Care Antitrust: New Methods and Provocative Implications" *The Milbank Quarterly* 87 (3): 607-632.

Dranove, David, and William D. White. 1996. "Specialization, Option Demand and the Pricing of Medical Specialists" *Journal of Economics and Management Strategy* 5: 277-306.

Elzinga, Kenneth G., and Anthony W. Swisher. 2011. "Limits of the Elzinga-Hogarty Test in Hospital Mergers: The Evanston Case" *International Journal of the Economics of Business* 18 (1): 133-146.

European Commission (EC). 2004. *Guidelines on the assessment of horizontal mergers under the Council Regulation on the control of concentrations between undertakings. (2004/C 31/03)*. "Official Journal of the European Union" C 31: 5-18.

Evans, William N., Luke M. Froeb, and Gregory J. Werden. 1993. "Endogeneity in the concentration-price relationship: causes, consequences and cures" *The Journal of Industrial Economics* 4: 431-438.

Farrell, Joseph, David J. Balan, Keith Brand, and Brett W. Wendling. 2011. "Economics at the FTC: Hospital Mergers, Authorized Generic Drugs, and Consumer Credit Markets" *Review of Industrial Organization* 39 (4): 271-296.

Frank. Matthew B., John Hsu, Mary Beth Landrum, and Michael E. Chernew. 2015. "The impact of a tiered network on hospital choice" *Health Services Research* 50 (5): 1628-1648.

Friberg, Richard, and André Romahn. 2015. "Divestiture requirements as a tool for competition policy: A case from the Swedish beer market" *International Journal of Industrial Organization* 42: 1- 18.

Garmon, Christopher. 2016. "The Accuracy of Hospital Merger Screening Methods". *Working paper Federal Trade Commission*. Washington DC: Federal Trade Commission.

Gaynor, Martin, Kate Ho, and Robert J. Town. 2015. „The Industrial Organization of Health-Care Markets" *Journal of Economic Literature* 53 (2): 235-284.

Gaynor, Martin, Samuel A. Kleiner., and William B. Vogt. 2011. *A Structural Approach to Market Definition with an Application to the Hospital Industry* "NBER working paper 16656". Cambridge: National Bureau of Economic Research.

Gaynor, Martin, Carol Propper, and Stephan Seiler. 2016. "Free to Choose? Reform, Choice and Considation Sets in the English National Health Service" *American Economic Review* 106 (11): 3521-3557.

Gaynor, Martin, Rodrigo Moreno-Serra, and Carol Propper. 2013. "Death by Market Power: Reform, Competition, and Patient Outcomes in the National Health Service" *American Economic Journal: Economic Policy* 5 (4): 134-66.

Gaynor, Martin, and Robert J. Town. 2012. *Chapter 9. Competition in Health Care Markets*. In: "Handbook of Health Economics Volume 2". (eds: McGuire, T., M.V. Pauly & P.P. Barros). Amsterdam: Elsevier North-Holland. 499-637.

Gowrisankaran. G., A. Nevo & R. Town. 2015. "Mergers when prices are negotiated: Evidence from the hospital industry" *American Economic Review* 105 (1): 172-203.

Greenfield, Daniel, Nicholas Kreisle, and Mark Williams. 2015. *Simulating a Homogeneous Product Merger: A Case Study on Model Fit and Performance* "Federal Trade Commission Working paper 327" Washington: Federal Trade Commission.

Gutacker, Nils, Luigi Siciliani, Giuseppe Moscelli, and Hugh Gravelle. 2016. "Choice of hospital: Which type of quality matters?" *Journal of Health Economics*. 50: 230-246.

Halbersma, Rein. 2013. "MergerAnalysis: Merger Analysis package". R package version 0.9.6. http://www.R-project.org/

Ho, Katherine, and Ariel. Pakes. 2014. "Hospital choices, hospital prices, and financial incentives to physicians" *American Economic Review* 104 (12): 3841-3884.

Ho. Katherine. 2009. "Insurer-Provider Networks in the Medical Care Market" *American Economic Review* 99 (1): 393-430.

Huber, Peter J. 1964. "Robust estimation of a location parameter" *The Annals of Mathematical Statistics* 35 (1): 73-101

Kalbfleisch, Pieter. 2005. *European Merger Control: A Case of Second Mover Advantage?* In: "Modeling European Mergers: Theory, Competition Policy & Case Studies". (eds. Bergeijk, van, P.A.G. & E. Kloosterhuis). Cheltenham: Edward Elgar Publishing Limited. 27-34.

Kaplow, Louis. 2011. "Market Definition and the Merger Guidelines" *Review of Industrial Organization* 39 (1-2): 107-125.

Kessler, Daniel, and Mark McClellan. 2000. "Is hospital competition socially wasteful?" *Quarterly Journal of Economics* 115 (2): 577-615.

MacKinnon, James G., and Halbert White. 1985. "Some Heteroskedasticity-Consistent Covariance Matrix Estimators with Improved Finite Sample Properties" *Journal of Econometrics* 29: 305–325.

McFadden, Daniel. 1974. *Conditional logit analysis of qualitative choice behavior*. In: "Frontiers in econometrics" (ed. Zarembka, P.). New York: Academic Press. 105-142.

Peters, Craig. 2006. "Evaluating the Performance of Merger Simulation: Evidence from the US Airline Industry" *The Journal of Law & Economics* 49 (2): 627-649.

Pinkse, Joris, and Margaret E. Slade. 2004. "Mergers, brand competition and the price of a pint" *European Economic Review* 48 (3): 617-643.

Pope, Devin G. 2009. "Reacting to rankings: Evidence from "America's Best Hospitals" *Journal of Health Economics* 28 (6): 1154-1165.

Roos, Anne-Fleur, Ramsis R. Croes, Victoria Shestalova, Marco Varkevisser, and Frederik T. Schut. 2017. *Price effects of a hospital merger: heterogeneity across health insurers, hospital products and hospital locations*. "Working paper April 2017". Rotterdam: Erasmus University Rotterdam.

Rousseeuw, Peter J., and Katrien van Driessen. 1999. "A fast algorithm for the minimum covariance determinant estimator" *Technometrics* 41: 212–223.

Sacher, Seth, and Louis Silvia. 1998. "Antitrust issues in defining the product market for hospital services" *International Journal of the Economics of Business* 5 (2): 181-202.

Schut, Frederik T., and Wynand P.M.M van de Ven. 2005. "Rationing and competition in the Dutch healthcare system" *Health Economics* 14: S59-S74.

Schut, Frederik T., and Wynand P.M.M. van de Ven. 2011. "Effects of purchaser competition in the Dutch health system: is the glass half full or half empty?" *Health Economics, Policy and Law* 6: 109-123.

Shapiro, Carl. 2010. "The 2010 Horizontal Merger Guidelines: From Hedgehog to Fox in Fourty Years" *Antitrust Law Journal* 7: 701-759.

Staiger, Douglas, and James H. Stock. 1997. "Instrumental Variables Regression with Weak Instruments" *Econometrica* 65: 557-586.

Stock, James H., and Motohiro Yogo. 2005. *Testing for Weak Instruments in Linear IV Regression*. In: "Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg". (eds. Andrews, D.W.K., and J.H. Stock). Cambridge: Cambridge University Press. 80-108.

Tenn, Steven. 2011. "The Price Effects of Hospital Mergers: A Case Study of the Sutter-Summit Transaction" *International Journal of the Economics of Business* 18 (1): 65-82.

Town, Robert J., and Gregory Vistnes. 2001. "Hospital competition in HMO networks" *Journal of Health Economics* 20 (5): 733–753.

Train, Kenneth. 2009. *Chapter 2: Properties of Discrete Choice Models*. In: "Discrete choice methods with simulation" (2nd ed.). New York: Cambridge University Press. 11-75.

Walker, Mike. 2005. "The Potential for Significant Inaccuracies in Merger Simulation Models" *Journal of Competition Law & Economics* 1 (3): 473-496.

Weinberg, Matthew C., and Daniel Hosken. 2013. "Evidence on the Accuracy of Merger Simulations" *Review of Economics and Statistics* 95 (5): 1584-1600.

Weinberg, Matthew C. 2011. "More Evidence on the Performance of Merger Simulations" *American Economic Review* 101 (3): 51-55.

Werden, Gregory J. 2005. *Merger Simulation: Potentials and Pitfalls*. In: "Modeling European Mergers: Theory, Competition Policy & Case Studies". (eds. Bergeijk, van P.A.G., and E. Kloosterhuis). Cheltenham: Edward Elgar Publishing Limited. 37-52.

Werden, Gregory J., and Luke M. Froeb. 2006. *Chapter 2: Unilateral Competitive Effects of Horizontal Mergers*. In: "Handbook of Antitrust Economics". (ed. P. Buccirossi). Cambridge: MIT Press. 43-104.

Werden, Gregory J., Luke M. Froeb, and David T. Scheffman. 2004. "A Daubert Discipline for Merger Simulation." *Antitrust Magazine* 18 (3): 89-95.

Varkevisser, Marco, Cory Capps, and Frederik T. Schut. 2008. "Defining hospital markets for antitrust enforcement: new approaches and their applicability to The Netherlands" *Health Economics, Policy and Law* 3 (1): 7-29.

Varkevisser, Marco, Stéphanie A. van der Geest, and Frederik T. Schut. 2010. "Assessing hospital competition when prices don't matter to patients: the use of time-elasticities" *International Journal of Health Care Finance and Economics* 10 (1): 43-60.

Varkevisser, Marco, Stéphanie A. van der Geest, and Frederik T. Schut. 2012. "Do patients choose hospitals with high quality ratings? Empirical evidence from the market for angioplasty in the Netherlands" *Journal of Health Economics* 31 (2): 371-378.

Varkevisser, Marco, and Frederik T. Schut. 2012. "The impact of geographic market definition on the stringency of hospital merger control in Germany and the Netherlands" *Health Economics, Policy and Law*. 7: 363-381.

Ven, van de. Wynand P.M.M., and Frederik T. Schut. 2008. "Universal Mandatory Health Insurance in The Netherlands: a Model for the United States?" *Health Affairs* 27 (3): 771-781.