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Do Hospital Mergers Reduce Waiting Times? Theory and Evidence from the English NHS[*]

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Abstract

We analyse—theoretically and empirically—the effect of hospital mergers on waiting times in healthcare markets where prices are fixed. Using a spatial modelling framework where patients choose provider based on travelling distance and waiting times, we show that the effect is theoretically ambiguous. In the presence of cost synergies, the scope for lower waiting times as a result of the merger is larger if the hospitals are more profit-oriented. This result is arguably confirmed by our empirical analysis, which is based on a conditional flexible difference-in-differences methodology applied to a long panel of data on hospital mergers in the English NHS, where we find that the effects of a merger on waiting times crucially rely on a legal status that can reasonably be linked to the degree of profit-orientation. Whereas hospital mergers involving Foundation Trusts tend to reduce waiting times, the corresponding effect of mergers involving hospitals without this legal status tends to go in the opposite direction.

Keywords: Hospital merger; waiting times; profit-orientation.

JEL Classification: I11; I18; L21; L41.

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1 Introduction

Waiting times for elective treatments is a major policy concern in a number of OECD countries, particularly in countries with a publicly funded healthcare system where waiting times act as a non-price rationing mechanism.[1] For common procedures like cataract operation, hip replacement and knee replacement, the median waiting times across 17 OECD countries in 2018 were 95, 110 and 140 days, respectively, but with large cross-country variation (OECD, 2020). In many countries, efforts to reduce waiting times for these and other elective treatments have been largely unsuccessful over the past decade, and waiting times are expected to increase even further in the wake of the COVID-19 pandemic (OECD, 2020). Besides the obvious patient utility losses due to postponement of health benefits, long waiting times may also aggravate symptoms and lead to worse health outcomes.

Governments in various countries have implemented a number of different policy measures in order tackle the problem of excessively long waiting times (see, e.g., Siciliani et al., 2013). Some of these policies are linked to competition (Sá et al., 2019) and are thus in line with a dominant policy trend over the past decades, where many countries have introduced or reinforced various types of market based reforms that stimulate provider competition within publicly funded healthcare systems. One example is the internal market in the English NHS, where hospital competition is fostered through a combination of patient choice and activity-based funding, and several other countries have created similar 'quasi-markets' for health care provision.[2] These policy reforms have been implemented with the aim of improving the efficiency and quality of healthcare provision, also in terms of lower waiting times.

At the same time, one perhaps inevitable consequence of the marketisation of healthcare provision has been a marked increase in hospital merger activity, leading to increasingly consolidated hospital markets in many countries (Mariani et al., 2022).[3] Are such consolidations likely to contribute towards lowering waiting times for elective treatments, or are they instead aggravating the problem of excessively long waiting times? As in markets for other goods or services, a hospital merger might yield benefits in the form of more efficient provision of healthcare, but it also leads to higher market concentration and thus potentially less competition. Both types

[1] In the recent OECD Waiting Times Policy Questionnaire, respondents from 26 out of 34 countries categorise waiting times as a 'high' or 'medium-high' health policy priority (OECD, 2020).

[2] Siciliani et al. (2017) give an overview of similar policies in five other European countries.

[3] Based on a survey study on mergers among Dutch healthcare executives, Postma and Roos (2016) find some indications that hospital mergers have been completed partly in response to increased competitive pressure brought about by market based policy reforms.

of effects might in turn have non-trivial consequences for waiting times, and the purpose of the present paper is to investigate—both theoretically and empirically—how hospital mergers affect waiting times for elective treatments.

In order to identify the potential theoretical mechanisms at play, we build a model of hospital competition with regulated prices in a spatial framework, based on Brekke et al. (2008), where patients make their choice of provider based on travelling distance and waiting times, and where hospital objectives are given by a combination of profits and patient utility. The assumption of semi-altruistic hospitals implies that the equilibrium outcome is such that the marginal patient is financially unprofitable to treat, which has important implications for the effect of a merger on waiting times. In such a setting, we show that a merger between two competing hospitals leads to an internalisation of two different competition externalities, related to (i) altruistic competition to attract patients, and (ii) profit-oriented competition to avoid treating unprofitable patients. The internalisation of the first (second) externality contributes to higher (lower) waiting times, all else being equal. In addition, a merger might also imply some cost synergies that allow the merged entity to treat patients in a more cost-efficient way, which in turn will contribute to a waiting time reduction in equilibrium. While the overall effect of a hospital merger on waiting times is theoretically ambiguous, we provide an exact characterisation of the conditions under which this effect is either positive or negative. A key insight from this analysis is that, in the presence of treatment cost synergies, the scope for lower waiting times as a result of the merger is larger if the hospitals are more profit-oriented (less altruistic).

In the empirical part of our analysis, we use 20 years of panel data on English NHS hospitals to estimate econometrically whether hospital mergers has had a significant effect on waiting times in a context that institutionally matches our theoretical model, where hospitals compete for patients under regulated prices. Estimating unbiased effects of mergers is notoriously challenging, and in order to deal with the potential problems of selection bias we employ a state-of-the-art empirical strategy that is based on a combination of propensity score matching and difference-in-differences (DID) methodology. More specifically, we use the flexible conditional DID approach proposed by Dettmann et al. (2020), which is a modification of the matching and DID approach of Heckman et al. (1998) for the staggered treatment adoption design (as in Callaway and Sant'Anna, 2021), to estimate the average treatment effect for the treated with time-varying treatment and variable duration.

We find few indications that hospital mergers have any significant effects on waiting times in estimations based on the full set of mergers. However, our empirical analysis also reveals that the absence of significant effects masks an important heterogeneity among hospitals. By using hospitals' legal status (whether or not they are so-called Foundation Trusts) as a proxy for their degree of profit orientation, we show that mergers involving more profit-oriented hospitals lead to significant reductions in waiting times, whereas the opposite is the case for less profit-oriented (more altruistic) hospitals.[4] These findings are in line with the results from our theoretical model in the presence of cost synergies from the merger.[5] Thus, the effects of hospital mergers on waiting times crucially depends on how profit-oriented the hospitals are. This is the main result emanating from our paper, both theoretically and empirically.

Our paper makes both theoretical and empirical contributions to the literature. To the best of our knowledge, we offer the first formal theoretical analysis of the effects of hospital mergers on waiting times in a context of regulated prices. This analysis complements the theoretical analysis of the effect of hospital mergers on treatment quality by Brekke et al. (2017) for a similar institutional context.[6,7] Although waiting times could be seen as a form of 'negative quality', there are important differences between these two variables which imply that results from models of quality competition do not automatically carry over to the case of waiting times.[8] In this sense, our theoretical analysis in the present paper is more closely related to the existing theoretical literature on the more general relationship between competition and waiting times in regulated hospital markets, which has been studied in a static context by Brekke et al. (2008) and in a dynamic context by Sá et al. (2019). In relation to this literature, the most novel aspect of our theoretical analysis is that we show how the presence of cost synergies makes hospitals' degree of profit orientation a key factor in determining the effects of a merger on waiting times.

We also contribute to the relatively scant empirical literature on the effects of hospital mergers on waiting times in healthcare markets with regulated prices.[9] A key contribution to

[4] Having a legal status as Foundation Trust implies that the hospital has a considerable degree of autonomy in terms of governance and financial flexibility, including the ability to retain financial surpluses, which makes it reasonable to assume that they are on average more profit-oriented than hospitals without this autonomy.

[5] In a relatively recent empirical study, Schmitt (2017) finds significant costs savings of between 4 and 7 per cent in the years following a merger. Overall, though, the empirical literature on the cost effects of hospital mergers paints a mixed picture.

[6] Han et al. (2017) perform an experimental analysis of the effects of hospital mergers on quality based on the model by Brekke et al. (2017).

[7] In a somewhat different institutional context, Bisceglia et al. (2023) consider a mixed oligopoly with two private and one public healthcare provider and study theoretically the effects of a merger between the two private providers on prices, quality and welfare.

[8] A crucial difference between quality and waiting times is that, while increasing quality has a direct and an indirect cost for the provider, reducing waiting times only has an indirect cost through a higher demand.

[9] Our paper also relates more generally to a wider empirical literature on the effects of hospital mergers on a

this literature is Gaynor et al. (2012). Using similar hospital data from the English NHS, but during an earlier and much shorter time period, they find that hospital mergers lead on average to an increase in waiting times. A similar positive effect of hospital mergers on waiting times is also found by Westra et al. (2022) using data from Netherlands. On the other hand, Johar and Savage (2014) find less clear-cut effects of hospital mergers in New South Wales, Australia, with positive waiting time effects for some patient groups and negative effects for others.[10] We contribute to this literature in at least four different ways. First, the length of our panel allows us to estimate effects over a longer time period than in previous studies. Second, we take advantage of recent econometric developments of alternative DID approaches based on the assumption of heterogeneous treatment (e.g., Athey and Imbens, 2022; Imai et al., forthcoming; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Dettmann et al., 2020) that allows us to estimate the average treatment effect for the treated with time-varying treatment and variable duration. Third, we explore the importance of hospital objectives and show that the effects of mergers on waiting times depend crucially on the whether the merging hospitals are profit-oriented or not. And finally, our theoretical analysis allows us to interpret and relate our empirical findings to potential theoretical mechanisms in a way that is missing from the existing empirical literature.

The rest of the paper is organised as follows. The theoretical model and analysis are presented in Section 2. In Section 3 we describe the institutional background for our empirical analysis, whereas our empirical strategy is laid out in Section 4. In Section 5 we describe the data and main variables, and show some descriptive statistics. Our empirical results are presented and discussed in Section 6. Finally, some concluding remarks are offered in Section 7. Additional details on the theoretical as well as on the empirical models are contained in the Appendix.

2 Theoretical model

We conduct our theoretical analysis within a modelling framework based on Brekke et al. (2008). Consider a publicly funded market for healthcare where three hospitals are equidistantly located

wide range of outcomes, including service mix (e.g., Krishnan et al., 2004), efficiency (e.g., Dranove, 1998; Preyra and Pink, 2006), quality (e.g., Ho and Hamilton, 2000) and output (e.g., Cirulli and Marini, 2023).

[10] Christiansen and Vrangbæk (2018) report a reduction in average waiting times following a structural reform in the Danish hospital market leading to fewer and larger hospitals. However, since this is a purely descriptive analysis, not much can be said about causal effects.

on a circle with circumference equal to one. Patients are uniformly distributed on the same circle, which we can interpret as representing either a geographical space or a disease space. With the former interpretation, the distance between a hospital and a particular patient represents the patient's physical travelling distance to that hospital. With the latter interpretation, the same distance represents the mismatch between the patient's specific diagnosis and the speciality mix (i.e., the treatments and services) offered by the hospital.

Each of the patients may benefit from being treated at one of the hospitals in the market and can freely choose which hospital to attend. Because of public insurance, we assume that hospital treatment is free of charge for the patients. However, each patient that decides to seek treatment at one of the hospitals is required to join a waiting list and therefore suffers the disutility of waiting, in addition to the disutility caused by travelling (or mismatch).

Apart from patient heterogeneity in the horizontal dimension (location on the circle), we assume that patients also differ along another dimension. More specifically, we assume that a fraction λ of the patients have no valuable outside option (i.e., the utility of not seeking treatment at one of the hospitals is zero), whereas the remaining patients have an outside option that gives a strictly positive utility $\gamma > 0$. Thus, γ also measures the difference in outside options for the two patient types. We can interpret this difference either as a difference in patient severity (the utility of being untreated is higher for lower-severity patients) or as a difference in the ability to seek treatment in another market (some patients might be covered by insurance that enables them to seek treatment in the private sector, for example). We assume that the densities of the two patient types are constant along the entire circle.

2.1 Patient utility and demand

The utility of a patient with no valuable outside option who is located at x and seeks treatment at Hospital i, located at z_i, is given by

$$u(x, z_i) = v - w_i - t|x - z_i|, \tag{1}$$

where $v > 0$ is the gross valuation of treatment, w_i is the waiting time at Hospital i, and $t > 0$ measures the marginal disutility of travelling.[11] The equivalent utility of an otherwise similar

[11] Since we have normalised the marginal disutility of waiting to one, we can interpret t as the disutility of travelling relative to waiting.

patient with a valuable outside option is given by

$$\widehat{u}(x, z_i) = v - \gamma - w_i - t|x - z_i|. \tag{2}$$

Throughout the analysis we will focus on equilibrium outcomes in which every patient with no valuable outside option seeks treatment at one of the hospitals in the market, while some of the remaining patients will choose to exercise their (valuable) outside option. This implies that, in equilibrium, hospitals compete only in the demand segment consisting of patients with no valuable outside option. In the remaining demand segment, each hospital is a local monopolist. We will subsequently refer to these two demand segments as the competitive and monopolistic segments, respectively.

Let the hospitals that are adjacent to Hospital i in the clockwise and anti-clockwise directions be denoted by $i+1$ and $i-1$, respectively.[12] If every patient in the competitive segment makes a utility-maximising choice of hospital, the patient who is indifferent between Hospital i and a neighbouring Hospital j is located at a distance from Hospital i given by

$$x_{i,j}^c = \frac{1}{6} + \frac{w_j - w_i}{2t}, \quad j = i-1, i+1. \tag{3}$$

Since each hospital has two competing neighbours, and since the density of patients in the competitive segment is constant and equal to λ, the demand for Hospital i from this segment is given by

$$q_i^c(\mathbf{w}) = \lambda\left(x_{i,i-1}^c + x_{i,i+1}^c\right) = \lambda\left(\frac{1}{3} + \frac{w_{i-1} + w_{i+1} - 2w_i}{2t}\right), \tag{4}$$

where $\mathbf{w} = (w_i, w_{i-1}, w_{i+1})$.

In the monopolistic segment, each patient chooses between attending the nearest hospital or opting out of the market. If every patient in this segment makes a utility-maximising choice, the patient who is indifferent between being treated at Hospital i and exercising the outside option is located at a distance from Hospital i given by

$$x_i^m = \frac{v - \gamma - w_i}{t}. \tag{5}$$

Since there are indifferent patients on both sides of each hospital, and since the density of patients in the monopolistic segment is constant and equal to $1-\lambda$, the demand for Hospital i

[12] This implies a slight abuse of notation, since $i+1 = 1$ if $i = 3$ and $i-1 = 3$ if $i = 1$.

from this segment is given by

$$q_i^m(w_i) = 2(1-\lambda)x_i^m = \frac{2(1-\lambda)(v-\gamma-w_i)}{t}. \tag{6}$$

Total demand for Hospital i, from both segments, is thus given by

$$q_i^d(\mathbf{w}) = q_i^c(\mathbf{w}) + q_i^m(w_i) = \frac{2(1-\lambda)(v-\gamma-w_i)}{t} + \frac{\lambda}{3} - \frac{\lambda}{t}w_i + \frac{\lambda}{2t}(w_{i-1}+w_{i+1}). \tag{7}$$

Notice that demand for Hospital i is decreasing in own waiting time and increasing in the waiting times of the competing hospitals. Notice also that demand responds stronger to waiting time changes in the monopolistic than in the competitive segment. Thus, a higher value of λ (i.e., a relatively larger competitive segment) reduces the demand-responsiveness to own waiting time.

2.2 Hospital objectives

We assume that hospitals are prospectively financed by a third-party payer offering a lump-sum transfer T and a fixed per-treatment price p. The cost of hospital treatments is given by a strictly convex cost function $C_i(q_i^s)$, where q_i^s is Hospital i's supply of treatments. The strict convexity of the cost function captures an important feature in the context of waiting times, namely that hospitals face some capacity constraints which make it increasingly costly to expand the supply of treatments. The profits of Hospital i are thus given by

$$\pi_i = T + pq_i^s - C_i(q_i^s). \tag{8}$$

However, we adopt the commonly used assumption that hospitals have semi-altruistic objectives, maximising a weighted average of profits and patient utility. More specifically, we assume that the objective function of Hospital i is given by

$$\Omega_i = \alpha\pi_i + (1-\alpha)B_i, \tag{9}$$

where B_i is the total utility of the patients being treated at Hospital i. The parameter $\alpha \in (0,1)$ can thus be interpreted as the degree to which Hospital i is profit oriented. In the extreme case of $\alpha = 1$, the hospital is a pure profit-maximiser.

Regarding the hospitals' semi-altruistic preferences, we make the arguably reasonable assumption that each hospital has a greater concern for its own patients than for patients treated by other hospitals. For analytical convenience, we make the simplifying assumption that each hospital cares only about its own patients.[13] The total utility of patients treated by Hospital i, which depends both on how many patients are treated and how long they have to wait, is given by

$$\begin{aligned} B_i(\mathbf{w}) &= \lambda \left(\int_0^{x^c_{i,i-i}} (v - w_i - ts)\, ds + \int_0^{x^c_{i,i+1}} (v - w_i - ts)\, ds \right) \\ &\quad + 2(1-\lambda) \int_0^{x^m_i} (v - \gamma - w_i - ts)\, ds. \end{aligned} \tag{10}$$

The effect of a higher waiting time at Hospital i on the total utility of its patients is the sum of the utility effects for marginal and inframarginal patients, and can be expressed as

$$\frac{\partial B_i(\mathbf{w})}{\partial w_i} = -q^d_i(\mathbf{w}) - \frac{\lambda}{t}\left(v - \frac{t}{6} - \frac{2w_i + \sum_{j \neq i} w_j}{4} \right) < 0. \tag{11}$$

The first term in (11) is the utility loss for inframarginal patients, arising from the fact that the hospital's patients have to wait longer for treatment. Additionally, the demand loss associated with a higher waiting time means that fewer patients will be treated at the hospital. The corresponding utility loss at the margin is zero in the monopolistic segment (since, for the marginal patient in this segment, the value of being treated at Hospital i is equal to the value of the outside option), but strictly positive in the competitive segment. The utility loss associated with lower demand in the competitive segment is captured by the second term in (11).

2.3 Equilibrium waiting times

Our analysis rests on the basic assumption that, similar to a price, waiting time acts as an equilibrating mechanism between supply and demand, which implies that $q^d_i(\mathbf{w}) = q^s_i$ in equilibrium.[14] As in Brekke et al. (2008), we assume that the hospitals play a simultaneous-move game in which each hospital announces a waiting time for being treated, taking as given the waiting times announced by the competing hospitals. Each hospital will then supply treatments at a level which equals demand at the announced waiting times. Notice that the convexity of the treatment cost function makes it costly for a hospital to lower its waiting time, since the

[13] We can interpret this as the hospitals exhibiting 'warm-glow' altruistic preferences.

[14] This is the standard assumption in the literature since the seminal paper by Lindsay and Feigenbaum (1984). See Brekke et al. (2008) for a more elaborate discussion of this assumption.

corresponding demand increase implies that the hospital must operate at higher marginal cost. We also assume that hospitals cannot discriminate between different types of patients or turn down any patient who seeks treatment. Thus, we do not allow for explicit rationing. Demand is only implicitly rationed through waiting times.

Substituting $q_i^d(\mathbf{w})$ from (7) for q_i^s in (8), the maximisation problem of Hospital i is given by

$$\max_{w_i} \Omega_i(\mathbf{w}) = \alpha \left(T + p q_i^d(\mathbf{w}) - C_i\left(q_i^d(\mathbf{w})\right)\right) + (1-\alpha) B_i(\mathbf{w}). \quad (12)$$

Deriving the first-order condition for this maximisation problem and applying symmetry (i.e., $w_i = w_{i-1} = w_{i+1}$), the Nash equilibrium waiting time, equal for all hospitals and denoted w^*, is implicitly given by

$$\alpha \left(p - \frac{\partial C_i(\cdot)}{\partial q_i} \right) \frac{\partial q_i^d(w^*)}{\partial w_i} + (1-\alpha) \frac{\partial B_i(w^*)}{\partial w_i} = 0. \quad (13)$$

The key mechanisms of the model can be deduced from (13). Consider first the special case of purely profit-maximising hospitals; i.e., $\alpha = 1$. In this case, the second term in (13) vanishes and the equilibrium waiting time is given by the level at which price is equal to marginal treatment costs for each hospital. This can be explained as follows. A profit-maximising hospital wants to attract patients as long as they are profitable to treat; i.e., as long as the regulated price p exceeds the marginal treatment cost. Regardless of the waiting times set by competing hospitals, each hospital maximises its own profits by setting a waiting time such that the profit contribution from the marginal patient is zero. Since the price is fixed and not dependent on waiting times, each hospital has one instrument (waiting time) to control one variable (marginal cost) and there are therefore no competition externalities between the hospitals.[15]

This changes when hospitals have semi-altruistic preferences. For any $\alpha < 1$, the second term in (13) is negative (since $\partial B_i / \partial w_i < 0$). This implies that the first term must be positive in equilibrium. Since $\partial q_i^d / \partial w_i < 0$, the first term is positive only if the price is lower than marginal cost. Thus, if $\alpha < 1$, the equilibrium waiting times are such that each hospital operates at a negative price-cost margin.[16] In such an equilibrium, there are two different competition

[15] This property does not depend on symmetry. In an asymmetric game between profit-maximising hospitals with different treatment costs, the Nash equilibrium would be a set of waiting times implicitly given by a set of first-order conditions similar to (13), where these waiting times are such that the price is equal to marginal treatment cost for each hospital.

[16] When treatment costs are strictly convex, notice that a negative price-cost margin does not mean that profits are negative, even for $T = 0$..

externalities at play. (i) Since the hospitals' semi-altruistic preferences are such that they care more about their own patients than the patients treated by competing hospitals, each hospital has an incentive to reduce its own waiting time in order to attract more patients. In other words, the hospitals' waiting time decisions are partly determined by *altruistic competition for patients*. (ii) Since the hospitals operate at a negative price-cost margin in equilibrium, this means that the marginal patient is financially unprofitable to treat. Thus, for purely profit-oriented reasons, each hospital has an incentive to increase its own waiting time in order to steer unprofitable patients towards neighbouring hospitals. In other words, the hospitals' waiting time decisions are also partly determined by *competition to avoid treating unprofitable patients*. The equilibrium waiting time is at a level where the conflicting incentives given by (i) and (ii) are optimally balanced.

In order to derive closed-form solutions, we assume that the treatment cost function of Hospital i takes the following quadratic form:

$$C_i\left(q_i\right) = \frac{c}{2}q_i^2, \tag{14}$$

where the parameter $c > 0$ captures the degree of cost convexity. Let us first determine the strategic nature of the game, which is given by the sign of the following expression:

$$\frac{\partial^2 \Omega_i}{\partial w_i \partial w_j} = \lambda \frac{2\alpha\left(2-\lambda\right)c - \left(1-\alpha\right)t}{4t^2} > 0. \tag{15}$$

The positive sign of (15) is ensured by imposing the parameter conditions needed to ensure equilibrium existence (see the Appendix for details), and implies that waiting times are *strategic complements*. This strategic complementarity results from two counteracting incentives. Notice first that $\partial^2 \pi_i / \partial w_i \partial w_j = \lambda\left(2-\lambda\right)c/2t^2 > 0$. If Hospital j increases its waiting time, this results in more patients choosing the neighbouring Hospital i, all else being equal. This inflow of patients increases Hospital i's marginal treatment costs, making the marginal patient less profitable (or more unprofitable) to treat, which in turn gives Hospital i an incentive to increase its waiting time for profit-related reasons. On the other hand, notice that $\partial^2 B_i / \partial w_i \partial w_j = -\lambda/4t < 0$. In other words, the demand inflow to Hospital i caused by the higher waiting time at Hospital j increases Hospital i's altruistic incentive to attract more patients.[17] Thus,

[17] Since $\partial B_i / \partial w_i < 0$, a lower (more negative) value of $\partial B_i / \partial w_i$ implies that the increase in B_i resulting from a marginal reduction in w_i is larger.

for purely altruistic reasons, Hospital i has an incentive to respond to a higher waiting time at Hospital j by *lowering* its own waiting time. Nevertheless, it turns out that, within the parameter space for which the Nash equilibrium exists, the former (profit-oriented) incentive dominates, making waiting times strategic complements.

By solving the maximisation problem of Hospital i and applying symmetry, i.e., $w_i = w_{i-1} = w_{i+1} = w^*$, we derive the closed-form solution for the Nash equilibrium waiting time:

$$w^* = \frac{2(2-\lambda)\alpha((\lambda c - 3p)t + 6(1-\lambda)c(v-\gamma)) - (1-\alpha)t(\lambda t + 6(\lambda v + 2(1-\lambda)(v-\gamma)))}{6(2-\lambda)(2\alpha(1-\lambda)c - (1-\alpha)t)}. \tag{16}$$

In order for the equilibrium to exist, some parameter restrictions need to be imposed. More specifically, we need to impose both a lower and upper bound on the cost parameter c, such that $\underline{c} < c < \overline{c}$. In other words, the degree of cost convexity cannot be too low nor too high. In addition, we also need to impose a lower bound on the difference in outside options for the two patient types, such that $\gamma > \underline{\gamma}$. Further details are provided in the Appendix.

2.4 Hospital merger

Suppose that Hospital i and a neighbouring Hospital j merge. We will here assume that a merger only implies a coordination of waiting time choices, such that the merged entity chooses w_i and w_j to maximise $\Omega_i + \Omega_j$. Consider the choice of w_i. The first-order condition for the optimal choice is given by

$$\frac{\partial \Omega_i}{\partial w_i} + \frac{\partial \Omega_j}{\partial w_i} = 0. \tag{17}$$

Let the equilibrium waiting time at Hospital i (which is now a branch of the merged entity) be given by w_i^{**}. Since $(\partial \Omega_i / \partial w_i)|_{w^*} = 0$ and $\Omega_i + \Omega_j$ is globally concave in waiting times, it must be the case that

$$w_i^{**} > (<)\, w_i^* \quad \text{if} \quad \left.\frac{\partial \Omega_j}{\partial w_i}\right|_{w^*} > (<)\, 0. \tag{18}$$

Due to symmetry, a similar condition applies for w_j^{**}. Thus, the effect of the merger on the merging hospitals' waiting times depends on the sign of $\partial \Omega_j / \partial w_i$ when evaluated at the pre-merger equilibrium. Since waiting times are strategic complements, it follows that the hospital not taking part in the merger will adjust its waiting time in the same direction as the merger participants, but with a smaller magnitude. Using (16), we derive

$$\left.\frac{\partial \Omega_j}{\partial w_i}\right|_{w^*} = \frac{\lambda(1-\alpha)}{6t(2-\lambda)}\left[6(1-\lambda)\gamma - t\right], \tag{19}$$

which allows us to reach the following conclusions:

Proposition 1 *(i) If hospitals are pure profit-maximisers, a merger has no effect on waiting times for any of the hospitals in the market.*

(ii) If hospitals are semi-altruistic, there exists a threshold value of γ*, given by*

$$\widehat{\gamma} := \frac{t}{6(1-\lambda)} > \underline{\gamma}, \tag{20}$$

such that a merger will lead to higher (lower) waiting times at the merged hospitals if $\gamma > (<)\, \widehat{\gamma}$*.*

(iii) The waiting time of the hospital that does not take part in the merger will move in the same direction as the waiting times of the merged hospitals, but with a smaller magnitude of change.

The proof follows straightforwardly from (19) and a comparison of $\widehat{\gamma}$ and $\underline{\gamma}$.[18]

The intuition behind the results in Proposition 1 follows from the identification of competition externalities in the pre-merger game, which were discussed in the previous subsection. In case of profit-maximising hospitals ($\alpha = 1$), there are no competition externalities, so a merger without any synergies has no effect on waiting times. On the other hand, if hospitals are semi-altruistic ($\alpha < 1$), we know that there are two different competition externalities in the pre-merger game that go in opposite directions. The altruistic competition for patients implies that each hospital has an incentive to set waiting times lower than what is jointly optimal, while the profit-oriented competition to avoid treating unprofitable patients gives each hospital an incentive to set waiting times higher than what is jointly optimal. Both of these effects are internalised by the merger, and whether the merger leads to higher or lower waiting times depends on the relative strength of the two competition externalities. If the altruistic externality is relatively stronger, the merger leads to higher waiting times. On the other hand, if the profit-related externality is stronger, waiting times will go down as a result of the merger.

[18] Using the expression for $\underline{\gamma}$ from (A9) in the Appendix, it is straightforward to show that

$$\widehat{\gamma} - \underline{\gamma} = \frac{(2-\lambda)\alpha t p}{2(1-\lambda)((2-\lambda)\alpha c - (1-\alpha)t)} > 0.$$

Which type of externality is stronger depends crucially on three parameters: γ, λ and t. All else equal, the scope for a merger to increase waiting times is larger if (i) the difference in outside options for the two patient types (γ) is higher, (ii) the relative size of the competitive segment (λ) is smaller, and/or (iii) the disutility of travelling (t) is smaller. Each of these three parameters affects the relative strength of the two competition externalities through different, and partly counteracting, mechanisms. We will here identify and describe only the dominating ones.

For the first two parameters (γ and λ), the dominating mechanism is the same. A higher value of γ implies that fewer patients in the monopolistic segment seek treatment at one of the hospitals in the market. All else equal, this reduces the demand for each hospital. A similar demand reduction occurs if the share of patients with a viable outside option is higher (i.e., if λ is lower). Because of treatment cost convexity, lower demand reduces the marginal treatment cost, which in turn increases the price-cost margin. Consequently, when the marginal patient becomes less unprofitable to treat, the profit-related competition externality becomes relatively less important, which increases the scope for the altruistic competition externality to dominate, and thus increases the scope for a merger to increase waiting times.

For the parameter t, the dominating mechanism is somewhat different. All else equal, a lower disutility of travelling increases the net utility of treatment for each patient, and it also makes demand more responsive to waiting times. Both of these effects imply that the increase in total patient utility at Hospital i, resulting from a marginal reduction in w_i, is higher, which in turn increases the marginal altruistic gain of lowering waiting times for Hospital i (i.e., the second term in (11) becomes larger in absolute value). In turn, this increases the relative importance of the altruistic competition externality, and thus increases the scope for higher waiting times as a result of the merger.

An alternative to a two-hospital merger is that all three hospitals merge, which implies merger to monopoly. The resulting effects on waiting times follow very intuitively from the above analysis. The direction of the waiting time effect is still determined by whether γ is above or below $\widehat{\gamma}$, but the *magnitude* of the effect, whether positive or negative, is larger in a three-hospital merger, since all competition externalities are internalised in a merger to monopoly. In the Appendix we present closed-form solutions for the post-merger waiting times in the cases of both a two-hospital and three-hospital merger.

2.5 Cost synergies

In the previous subsection we analysed the effects of a hospital merger under the assumption that such a merger only implies a coordination of waiting time decisions. In other words, a merger works exclusively as a device to internalise competition externalities between the merging hospitals. However, a merger might also enable the merging hospitals to realise some cost synergies that allow them to treat their patients more efficiently. In order to consider the potential effects of such synergies, suppose that the merger yields a reduction in the cost parameter c, such that the post-merger treatment cost function for Hospital i, if it takes part in the merger, is given by

$$C_i(q_i) = \frac{c-\delta}{2} q_i^2. \tag{21}$$

where $\delta > 0$ measures the magnitude of the cost synergies. The cost function of the hospital that does not take part in the merger is unaffected.

Consider once more a merger between Hospital i and Hospital j. As before, the first-order condition for the optimal choice of w_i in the post-merger game is given by (17), and the merger will lead to a higher (lower) waiting time at the merged hospitals if

$$\left.\frac{\partial \Omega_i}{\partial w_i}\right|_{w^*} + \left.\frac{\partial \Omega_j}{\partial w_i}\right|_{w^*} > (<)\, 0. \tag{22}$$

However, differently from the case of no merger synergies, we now have that

$$\left.\frac{\partial \Omega_i}{\partial w_i}\right|_{w^*} = -\alpha\delta \frac{6(1-\lambda)(\lambda(1-\alpha)\gamma + (2-\lambda)\alpha p) - \lambda(1-\alpha)t}{3t(2\alpha(1-\lambda)c - (1-\alpha)t)} < 0. \tag{23}$$

Furthermore,

$$\left.\frac{\partial \Omega_i}{\partial w_j}\right|_{w^*} = \frac{\lambda(1-\alpha)(6(1-\lambda)\gamma - t)}{6t(2-\lambda)} + \frac{\lambda\alpha\delta(6(1-\lambda)(\lambda(1-\alpha)\gamma + (2-\lambda)\alpha p) - \lambda(1-\alpha)t)}{6t(2-\lambda)(2\alpha(1-\lambda)c - (1-\alpha)t)}. \tag{24}$$

As can be seen from (23) and (24), the presence of merger synergies affects the waiting time response to the merger in two different ways. First, since the merger reduces marginal treatment costs, the marginal patient becomes less unprofitable to treat, which therefore reduces the incentive to avoid treating unprofitable patients. This (first-order) effect is captured by (23) and leads to lower waiting times, all else being equal. But there is also a second-order effect, captured by the second term in (24). Because the price-cost margin increases, the relative importance of the profit-oriented competition externality is reduced. All else equal, this enlarges the scope for higher waiting times when the merged entity internalises the two competition externalities. Thus, the second-order effect counteracts the first-order effect. By combining (23) and (24) we derive

$$\left.\frac{\partial \Omega_i}{\partial w_i}\right|_{w^*} + \left.\frac{\partial \Omega_j}{\partial w_i}\right|_{w^*} = \frac{\lambda(1-\alpha)(6(1-\lambda)\gamma - t)}{6t(2-\lambda)} + \frac{\lambda\alpha\delta(6(1-\lambda)(\lambda(1-\alpha)\gamma + (2-\lambda)\alpha p) - \lambda(1-\alpha)t)}{6t(2-\lambda)(2\alpha(1-\lambda)c - (1-\alpha)t)}, \quad (25)$$

where the second term in (25) is the sum of the above-mentioned first-order and second-order effects. This term is positive, which confirms that the first-order effect always dominates the second-order effect.[19]

The sign of (25) is generally ambiguous, but the positive sign of the second term implies that the presence of merger synergies increases the scope for lower waiting times as a result of the merger. Another interesting implication of (25) is that, in the presence of merger synergies, a merger leads to lower waiting times even if hospitals are profit-maximisers ($\alpha = 1$). In this case, the hospital that does not take part in the merger will also respond by lowering its waiting time, even if its cost function remains the same, and even if there are no competition externalities between the hospitals. The reason is simply explained by strategic complementarity. Because of the cost synergies, the merged hospitals will reduce their waiting times and serve a larger share of total demand. The corresponding demand reduction for the outside hospital implies that the cost of treating the (new) marginal patient goes down. The hospital can therefore increase its profits by lowering its waiting time and regain some of its lost demand. Since the magnitude of the first term in (25) is decreasing in α and goes to zero when $\alpha \to 1$, the above described effect of the merger–a waiting time reduction for all hospitals–must hold not only for $\alpha = 1$, but also for values of α sufficiently close to one. The next proposition summarises these results:

Proposition 2 *Suppose that a merger entails some cost synergies that reduce the marginal treatment costs of the merged hospitals. In this case, (i) the scope for lower waiting times as a result of the merger is enlarged, and (ii) a merger always leads to lower waiting times, for all hospitals in the market, if the hospitals are sufficiently profit-oriented.*

[19] The positive sign of the second term in (25) is easily confirmed by applying the equilibrium existence conditions $\underline{c} < c < \overline{c}$ and $\gamma > \underline{\gamma}$.

3 Institutional background

We now turn to the empirical part of the analysis, where we aim to test how hospital mergers affect waiting times in a context of regulated prices, using 20 years of longitudinal data from the English National Health Service (NHS). The English experience is particularly suited to our purposes. Over the past couple of decades, several waves of hospital consolidation have significantly reduced the number of providers operating in England from about 200 in 2000, each serving on average a population of 245,000 people, to about 145 in 2020, each serving on average a population of 450,000 people. Most of these consolidations in the form of hospital mergers are attributable to the internal market reform.

The internal market was established by the National Health Service and Community Care Act 1990 to separate the roles of purchasers (health authorities) and providers (hospital trusts) within the English NHS. The goal of the reform was to improve quality of healthcare services by reducing the monopolistic power in the public healthcare sector. Competition was expected to promote efficiency and responsiveness, empowering decentralised decision-making rather than relying on central control and planning (Goddard and Ferguson, 1997). However, instead of competing to offer the best services, providers began to offer services jointly, resulting first in concentration of services and later in formal mergers.

This led to a consistent reduction in the number of hospital trusts, with fewer and larger hospitals becoming the norm.[20] The increasing concentration of hospitals in some areas undermined the competition principle advocated by the internal market reform. For this reason, in the 2000s the government endorsed outsourcing of medical services and promoted the involvement of private sector providers in order to contrast hospitals' concentration and to support the internal market competition. Specifically, the NHS Plan, published in 2000, promoted closer relationships between the private sector and the NHS with the intended purpose of reducing waiting times. In the context of these organisational changes, the aim of our empirical analysis is to investigate whether the above described merging activity has had any significant effect on hospital waiting times.

[20] For simplicity, we will henceforth refer to hospital trusts as hospitals.

4 Empirical strategy

Before offering a more detailed description of our data, we lay out our empirical strategy in this section. Our aim is to test whether hospital mergers lead to any significant differences in waiting times between merged and non-merged hospitals. However, since the decision to merge is voluntary and since different mergers take place in different years, we face the challenge of potential selection bias. In order to deal with this challenge, we choose an empirical strategy that is based on a combination of propensity score matching (PSM) and difference-in-differences methodology (DID). In the following we will offer a relatively brief description of this approach. For a more detailed description we refer the interested reader to Cirulli and Marini (2023), who apply the same empirical strategy to a subset of the same data.

We use the flexible conditional DID approach (Dettmann et al., 2020), a modification of the matching and DID approach of Heckman et al. (1998) for the staggered treatment adoption design (as in Callaway and Sant'Anna, 2021), where units that are treated once in the observation time are regarded as treated units from that date onwards and where time is defined in relation to the treatment start. This approach is a two-step process, where the first step (pre-processing) involves a rearranging of the original dataset into individual selection groups for every treated unit. Potential controls for every treated unit are limited to those observed just at the individual matching date, and the observation time of both the matching variables and the outcomes is normalised such that they are measured with respect to the individual treatment start. In the second step (estimation), a matching process aims to eliminate any systematic differences between treated and untreated, and the *average treatment effect for the treated* (ATT) is estimated conditional on observable characteristics. In contrast to the standard DID model, the flexible conditional DID model compares individual differences in outcome development between treated and untreated.

4.1 Overall ATT

The ATT estimator for the flexible conditional DID estimator developed by Dettmann et al. (2020) is built on the estimate of group-time average treatment effects with the number of groups equal to the number of treated observations and respective group sizes of one. Single group-time estimators are then summarised in a simple weighted average with respective group weights of one. Control observations are individually selected for every treated unit and outcomes are individually compared. The ATT estimator, defined as the mean of the individual comparisons, is given by the following equation:

$$ATT = \frac{1}{N}\sum_{i=1}^{N}[(w_{i,t_{0i}+\beta_i} - w_{i,t_{0i}}) - (w_{j,t_{0i}+\beta_i} - w_{j,t_{0i}})], \tag{26}$$

where $w_{i,t}$ and $w_{j,t}$ are the waiting times at, respectively, the treated (merged) hospital i and its untreated matched counterpart (hospital j) at time t, where $i, j = 1, ..., N$, and $t = 1, ..., T$. Notice that the estimator includes individual treatment start dates, t_{0i}, and a flexible number of years, $t_{0i} + \beta_i$, which reflects the unit-specific duration from treatment start to outcome observation.

4.2 Year-by-year ATT

Because of heterogeneous treatment durations, the ATT in (26) is a weighted average of different observation periods. We therefore complement our analysis by also estimating a standard fixed effect DID model in which we compare, year by year, the change in waiting times for merged hospitals before and after the merger with the change in waiting times for non-merged hospitals in the comparison group. This model is given by

$$w_{it} = \tau_0 + \tau_1 M_i + \sum_{t=1}^{20}\tau_{2t}D_{it} + \sum_{t=1}^{20}\delta_t M_i D_{it} + \sum_{t=1}^{20}\sum_{k=1}^{6}\tau_{3k}X_{kit} + \mu_i + \epsilon_{it}, \tag{27}$$

where w_{it} is the hospital waiting time for hospital i in year t, where t covers 20 years from 2000 to 2019, corresponding to the total time span of our dataset (see Section 5 below for further details). Hospital mergers are identified by the dummy variable M_i, which takes the value 1 if hospital i is the result of a merger and 0 otherwise, and which controls for all time invariant differences between treated and untreated hospitals. Furthermore, D_{it} is count dummy variable with relative difference to treatment start, which controls for all other unobserved temporal factors that might affect the dependent variable. Finally, X_{kit} is the observable time-variant factor k (inputs, controls, hospital characteristics) that might affect our dependent variable for hospital i in year t, μ_i is a hospital fixed effect, and ϵ_{it} is an error term. The interaction between D_{it} and M_i identifies the change in hospital waiting times for merged hospitals relative to non-merged hospitals (i.e., the year-by-year ATT). Our main interest therefore lies in the sign and statistical significance of the coefficient δ_t, which measures the average effect of hospital mergers on the waiting times of merged hospitals t years after the merger.

4.3 Conditional parallel trend assumption

Since the flexible conditional DID approach is a combination of propensity score matching and DID methodology, the conditional independence assumption for matching and the common trend assumption for DID are replaced by the *conditional parallel trend assumption* (as proposed by Callaway and Sant'Anna, 2021), which states that unobservable individual characteristics must be invariant over time for units with the same observed characteristics. To test the conditional PTA, we estimate a modified version of (27), as in Cerulli and Ventura (2019), given by

$$w_{it} = \tau_0 + \{\sum_{t=1}^{20} \delta_{t-l} D_{it-l}\}_{l=F}^{L} + \sum_{t=1}^{20} \sum_{k=1}^{6} \tau_{1k} X_{kit} + \mu_i + \epsilon_{it}, \tag{28}$$

where F denotes post-treatment time and L denotes pre-treatment time, with $F \geq l \geq L$. Compared to (27), D_{it} is now a dummy variable with relative difference to treatment start defined by l.

In order to test for the conditional PTA implied by (28), we need to perform two different tests, using time leads and time trends, respectively. If the hypothesis $\delta_{t-l} = 0$ is not rejected neither for $l = L$ nor for $F \geq l \geq L$, we can conclude that both tests are passed and therefore that the conditional PTA holds (Cerulli and Ventura, 2019).

5 Data and descriptive statistics

We have longitudinal annual data for a period of 20 years from 2000 to 2019, which contains information on all acute and specialist hospitals in England with a unique identifier for each hospital. Our unique data set combines information from several data sources: administrative data providing information on activity, expenditure, resource use, performance and staffing, as well as hospital characteristics, extracted and/or derived from the Hospital Episode Statistics (HES), the Hospital Activity Statistics (HAS), the NHS Foundation trust Directory, the Medical and Dental Workforce Census (Department of Health), and from the websites of individual hospitals. The dataset contains 3,303 observations for 197 hospitals in 2000, 186 in 2001, 175 in 2002, 172 in 2003, 2004 and 2005, 171 in 2006, 169 in 2007 and 2008, 166 in 2009 and 2010, 165 in 2011, 160 in 2012 and 2013, 157 in 2014, 153 in 2015, 152 in 2016, 150 in 2017, 147 in 2018 and 144 in 2019.

5.1 Variable definitions and measurements

5.1.1 Dependent variable, merger variable and controls

Our dependent variable is hospital waiting time, i.e. the number of days a patient has to wait, on average, from referral (i.e., the date of the decision to admit) to treatment (i.e., the date of actual admission). The impact of a hospital merger on waiting times is assessed by constructing a dummy variable for hospital merger status which takes a value of one in the year a new merged hospital is established and in all subsequent years, and a value of zero in all years prior to a merger.

In order to account for other factors that may be correlated with our dependent variable, we control for several hospital characteristics, such as the number of hospital theatres, the number of diagnostic tests performed, the share of medical staff, and whether the hospital is a teaching hospital. Moreover, we include the proportion of patients aged below 14 and above 60, as well as the proportion of female patients, these being the most demanding categories in terms of hospital services. All continuous control variables are log-transformed.

Finally, we distinguish between two different types of hospitals in order to incorporate one of the key elements of the theory model presented in Section 2, namely hospitals' degree of profit-orientation. This is obviously not a directly observable variable, but it can reasonably be proxied by whether or not a hospital holds the status of Foundation Trust (FT).[21] This is a legal status that implies a higher degree of independence from the Department of Heath and gives the hospital a considerable amount of autonomy in terms of governance and financial flexibility. In particular, the fact that FTs are allowed to retain financial surpluses naturally implies that the generation of such surpluses becomes more valuable, all else being equal. Thus, it is reasonable to assume that FTs are on average more profit-oriented then other hospitals. We therefore create a dummy variable FT that takes the value 1 if the hospital is a Foundation Trust and 0 if not, and use this variable as a proxy for the parameter α in the theory model (in the sense that $FT = 1$ implies a higher value of α than $FT = 0$).

[21] NHS Foundation Trusts originate from the HSC Act 2003, a bill that was passed by the UK Parliament in 2003 allowing some NHS trusts to acquire a new legal status as Foundation Trust and become non-profit public benefit corporations in charge of providing goods and services for the purposes of the NHS in England (HSC Act 2003, Part 1, section 1).

5.1.2 Variables used in the pre-processing and in the PSM

Since mergers are often implemented to improve issues related to financial performance, we adopt the same strategy as Cirulli and Marini (2023) by using pre-treatment financial characteristics in the pre-processing and PSM stages. In the pre-processing stage we use the variable retained surplus, which is the difference between income and expenditures adjusted by receivable and payable interest and payable dividends. For the propensity score matching, we use two different variables: (i) managers' and directors' costs as a share of total hospital costs, and (ii) a performance measure labelled pseudo-ROI, which is defined as a hospital's surplus relative to its total costs.[22] Only the former variable is log-transformed, since the second variable is defined by a surplus that can be either positive or negative.

5.2 Descriptive statistics

Descriptive statistics for our overall sample are displayed in Table 1, which reveals a quite extensive merger activity. Among 3,303 hospital-year observations in our sample, about 19 per cent of them are related to hospitals that were involved in a merger at some point during the observation period. Regarding our dependent variable, we see that a patient has to wait 67 days, on average, from referral to treatment.

[Table 1 here]

The summary statistics on the other hospital characteristics reveal that hospitals on average operate with a capacity of about 18 operating theatres and 28 per cent of medical staff, carry out over 200,000 diagnostic tests per year, and about 36 per cent of the hospitals are teaching hospitals. Regarding the patient characteristics, we see that patients aged below 14 years and above 60 years represent almost 60 percent of the treated patients (13 per cent and 44 per cent, respectively), while around 56 per cent of the treated patients are female. On average, hospitals have an annual deficit (negative retained surplus) of more than 4 million GBP. Nevertheless, our performance measure (pseudo-ROI) is on average positive, though hospital surpluses amount only to 1.2 per cent of total hospital costs. Managers' and directors' costs represent also a relatively small share (3.3 per cent) of total hospital costs.

[22] Whereas the Return on Investment (ROI) measures the return on a particular investment relative to its cost, the pseudo-ROI measures the return on a potential investment (the surplus) relative to its costs (total hospital costs).

In Table 2 we compare the summary statistics of hospitals that went through organisational change and merged during the sample period with those that did not. The mean differences (reported in the last column of Table 2) for waiting times suggest that merged hospitals have shorter waiting times than hospitals that did not merge, and the difference is significant at the one per cent level.

[Table 2 here]

Mean differences in operating theatres, diagnostic tests and medical staff suggest that merged hospitals tend to increase their activity after the merger. Moreover, merged hospitals are more likely to be teaching hospitals. Mean differences in patient characteristics reveal that the proportions of both older and female patients increase in merged hospitals (by around 1.6 and 2 per cent, respectively), while the proportion of young patient decreases by almost 2 per cent.

As previously explained, the DID identification strategy relies on the assumption that trends in the dependent variable are similar for treated and untreated hospitals in the absence of the treatment, and therefore that any deviation from the common trend should be induced only by the treatment. A first indication of whether this assumption holds for our sample is given by Figure 1, which displays the trends in waiting times for treated (merged) and non-treated (non-merged) hospitals. We see that the two trend lines are fairly similar, though not perfectly aligned. A statistical test for conditional PTA will be presented in Section 6.2.

[Figure 1 here]

5.3 Data structure in the flexible conditional DID

Before presenting the empirical results, it is useful to briefly explain the structure of the data when using a flexible conditional DID approach (Dettmann et al., 2020). Since mergers occurred in a staggered way, each year contains a mix of hospital pre-treatment, treatment and post-treatment characteristics, which implies that each treated hospital could in principle also be a non-treated one, depending on which year we consider. As explained in Section 4, our empirical analysis is conducted in two phases, which we have referred to as pre-processing and estimation. In the pre-processing phase, where we rearrange the data set according to a set of selected pre-treatment characteristics, we set the duration of the pre-treatment period to one year before the merger. Subsequently, in the estimation phase, we define the pre-treatment outcome development and its relative time specification. As the pre-treatment outcome is a selected period of outcome development before the treatment starts, we set this time span from two years to one year before the merger, and we further assume that the outcome will develop over two years after the merger. The choice of these time spans are partly influenced by the observation that hospitals 'can take from one to two years to identify their preferred merger partners, and one to four years to gain approvals and complete the merger process' (Collins, 2015, p. 23).

6 Empirical results

In this section we present our empirical results. We start out by showing the results of the pre-processing and matching procedure (in Section 6.1) and the test of the conditional parallel trends assumption (in Section 6.2), before the main results on the effect of hospital mergers on waiting times are presented in Section 6.3 and 6.4.

6.1 Pre-processing and matching

In the pre-processing phase, the data is filtered by exact matching on retained surplus to select one or more non-merged hospitals as potential controls for each of the merged hospitals, based on a time period of one year before the treatment start (i.e., year of the merger). This process leads to a rearrangement of the data into 44 individual selection groups, each containing one merged hospital and a set of non-merged hospitals with identical retained surplus (one year before the merger). We then use this temporary dataset to perform PMS estimations using nearest neighbour matching with replacement for the previously described matching variables, based on a pre-treatment time period defined from two years to one year before the treatment start.

[Table 3 here]

The matching results and corresponding tests are reported in Table 3. The matching procedure selects 14 out of 44 treated hospitals and 13 out of 102 non-treated hospitals. Thus, in some cases, a non-treated hospital is used as partner for more than one treated hospital, which is typical feature of the implemented nearest neighbour matching with replacement. For each of the matching variables, the ps-test (as developed by Leuven and Sianesi, 2003) reports the means in the treated and in the control group, a measure for the standardised percentage difference between the means in both groups (labelled %bias), and a test if the means in the control group equal the ones in the treated group. According to the ps-test, as we can see from Table 3, the means of all the matching variables are balanced. As matching is based on the statistical distance function, the Kolmogorov-Smirnov (KS) test, which is a nonparametric test for equality of continuous distribution functions, is also reported. In Table 3, the corrected p-values of 0.997 and 0.847 for the two matching variables indicate that the variable distributions are not significantly different for the treated and the control group. Finally, in order to obtain a graphical impression of the comparability of the matched groups, we have also made quantile-quantile plots of each matching variable and waiting time. These plots are shown in Figure A1 in the Appendix.

6.2 Conditional parallel trends assumption

As previously explained, our empirical strategy rests of the conditional parallel trends assumption. In order to test for this, we use the strategy outlined in Section 4.3. The results derived from the estimation of (28), using both leads and lags, are displayed in Table 4. We set leads to two years before the merger (i.e., $l = L = t + 2$ in (28)). In Table 4 this variable is labelled as Merged_{t-2} and Merged_{t-1}. We also align the post-treatment time to the outcome development (i.e., $l = F = t - 2$ in (28)), namely two years after the merger, in accordance with the matching-DID estimation model (Goddard and Ferguson, 1997; Collins, 2015). These variables are labelled as Merged_{t+1} and Merged_{t+2}. Finally, the variable Merged_{t} is the binary time-varying treatment, defined as the tendency of treated hospitals to increase their waiting times in a specific year compared with a baseline reference and measured as the average development of hospital waiting in the two years after merger, given the pre-treatment features in the year before merger. The results in Table 4 show that the conditional PTA is passed in all specifications, with (Column B) and without (Column A) controls.

[Table 4 here]

6.3 Effect of hospital mergers on waiting times

Once we have established the validity of our empirical strategy, we start out by estimating the overall average treatment effect for the treated (ATT), as defined by (26), obtained with a canonical fixed effects DID model with standard errors allowing for intra-group correlations under the assumption that the observation period spans from the earliest treatment start to the end of our sample. The resulting conditional DID for the ATT, from the start of the treatment until two years afterwards, is a difference between the mean differences of the treated (merged hospitals) and the mean differences of the non-treated (non-merged hospitals). The estimation results are displayed in Table 5, without (Column A) and with (Column B) controls.

[Table 5 here]

The sign of the point estimates shown in Table 5 indicates that the general reduction in waiting times tend to be smaller for merged than for non-merged hospitals. In other words, hospital mergers tend to increase waiting times. However, when assessing the statistical significance of these differences, the p-values of the modified t-tests for corrected standard errors suggest that the differences are not significant.

We proceed by estimating the fixed effects DID model given by (27) in order to obtain year-by-year ATT estimates. Since the post-treatment outcome development is set equal to two years (as explained in Section 5.3), both the hospital merger effect ($\tau_{2.t}$, with $t = 1, ..., 17$) and ATT (δ_t, with $t = 1, ..., 17$) start from year 2003 onwards. Whereas the dummy variable M_i is dropped because of collinearity, the other two relevant variables, *Post merged* (D_{it}) and the interaction between *Merged* and *Post merged* (M_i and D_{it}), are used to verify the effect of hospital mergers on hospital waiting. In particular, both the count dummy D_{it} and the interaction between D_{it} and M_i dummies are modified to account for the relative distance from treatment start. For example, for a hospital merged in 2001, D_{it} equals 1 in 2003, 2 in 2004, and so on. The interaction between the D_{it} and M_i dummies is modified accordingly, with $M_i = 1$ if the panel item is treated and $M_i = 0$ otherwise. The $\tau_{2.t}$-coefficients give the change in the dependent variable, whereas the δ_t-coefficients indicate the DID estimates for the change, between year t and the year when the treatment started.

[Table 6 here]

The year-by-year fixed effects DID results are shown in Table 6, with (Column B) and without (Column A) controls. For both sets of estimations, the δ_t-coefficients have almost exclusively positive point estimates, suggesting that merged hospitals have longer waiting times than non-merged hospitals in each year after the merger. However, the vast majority of these coefficients are non-significant.

6.4 Profit-oriented versus semi-altruistic hospitals

We now extend our analysis by exploring the potential importance of hospitals' profit-orientation, where we classify hospitals according to whether the hospital is a Foundation Trust or not, using the dummy variable FT as described in Section 5. We label hospitals as being 'profit-oriented' if $FT = 1$ and 'semi-altruistic' if $FT = 0$.[23] Thus, we re-estimate (27) with a fixed effects DID model to account for the effect of the merged status after the merger occurred and ATT year by year, accounting additionally for the effect of the FT variable. The results are shown in Table 7, with the estimated effects of mergers involving profit-oriented hospitals displayed in Column A (without controls) and Column B (with controls), and the corresponding merger effects for semi-altruistic hospitals in Columns C and D (respectively without and with controls).

[Table 7 here]

These results reveal a quite interesting and consistent pattern. For mergers involving profit-oriented hospitals, the δ_t-coefficients are mostly statistically significant and all the significant coefficients have a negative sign. The magnitudes are also sizeable, with waiting time reductions in treated hospitals of more than 30 per cent from the fifth to the ninth year after the merger, compared with the non-treated controls. For semi-altruistic hospitals, in contrast, all statistically significant δ_t-coefficients have a positive sign, suggesting that mergers between such hospitals led to longer waiting times, compared with their non-merged counterparts, in several of the post-merger years.

Overall, our results suggest that the effect of hospital mergers on waiting times depends crucially on whether hospitals are profit-oriented or not. Whereas mergers between profit-oriented hospitals tend to reduce waiting times, the opposite tends to be the case for mergers involving semi-altruistic hospitals. These opposite tendencies can also explain the general lack of significant effects when the degree of profit-orientation is not controlled for.

How can the contrasting results for profit-oriented and semi-altruistic hospitals be explained? Our theoretical analysis in Section 2 identifies three different mechanisms whereby a hospital merger can affect waiting times, related to (i) profit-oriented competition to avoid treating unprofitable patients, (ii) altruistic competition for patients and (iii) merger-induced cost synergies. Mechanisms (i) and (iii) contribute to a waiting time reduction as a result of the merger,

[23] The summary statistics for each of these two categories of hospitals are shown in Table A1 and A2 in the Appendix.

whereas mechanism (ii) contributes to a waiting time increase. Our analysis also shows that the magnitudes of (i) and (ii) become weaker if hospitals are more profit-oriented and vanish for the special case of profit-maximising hospitals. However, Proposition 1 confirms that the sign of the combined effect of (i) and (ii) does not depend on the degree of profit-orientation. Thus, the first conclusion we can draw is that, in light of our theory model, opposite waiting time effects of a merger for profit-oriented and semi-altruistic hospitals cannot be explained without the presence of cost synergies.

On the other hand, as long as a hospital merger entails some cost synergies, our empirical results are fully in line with Proposition 2 in the theory section, which states that the scope for a waiting time reduction as a result of a merger is larger if the merging hospitals are more profit-oriented. Furthermore, the case of opposite effects for profit-oriented and semi-altruistic hospitals would arise from the theory model under the following circumstances: suppose that there are some moderate cost synergies involved in a merger, and suppose in addition that profit-oriented competition to avoid treating unprofitable patients is weaker than the competition to attract patients for altruistic reasons, such that the sum of (i) and (ii) leads to a waiting time increase, all else equal. Since the magnitude of (i)+(ii) is smaller for profit-oriented than for semi-altruistic hospitals, a sufficiently large difference in the degree of profit-orientation would imply that (iii) dominates (i)+(ii) for mergers involving the former type of hospitals, whereas (iii) is dominated by (i)+(ii) for mergers involving the latter type, which would produce the kind of results we report in Table 7.

6.5 Sensitivity analysis

In order to check the robustness of our results, we have conducted sensitivity analyses on (27) using different combinations of control variables. In particular, we have considered three measures of performed diagnostic tests (total number of tests vs. CT and MRI scans). Results across different specifications do not differ significantly and are available upon request.

7 Concluding remarks

A major health policy concern in many countries is the amount of time patients have to wait for necessary medical treatment. Average waiting times are likely to depend on a number of different factors related to both the organisation and the funding of health care provision. In this paper we have focused on one particular factor, namely the degree of hospital market concentration. More specifically, we have analysed—both theoretically and empirically—the effect of hospital mergers on waiting times.

In the theoretical analysis we have identified several potential mechanisms through which a hospital merger could effect waiting times. Some of these mechanisms go in opposite directions, which implies that the overall effect is *a priori* ambiguous. However, a main insight that emerges from our theoretical analysis is that, in the presence of cost synergies from a merger, the scope for hospital mergers to reduce waiting times is larger if the hospitals are more profit-oriented.

Our empirical analysis provides, at least to some extent, a confirmation of this theoretical insight. Using a state-of-the-art flexible conditional DID approach to a long panel of data on hospital mergers in the English NHS, we find that mergers involving Foundation Trusts tend to reduce waiting times, whereas mergers involving hospitals without this particular legal status tend instead to increase waiting times. Under the reasonable assumption that Foundation Trust status implies a higher degree of profit-orientation in the hospitals' objectives, these results are consistent with, and can thus be explained by, our theoretical analysis.

Overall, we believe that the present paper can provide some guidance to policy makers when assessing the likely impact of hospital mergers on waiting times. In particular, we show that such impacts are not likely to be uniform across all types of mergers. Instead, our analysis points to hospital objectives—in particular the degree to which hospitals value profits over patient welfare—as a key determinant for how mergers are likely to affect waiting times.

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Appendix

Equilibrium existence in the symmetric pre-merger game

Equilibrium existence requires that each hospital's maximisation problem is well-defined. Concavity of Hospital i's objective function requires that

$$\frac{\partial^2 \Omega_i}{\partial w_i^2} = -\left(\frac{2\,(2-\lambda)^2\,\alpha c - (1-\alpha)\,(4-\lambda)\,t}{2t^2}\right) < 0, \tag{A1}$$

which holds if

$$c > c_1 := \frac{(1-\alpha)\,(4-\lambda)\,t}{2\alpha\,(2-\lambda)^2}. \tag{A2}$$

Furthermore, a sufficient condition for the *contraction property* to hold (see, for instance, Vives 2000, p.47) is

$$\frac{\partial^2 \Omega_i}{\partial\,(w_i)^2} + \sum_{j\neq i}\left|\frac{\partial^2 \Omega_i}{\partial w_i \partial w_j}\right| = -\frac{(2-\lambda)}{t^2}\left[2\alpha\,(1-\lambda)\,c - (1-\alpha)\,t\right] < 0. \tag{A3}$$

This property ensures (local) stability and uniqueness of the Nash equilibrium, and is satisfied if

$$c > c_2 := \frac{(1-\alpha)\,t}{2\alpha\,(1-\lambda)}. \tag{A4}$$

Notice that, since

$$c_2 - c_1 = \frac{\lambda\,(1-\alpha)\,t}{2\alpha\,(1-\lambda)\,(2-\lambda)^2} > 0, \tag{A5}$$

(A2) is always satisfied if (A4) holds.

Additionally, the existence of an *interior solution* equilibrium requires a further set of conditions. First, the equilibrium waiting time must be strictly positive. From (16), $w^* > 0$

if

$$c > c_3 := \frac{(1-\alpha)(\lambda(6v+t)+12(1-\lambda)(v-\gamma))t+6(2-\lambda)\alpha pt}{2(2-\lambda)\alpha(6(1-\lambda)(v-\gamma)+\lambda t)}. \tag{A6}$$

Second, an interior solution requires that some but not all patients in the monopolistic segment choose to attend the nearest hospital for treatment. By inserting $w_i = w^*$ into (6), it is straightforward to verify that $q_i^m(w^*) < (1-\lambda)(1/3)$ if

$$c > c_4 := 3p + \frac{(1-\alpha)(3\lambda\gamma+t)}{(2-\lambda)\alpha}, \tag{A7}$$

and $q_i^m(w^*) > 0$ if

$$c < \bar{c} := \frac{6\lambda(1-\alpha)\gamma+6(2-\lambda)\alpha p+\lambda(1-\alpha)t}{2\lambda(2-\lambda)\alpha}. \tag{A8}$$

The condition in (A7) ensures that the patient in the monopolistic segment who is located halfway between Hospital i and Hospital j would derive a negative net utility from seeking treatment at either of the hospitals. In contrast, we need to ensure that the equivalently located patient in the competitive segment derives a positive utility from seeking treatment. Since this patient is located at a distance of 1/6 from the nearest hospital in either direction, the net utility of seeking treatment at either of them is positive if

$$v - w^* - \frac{t}{6} > 0, \tag{A9}$$

which is true if

$$\gamma > \underline{\gamma} := \frac{(2-\lambda)(c-3p)\alpha t-(1-\alpha)t^2}{6(1-\lambda)((2-\lambda)\alpha c-(1-\alpha)t)}. \tag{A10}$$

Thus, a unique interior-solution Nash equilibrium exists if (i) the difference in outside options between the two patient types is sufficiently large, with the explicit condition given by (A10), and if (ii) the degree of cost convexity is neither too low nor too high; more specifically, if

$$\underline{c} < c < \bar{c}, \tag{A11}$$

where

$$\underline{c} := \max\{c_2, c_3, c_4\} \tag{A12}$$

In order to show that the parameter set given by (A11) is non-empty, consider the special case of profit-maximising hospitals. If we set $\alpha = 1$ in (A11) and (A12), the lower and upper bounds on c reduce to

$$\underline{c} = \max\left\{\frac{3pt}{6(1-\lambda)v + \lambda t}, 3p\right\} \tag{A13}$$

and

$$\bar{c} = \frac{3p}{\lambda}. \tag{A14}$$

Since

$$\frac{3p}{\lambda} - \frac{3pt}{6(1-\lambda)(v-\gamma) + \lambda t} = \frac{18(1-\lambda)p(v-\gamma)}{\lambda(6(1-\lambda)(v-\gamma) + \lambda t)} > 0, \tag{A15}$$

the parameter set $\underline{c} < c < \bar{c}$ is non-empty for $\alpha = 1$. By continuity, a sufficient condition for the parameter set in (A11) being non-empty is that the hospitals' degree of profit-orientation is sufficiently high.

Closed-form solution for the post-merger waiting times

In case of a *two-hospital merger*, the post-merger equilibrium is asymmetric. Let the waiting time at each of the merged hospitals be denoted by w_m^{**}, and let the waiting time at the hospital outside the merger be denoted by w_o^{**}. The closed-form expressions for these equilibrium waiting times are given by

$$w_m^{**} = w^* + \frac{\lambda(1-\alpha)(6\gamma(1-\lambda)-t)\left(2\alpha c(2-\lambda)^2 - (1-\alpha)(4-\lambda)t\right)t}{3(2-\lambda)(2\alpha c(1-\lambda) - t(1-\alpha))\Psi} \tag{A16}$$

and

$$w_o^{**} = w^* + \frac{\lambda^2(1-\alpha)(6\gamma(1-\lambda)-t)(2\alpha c(2-\lambda) - (1-\alpha)t)t}{3(2-\lambda)(2\alpha c(1-\lambda) - t(1-\alpha))\Psi}, \tag{A17}$$

where

$$\Psi := \alpha c(2-\lambda)(4-3\lambda)(4-\lambda) - 2t\left(8 - 7\lambda + \lambda^2\right)(1-\alpha) > 0, \tag{A18}$$

and w^* is the equilibrium waiting time in the pre-merger symmetric equilibrium, given by (16).

In the case of a *merger to monopoly*, let the post-merger waiting time (which is equal for each of the three branches of the merged hospital) be denoted by w^{***}. The closed-form expression for this waiting time is given by

$$w^{***} = w^* + \frac{\lambda(1-\alpha)(6(1-\lambda)\gamma - t)t}{6(1-\lambda)(2-\lambda)(2(1-\lambda)\alpha c - (1-\alpha)t)}. \tag{A19}$$

Comparing (A16) and (A19), the effect of enlarging the set of merger participants from two to three hospitals is given by

$$w^{***} - w_m^{**} = [6(1-\lambda)\gamma - t]\,\Theta, \tag{A20}$$

where

$$\Theta := \frac{t\lambda(1-\alpha)\left(c\alpha\left(8-4\lambda-\lambda^2\right)-4(1-\alpha)t\right)}{6(1-\lambda)(2\alpha c(1-\lambda)-t(1-\alpha))\Psi} > 0. \tag{A21}$$

Quantile-quantile plots

Figure A1 show the quantile-quantile plots of matching variables and outcome development in the case of waiting times. These plots compare the distributions in both groups by means of the plotted quantiles, where the 45 degree line represents identical distributions, and where treated (non-treated) hospitals are represented on the horizontal (vertical) axis. The plots reveal a small deviation from the 45 degree line for all displayed variables, mostly at the tails of the distributions.

[Figure A1 here]

Descriptive statistics for profit-oriented and semi-altruistic hospitals

Table A1 shows the summary statistics for merged versus non-merged hospitals among Foundation Trusts, which we label as 'profit-oriented' hospitals. A similar comparison for the remaining category of hospitals, which we label 'semi-altruistic hospitals', are shown in Table A2.

[Table A1 and A2 here]

Tables and Figures

Table 1: Summary statistics; all hospitals, 2000–2019.

Variable	Mean	Std. Dev.	Min.	Max.	N
Dependent variables					
Waiting times (days)	66.968	33.149	7	547	3254
Policy variable					
Merged (dummy)	0.189	0.391	0	1	3303
Hospital inputs					
Operating theatres (number)	17.874	10.486	0	72	3119
Diagnostic tests (number)	200521	112863	5089	798275	2379
Medical staff (%)	28.098	34.38	4.61	100	3295
Hospital characteristics					
Teaching (dummy)	0.364	0.481	0	1	3303
Patient characteristics					
Patients aged 0–14 (%)	13.181	13.217	0	100	3270
Patients aged 60+ (%)	43.753	11.357	0	70.738	3299
Female patients (%)	55.883	9.833	27.507	112.241	3298
Variable used in the pre-processing					
Retained surplus (000)	-4220	21576	-249654	283159	3156
Variables used in the PSM					
Managers and directors costs (%)	3.286	1.064	0.431	10.222	1035
Pseudo-ROI	1.192	5.728	-71.627	124.923	2103

Table 2: Mean comparisons; merged versus non-merged hospitals, 2000-2019.

	Merged = 1 by 2019		Merged = 0 in all years		
Variable	N	Mean	N	Mean	Difference
Dependent variables					
Waiting times (days)	621	60.28	2633	68.54	-8.263***
Hospital inputs					
Operating theatres (number)	576	26.43	2543	15.93	10.499***
Diagnostic tests (number)	383	296598	1996	182089	115071***
Medical staff (%)	623	34.74	2672	26.55	8.193***
Hospital characteristics					
Teaching (dummy)	625	0.56	2678	0.32	0.240***
Patient characteristics					
Patients aged 0–14 (%)	622	11.64	2648	13.54	-1.908***
Patients aged 60+ (%)	625	45.02	2674	43.46	1.561***
Female patients (%)	625	57.51	2673	55.50	2.011***
Variable used in the pre-processing					
Retained surplus (000)	595	-7379	2561	-3486	-3892***
Variables used in the PSM					
Managers and directors costs (%)	155	3.07	880	3.32	-0.250***
Pseudo-ROI	357	0.24	1746	1.39	-1.150***

Significance levels: * < 10% ** < 5% *** < 1%

Table 3: Selection of the appropriate control group and matching statistics.

	Non-treated	Treated
All	102	44
Matched sample	13	14

	ps-test						Combined	
	Mean			t-test			K-S test	
	Treated	Controls	%bias	t	$p > \|t\|$	Diff.	p-value	Corrected
Pseudo-Roi	3.2235	3.4343	-19.6	-0.52	0.609	0.1429	0.999	0.997
Manag. and direct. costs	1.1383	1.1218	7.7	0.20	0.840	0.2143	0.905	0.847
Outcome development	0.02474	0.01235	13.6	0.36	0.721	0.2143	0.905	0.847

Table 4: Conditional parallel trend results on waiting times.

Variables	Coeff. Std. Err. (A)	Coeff. Std. Err. (B)
Merged_{t-2} (δ_{-2})	0.081	0.047
	(0.073)	(0.058)
Merged_{t-1} (δ_{-1})	-0.043	-0.004
	(0.037)	(0.037)
Merged_{t} (δ_{0})	-0.012	-0.005
	(0.036)	(0.034)
Merged_{t+1} (δ_{+1})	0.030	0.033
	(0.028)	(0.035)
Merged_{t+1} (δ_{+1})	0.040	0.055
	(0.024)	(0.021)
Controls	NO	YES
PTA using the "leads"		
F(2, 26)	0.99	0.36
Prob > F	0.3841	0.6984
Parallel-trend	passed	passed
PTA using the "time-trend"		
F(1, 25)	0.70	0.11
Prob > F	0.4094	0.7479
Parallel-trend	passed	passed
Observations	534	369
Number of trusts	27	27

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Overall ATT estimates on waiting times.

	Mean Diff.		DID*	AI robust	z	$p > \|z\|$
	Treated	Control		S.E.		
Waiting times	-0.1365	-0.1709	0.0344	0.0860	0.4002	0.6955

* Consistent bias-corrected estimator as proposed in Abadie and Imbens (2006, 2011) .

Table 6: Year-by-year ATT estimates on waiting times.

Variables	Coeff. Std. Err. (A)	Coeff. Std. Err. (B)
Policy variables		
post merged_year 2003 ($\tau_{2.1}$)	-0.087	-0.077
	(0.056)	(0.058)
post merged_year 2004 ($\tau_{2.2}$)	-0.067	-0.072
	(0.089)	(0.093)
post merged_year 2005 ($\tau_{2.3}$)	-0.013	-0.020
	(0.115)	(0.121)
post merged_year 2006 ($\tau_{2.4}$)	-0.021	-0.028
	(0.127)	(0.132)
post merged_year 2007 ($\tau_{2.5}$)	-0.070	-0.068
	(0.139)	(0.135)
post merged_year 2008 ($\tau_{2.6}$)	-0.085	-0.071
	(0.157)	(0.155)
post merged_year 2009 ($\tau_{2.7}$)	-0.117	-0.138
	(0.178)	(0.192)
post merged_year 2010 ($\tau_{2.8}$)	-0.141	-0.178
	(0.207)	(0.213)
post merged_year 2011 ($\tau_{2.9}$)	-0.155	-0.189
	(0.223)	(0.229)
post merged_year 2012 ($\tau_{2.10}$)	-0.205	-0.193
	(0.259)	(0.253)
post merged_year 2013 ($\tau_{2.11}$)	-0.195	-0.097
	(0.281)	(0.277)
post merged_year 2014 ($\tau_{2.12}$)	-0.193	
	(0.319)	
post merged_year 2015 ($\tau_{2.13}$)	-0.204	
	(0.363)	
post merged_year 2016 ($\tau_{2.14}$)	-0.264	
	(0.380)	
post merged_year 2017 ($\tau_{2.15}$)	-0.269	
	(0.399)	
post merged_year 2018 ($\tau_{2.16}$)	-0.416	
	(0.421)	
post merged_year 2019 ($\tau_{2.17}$)	-0.352	
	(0.461)	
Merged*post merged_year 2003 (δ_1)	0.081**	0.079
	(0.036)	(0.050)
Merged*post merged_year 2004 (δ_2)	0.075	0.089
	(0.049)	(0.058)
Merged*post merged_year 2005 (δ_3)	0.056	0.067
	(0.061)	(0.063)
Merged*post merged_year 2006 (δ_4)	0.036	0.047
	(0.063)	(0.070)
Merged*post merged_year 2007 (δ_5)	-0.014	0.003
	(0.065)	(0.071)
Merged*post merged_year 2008 (δ_6)	0.006	0.026
	(0.064)	(0.078)
Merged*post merged_year 2009 (δ_7)	0.058	0.089

Continued on next page

Table 6 – continued from previous page

Variables	Coeff. Std. Err. (A)	Coeff. Std. Err. (B)
	(0.071)	(0.077)
Merged*post merged_year 2010 (δ_8)	0.048	0.099
	(0.079)	(0.083)
Merged*post merged_year 2011 (δ_9)	0.004	0.053
	(0.080)	(0.079)
Merged*post merged_year 2012 (δ_{10})	0.052	0.128
	(0.085)	(0.096)
Merged*post merged_year 2013 (δ_{11})	0.065	0.125
	(0.082)	(0.110)
Merged*post merged_year 2014 (δ_{12})	0.062	
	(0.090)	
Merged*post merged_year 2015 (δ_{13})	0.070	
	(0.099)	
Merged*post merged_year 2016 (δ_{14})	0.126	
	(0.100)	
Merged*post merged_year 2017 (δ_{15})	0.135	
	(0.108)	
Merged*post merged_year 2018 (δ_{16})	0.286**	
	(0.117)	
Merged*post merged_year 2019 (δ_{17})	0.234	
	(0.141)	
Controls	NO	YES
Year fixed effects	YES	YES
Trust fixed effects	YES	YES
Constant	4.477***	6.607**
	(0.032)	(2.471)
Observations	534	369
R-squared	0.790	0.861
Number of trusts	27	27

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Year-by-year ATT estimates on waiting times; profit-oriented versus semi-altruistic hospitals.

Variables	Profit-oriented trusts Coeff. Std. Err. (A)	Coeff. Std. Err. (B)	Semi-altruistic trusts Coeff. Std. Err. (C)	Coeff. Std. Err. (D)
Policy variables				
post merged_year 2003 ($\tau_{2.1}$)	-0.161***	-0.185***	-0.059	-0.038
	(0.024)	(0.023)	(0.065)	(0.064)
post merged_year 2004 ($\tau_{2.2}$)	-0.064	-0.100**	-0.020	-0.017
	(0.038)	(0.042)	(0.094)	(0.098)
post merged_year 2005 ($\tau_{2.3}$)	0.126***	0.077	0.022	0.031
	(0.040)	(0.048)	(0.123)	(0.128)
post merged_year 2006 ($\tau_{2.4}$)	0.077	0.008	0.017	0.023
	(0.053)	(0.051)	(0.142)	(0.140)
post merged_year 2007 ($\tau_{2.5}$)	-0.027	-0.117	-0.110	-0.101
	(0.049)	(0.072)	(0.151)	(0.143)
post merged_year 2008 ($\tau_{2.6}$)	0.002	-0.085	-0.167	-0.171
	(0.060)	(0.048)	(0.185)	(0.180)
post merged_year 2009 ($\tau_{2.7}$)	0.129*	-0.027	-0.366**	-0.375**
	(0.067)	(0.038)	(0.165)	(0.171)
post merged_year 2010 ($\tau_{2.8}$)	0.179***	0.051	-0.438**	-0.453**
	(0.055)	(0.064)	(0.170)	(0.181)
post merged_year 2011 ($\tau_{2.9}$)	0.128	-0.074	-0.414**	-0.405**
	(0.074)	(0.084)	(0.189)	(0.194)
post merged_year 2012 ($\tau_{2.10}$)	0.082	-0.075	-0.533**	-0.472**
	(0.074)	(0.058)	(0.225)	(0.215)
post merged_year 2013 ($\tau_{2.11}$)	0.147*		-0.511*	-0.443*
	(0.080)		(0.294)	(0.236)
post merged_year 2014 ($\tau_{2.12}$)	0.169*		-0.510	
	(0.083)		(0.338)	
post merged_year 2015 ($\tau_{2.13}$)	0.172		-0.487	
	(0.105)		(0.376)	
post merged_year 2016 ($\tau_{2.14}$)	0.050		-0.449	
	(0.101)		(0.396)	
post merged_year 2017 ($\tau_{2.15}$)	0.049		-0.359	
	(0.106)		(0.447)	
post merged_year 2018 ($\tau_{2.16}$)	-0.067		-0.520	
	(0.094)		(0.477)	
post merged_year 2019 ($\tau_{2.17}$)			-0.718	
			(0.502)	
Merged*post merged_year 2004 (δ_2)		-0.110	0.032	0.029
		(0.147)	(0.057)	(0.065)
Merged*post merged_year 2005 (δ_3)	0.078		-0.008	-0.019
	(0.117)		(0.063)	(0.070)
Merged*post merged_year 2006 (δ_4)	-0.090	-0.179	-0.030	-0.040
	(0.081)	(0.128)	(0.077)	(0.073)
Merged*post merged_year 2007 (δ_5)	-0.322***	-0.383	0.028	0.041
	(0.093)	(0.219)	(0.078)	(0.070)
Merged*post merged_year 2008 (δ_6)	-0.366***	-0.421*	0.078	0.126
	(0.097)	(0.234)	(0.106)	(0.096)
Merged*post merged_year 2009 (δ_7)	-0.309***	-0.371*	0.248***	0.279***

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Table 7 – continued from previous page

Variables	Coeff. Std. Err. (A)	Coeff. Std. Err. (B)	Coeff. Std. Err. (C)	Coeff. Std. Err. (D)
	(0.068)	(0.191)	(0.075)	(0.063)
Merged*post merged_year 2010 (δ_8)	-0.310***	-0.394***	0.246***	0.314***
	(0.023)	(0.130)	(0.085)	(0.086)
Merged*post merged_year 2011 (δ_9)	-0.323***	-0.400***	0.159*	0.192**
	(0.036)	(0.131)	(0.085)	(0.079)
Merged*post merged_year 2012 (δ_{10})	-0.269***	-0.358**	0.265**	0.305***
	(0.059)	(0.127)	(0.097)	(0.076)
Merged*post merged_year 2013 (δ_{11})	-0.199***	-0.293**	0.230	0.289***
	(0.064)	(0.112)	(0.138)	(0.098)
Merged*post merged_year 2014 (δ_{12})	-0.217***		0.234	
	(0.067)		(0.159)	
Merged*post merged_year 2015 (δ_{13})	-0.224***		0.220	
	(0.073)		(0.153)	
Merged*post merged_year 2016 (δ_{14})	-0.200**		0.206	
	(0.084)		(0.133)	
Merged*post merged_year 2017 (δ_{15})	-0.093		0.081	
	(0.076)		(0.172)	
Merged*post merged_year 2018 (δ_{16})	0.117		0.207*	
	(0.131)		(0.118)	
Merged*post merged_year 2019 (δ_{17})	0.023		0.326***	
	(0.099)		(0.112)	
Controls	NO	YES	NO	YES
Year fixed effects	YES	YES	YES	YES
Trust fixed effects	YES	YES	YES	YES
Constant	4.366***	7.292**	4.500***	2.644
	(0.040)	(2.798)	(0.031)	(2.917)
Observations	194	110	340	259
R-squared	0.602	0.785	0.853	0.891
Number of trusts	15	15	27	27

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.1: Mean Comparisons; merged versus non-merged profit-oriented hospitals.

	Merged = 1 by 2019		Merged = 0 in all years		
Variable	N	Mean	N	Mean	Difference
Dependent variables					
Waiting times (days)	272	53.54	1042	54.32	-8.235***
Hospital inputs					
Operating theatres (number)	244	27.52	970	16.21	10.485***
Diagnostic tests (number)	126	315059	613	182977	132082***
Medical staff (%)	275	44.76	1061	35.86	8.234***
Hospital characteristics					
Teaching (dummy)	276	10.96	1061	0.35	0.239***
Patient characteristics					
Patients aged 0–14 (%)	276	10.96	1048	13.79	-1.884***
Patients aged 60 and over (%)	276	46.77	1061	44.86	1.556***
Female patients (%)	276	59.92	1061	57.95	2.046***

Significance levels: $^{*} < 10\%$ $^{**} < 5\%$ $^{***} < 1\%$

Table A.2: Mean comparisons; merged versus non-merged semi-altruistic hospitals.

	Merged = 1 by 2019		Merged = 0 in all years		
Variable	N	Mean	N	Mean	Difference
Dependent variables					
Waiting times (days)	345	65.49	1595	77.84	-12.348***
Hospital inputs					
Operating theatres (number)	328	25.71	1577	15.78	9.929***
Diagnostic tests (number)	253	288902	1387	181753	107149***
Medical staff (%)	344	26.99	1615	20.40	6.596***
Hospital characteristics					
Teaching (dummy)	345	0.54	1621	0.3	0.236***
Patient characteristics					
Patients aged 0–14 (%)	342	12.20	1604	13.39	-1.182*
Patients aged 60 and over (%)	345	43.69	1617	42.53	1.167**
Female patients (%)	345	55.71	1616	53.87	1.837***

Significance levels: $^{*}< 10\%$ $^{**}< 5\%$ $^{***}< 1\%$

Figure 1: Waiting times trend over time; merged versus non-merged hospitals.

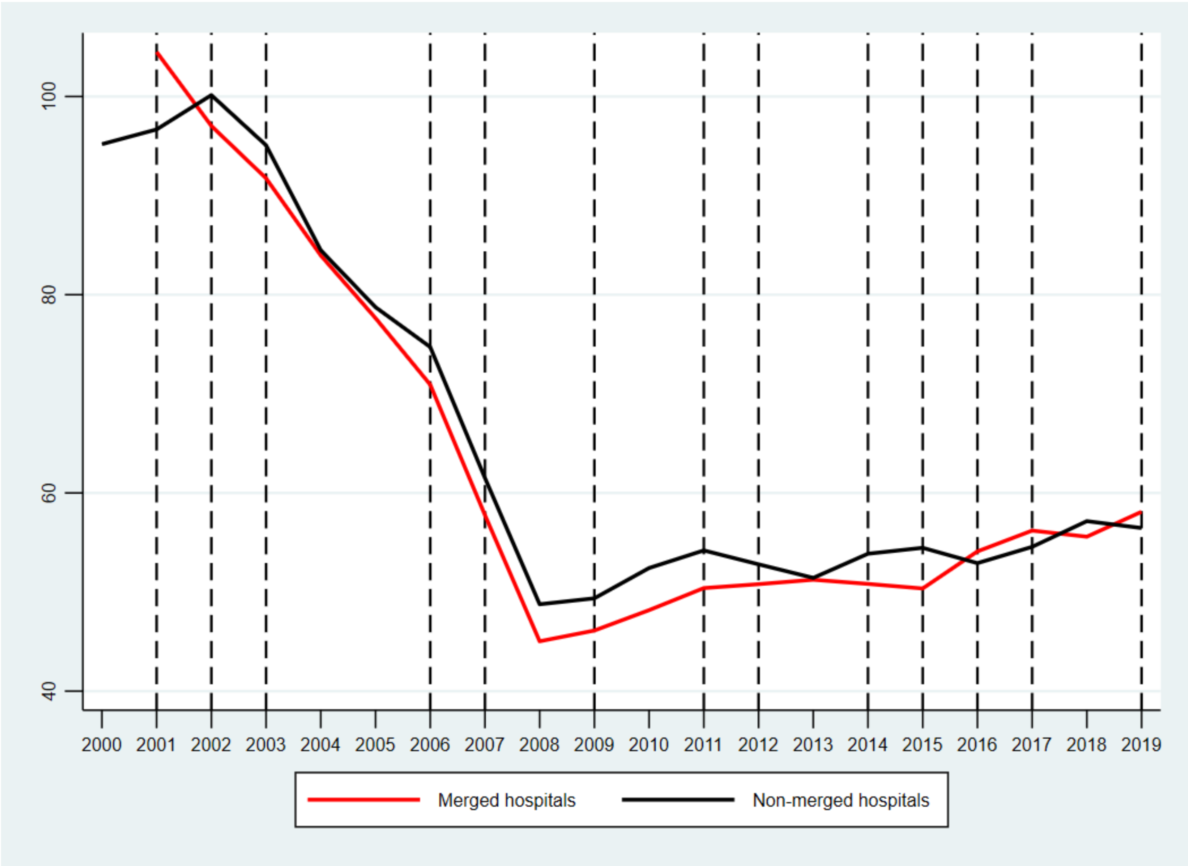

Figure A.1: Quantile-quantile plots of the continuous matching variables and waiting times.