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The Accuracy of Hospital Merger Screening Methods

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Abstract: This paper analyzes the accuracy of various prospective hospital merger screening methods used by antitrust agencies and the courts. The qualitative and quantitative predictions of the screening methods calculated with pre-merger data are compared with the actual post-merger price changes of 26 hospital mergers measured relative to controls. The evaluated screening methods include traditional structural measures (e.g., Herfindahl-Hirschman Index associated with various market definitions), measures derived from hospital competition models (e.g., diversion ratios, Willingness-to-Pay, and the Logit Competition Index), and hospital merger simulation. Diversion ratios, Willingness-to-Pay, and the Logit Competition Index are found to be more accurate at predicting post-merger price effects than traditional methods.

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[1] The views expressed in this paper are mine and not necessarily those of the Commission or any individual Commissioner. I thank Keith Brand, David Schmidt, Dan Hosken, Sean May, Michael Vita and participants of the International Industrial Organization Conference and FTC Microeconomics Conference for their suggestions and Michael Bohne, Chris Carman, Laura Kmitch, and Jordan Rhodes for their research assistance.

1. Introduction

The hospital industry is one of the largest and most dynamic sectors in the United States economy. In 2012, hospital services accounted for 5.4 percent of U.S. GDP, more than any other category of health expenditure.[2] A large fraction of U.S. hospital expenditures (40 percent) are financed with private health insurance or patient out-of-pocket payments. In recent years, the growth of privately-financed hospital expenditures has been driven almost entirely by hospital price increases.[3] In most states, hospital prices charged to private health insurance companies are unregulated and determined by negotiations between hospitals and health insurance companies. The negotiated prices are determined in large part by local competitive conditions and the ability of health insurance companies to substitute with competing hospitals in their managed care networks. Hospital antitrust enforcement plays a significant role in U.S. health care cost containment by preserving hospital competition and limiting hospital price growth, while also promoting quality and access to health care.

Over the past twenty years, hospital antitrust enforcement has undergone a transformation. Between 1993 and 2000, during the largest hospital merger wave in U.S. history, federal and state antitrust authorities challenged eight proposed hospital mergers in federal court and failed in each attempt. This string of setbacks led to an explosion of research on hospital competition and the effects of hospital mergers. One branch of the literature retrospectively studied the effects of past hospital mergers and found that the tools and assumptions upon which courts relied during the 1990s often led to incorrect conclusions about the likely effects of hospital mergers. Another branch of the literature attempted to model price formation in hospital markets and developed a set of tools to directly predict the price effects of hospital mergers. These tools (e.g., diversion ratios, Willingness-to-Pay, the Logit Competition Index, and merger simulation) were used by the federal antitrust agencies in recent hospital merger challenges and, unlike the 1990s, most of these challenges have been successful.

With the recent use of the new hospital merger screening tools in antitrust enforcement, it is important to evaluate their accuracy in predicting post-merger price changes. The original papers that developed the screening tools did not assess the accuracy of their predictions against actual post-merger outcomes. This paper offers the first comprehensive comparison of the predictions of a wide range of screening tools against the actual post-merger price changes of a relatively large sample of hospital mergers. The actual post-merger price changes (measured relative to controls) of 26 hospital mergers are compared to the qualitative (and, in some cases, quantitative) predictions of various screening methods. The screening methods include diversion ratios, Willingness-to-Pay (WTP), WTP-based merger simulation, the

[2] Centers for Medicare & Medicaid Services, Historical National Health Expenditure Data, http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsHistorical.html (accessed on 3/11/2014)
[3] 2012 Health Care Cost and Utilization Report, Health Care Cost Institute, http://www.healthcostinstitute.org (accessed on 3/11/2014)

Logit Competition Index (LOCI) and the traditional Herfendahl-Hirschman Index (HHI) calculated with various market definitions and market share measures.

The focus of the analysis is on evaluating methods that can be implemented with data that are likely available to regulators during the initial preliminary investigation of a merger. It is at this stage that delineating between possible anti-competitive mergers and beneficial or innocuous mergers is most useful and imposes the least regulatory cost. While a full phase investigation can provide the regulator with detailed data and other evidence to increase the precision of its estimates, a full phase investigation imposes significant costs on the merging parties and the regulator. The ideal screen for an initial investigation avoids "casting a wide net" and instead focuses the regulator on the mergers most likely to be anti-competitive. All of the screening methods evaluated in this paper can be calculated with data that is often available without a full phase investigation: patient discharge data and other public data sets (e.g., HCRIS and AHA data). It is important to note that this excludes merger simulations calibrated with health insurance claims data, as described in Brand and Balan (2013) and Brand and Garmon (2014). This paper only evaluates merger simulations calibrated with less-detailed hospital and discharge data.

Any evaluation of merger screening methods is complicated by active antitrust enforcement. Post-merger price effects are inherently noisy as hospital mergers are associated with many changes (e.g., cost changes, management changes, etc.) apart from reductions in competition. In an era of active and effective hospital antitrust enforcement, most mergers that are likely to be anti-competitive on balance are blocked or never proposed. Thus, a sample of consummated mergers taken from a period of active antitrust enforcement may be truncated and biased toward mergers with limited reductions in competition and significant pro-competitive effects (e.g., cost savings) (See Carlton (2009)). To address this issue, our sample of consummated hospital mergers includes 10 mergers in North Carolina that occurred between 1997 and 2001. This period was at the tail end of the federal and state hospital antitrust losing streak and before the successful hospital merger challenges of recent years. In addition, North Carolina introduced a hospital Certificate of Public Advantage (COPA) regulatory program in 1995 that gave merging hospitals participating in the program antitrust immunity. Only one pair of merging hospitals participated in North Carolina's COPA program,[4] but the option to participate, coupled with recent court rulings favoring hospital mergers, likely contributed to an environment in which competing hospitals felt safe to merge with less risk of an antitrust challenge.

Analyzing hospital mergers from North Carolina in the late 1990's and early 2000's may lessen the truncation problems caused by antitrust enforcement. However, the hospital industry has undergone many changes since the early 2000's, potentially limiting the

[4] In December 1995, Memorial Mission Hospital and St. Joseph's Hospital—the only two short-term, general acute care hospitals in Asheville, NC—entered into a joint management agreement to form Mission Health and simultaneously entered into a COPA agreement with the state of North Carolina, granting the merger antitrust immunity in exchange for regulation of Mission Health by the state. This merger is not included in the sample of hospital mergers analyzed in this paper.

applicability of findings from that period. Some have argued that methods used in hospital merger review and enforcement should evolve and account for the changes in health care delivery and finance that have occurred since the passage of the Affordable Care Act. (Guerin-Calvert, Maki, and Vladeck (2015)) To address these concerns and test the accuracy of hospital merger screens in this potentially new regime, our sample of hospital mergers also includes 16 recent transactions from 2007-2012.

The comparison of the actual post-merger price changes against the pre-merger predictions of the screening tools reveals that, apart from merger simulation, the new screening tools (i.e., diversion ratios, WTP, and LOCI) are more accurate than traditional concentration measures at flagging potentially anti-competitive hospital mergers for further review. However, the relationship between the new screening tools and post-merger price changes is not precise or robust to alternate specifications, so care should be taken when using the tools to screen mergers for further investigation. Merger simulation performs poorly, but this may be due to the limited data available to calibrate the simulation in the initial investigation. Finally, all of the traditional concentration measures tested are inaccurate at predicting post-merger price changes.

The paper is arranged as follows. Section 2 reviews hospital antitrust enforcement over the past 20 years and the hospital competition literature that developed alongside it. Section 3 describes the evaluated new screening tools and traditional concentration measures in detail. Section 4 describes the data, the criteria for merger selection, price measurement and price change estimation, and the construction/estimation of the screening tools. Section 5 compares the screening tools to the post-merger price changes and Section 6 concludes.

2. Literature and Case Review

Starting with the FTC's failed attempt in 1994 to block the merger of the only two hospitals in Ukiah, California, the federal and state antitrust authorities unsuccessfully challenged eight hospital mergers between 1994 and 2001. (Ashenfelter et al. (2011)) In six of the eight challenges, the courts found that the proposed merger was unlikely to reduce competition significantly because of the presence of numerous remaining competitors. These determinations were based on the courts' acceptance of relatively large geographic antitrust markets established using the Elzinga-Hogarty (EH) test (Elzinga and Hogarty (1973)) and Critical Loss Analysis.

The EH test posits that the relevant geographic market for antitrust analysis is the area for which inflows (i.e., sales by firms in the area to customers from outside the area) and outflows (i.e., sales by firms outside the area to customers living in the area) are sufficiently small. The two most common EH inflow/outflow thresholds used for market definition are 25 percent (a "weak" EH market, i.e., if the inflows into and outflows from an area are both less than 25 percent) and 10 percent (a "strong" EH market). Operationally, to determine an EH market for a particular merger, one would first find the smallest area from which the merging firms, and other nearby firms, draw 75 percent (or 90 percent for the "strong" standard) of their customers. If more than 25 percent (or 10 percent) of the customers who live in this area go outside to purchase the good, areas are added to the base draw area until the inflows and outflows are both below 25 (or 10) percent.

Critical Loss Analysis (CLA) is another related method for defining geographic markets in hospital merger challenges using patient flows. CLA calculates the loss of patients above which a small price increase (e.g., 5 percent) would be unprofitable for a hypothetical owner of all of the hospitals in an area (i.e., the "critical loss"). If estimates of the actual loss in response to the price increase exceed the critical loss, adjacent areas and hospitals are added to the market until the estimated actual loss no longer exceeds the critical loss.

Although the EH algorithm and CLA do not necessarily produce a unique area, the ubiquity of patient discharge data and the relative ease with which EH/CLA markets can be calculated with patient discharge data made the EH and CLA methods widespread in hospital merger challenges in the 1990s. However, as became apparent in the hospital merger challenges of the 1990s, the EH test and CLA often produce extremely large geographic hospital markets, particularly when the "strong" 10 percent criterion is applied in the EH test. In urban areas, the weak EH criterion will almost always result in a geographic market encompassing the entire metropolitan area and the strong criterion will often produce a market larger than the metropolitan area. For example, in overturning a lower court's ruling that the merger of the only two hospitals in Poplar Bluff, Missouri would be anticompetitive, the 8th Circuit U.S. Court of Appeals found that the relevant market included competing hospitals in Cape Girardeau (85 miles away from Poplar Bluff) and St. Louis (150 miles away) because significant numbers of patients in the merging parties' service area sought treatment in Cape Girardeau and St. Louis. Echoing the defendants' CLA arguments, the 8th Circuit U.S. Court of Appeals concluded that "the compelling and essentially unrefuted evidence that the switch to another provider by a small percentage of patients would constrain a price increase, shows that the FTC's proposed market is too narrow."[5]

In two of the eight unsuccessful hospital merger challenges in the 1990s, the merging parties argued—and the courts agreed—that the merging parties would not exercise any additional market power obtained through the merger because they were non-profit hospitals. Together, the courts' use of large EH/CLA-inspired geographic markets and its limited acceptance of the merging parties' non-profit defense prevented federal and state antitrust authorities from enjoining proposed hospital mergers they felt were anti-competitive. This spurred health economists to study the effects of hospital competition. Starting in the mid-1990s, a large hospital competition literature developed along two tracks. In the first track, economists empirically measured the cross-sectional relationship between hospital competition and outcomes (both price and quality) and retrospectively analyzed past hospital mergers to

[5] United States Court of Appeals, Eighth Circuit. FEDERAL TRADE COMMISSION; State of Missouri, by and through its Attorney General, Jeremiah W. (Jay) Nixon, v. TENET HEALTH CARE CORPORATION; Poplar Bluff Physicians Group, Inc., doing business as Doctors Regional Medical Center; 186 F.3d 1045

study their effects. Vogt and Town (2006) summarize this literature and conclude regarding price that "the great weight of the literature shows that hospital consolidation leads to price increases, although a few studies reach the opposite conclusion. Studies that examine consolidation among hospitals that are geographically close to one another consistently find that consolidation leads to price increases of 40 percent or more." Summarizing the literature on hospital competition and quality Vogt and Town conclude that "on balance, the evidence suggests that increasing hospital concentration lowers quality." Further, most analyses of hospital competition found a positive correlation between concentration and price even among non-profit hospitals. In addition, numerous retrospective studies of mergers of competing non-profit hospitals found significant post-merger price increases, casting doubt on the argument that non-profit hospitals do not exercise post-merger market power. (Vita and Sacher (2001), Haas-Wilson and Garmon (2011), Tenn (2011))

While the cross-sectional and retrospective hospital competition literature severely undermined the logic behind the courts' rulings in the 1990s, it did not provide tools to replace the EH test and CLA. In the second track of the new hospital competition literature, economists modelled hospital markets and developed new screening methods for hospital mergers. Town and Vistnes (2001) and Capps, Dranove, and Satterthwaite (2003) developed a new market power measure for hospitals—commonly referred to as Willingness-to-Pay (WTP)—from a bargaining model of the negotiation between health insurance companies and hospitals. Gaynor and Vogt (2003) developed a Bertrand model of hospital price competition and, from this model, Antwi, Gaynor, and Vogt (2013) derived a market power measure for hospitals, which they denote as the Logit Competition Index (LOCI). Both WTP and LOCI are based on the first-order pricing incentives of hospitals. In that regard, they are similar to the Upward Pricing Pressure Index (UPPI) (Farrell and Shapiro (2010)), which is often used to measure the potential lost competition from a merger in a differentiated products industry. Like UPPI, both WTP and LOCI predict a significant price increase after a hospital merger when the merging hospitals are close substitutes as measured by diversion ratios. Both WTP and LOCI can also be used as the basis for reduced-form hospital merger simulations. Gowrisankaran, Nevo, & Town (2015) recently developed a generalized model of hospital price formation in which the WTP and LOCI-based models are special cases.

In recent years, WTP, LOCI, diversion ratios, and merger simulation have been used in hospital antitrust litigation and regulation in both the U.S. and abroad. In the recent joint Federal Trade Commission (FTC)/State of Ohio challenge to Promedica's acquisition of St. Luke's Hospital in Toledo, Ohio, the plaintiff's economic expert used diversion ratios, WTP, and merger simulation to argue that the merger would significantly reduce hospital competition and lead to higher prices. The federal district court agreed with the plaintiff's analysis and issued a preliminary injunction, while the plaintiffs also prevailed in administrative litigation and the defendant's appeal to the Sixth Circuit.[6] In the FTC's challenge of the proposed merger between OSF Healthcare and Rockford Health, the FTC's economic expert used diversion ratios

[6] http://www.ftc.gov/enforcement/cases-proceedings/101-0167/promedica-health-system-inc-corporation-matter (accessed on September 30, 2014)

and WTP to argue that the merger would be anticompetitive and, again, the federal district court sided with the FTC and enjoined the merger.[7] Finally, the U.K. Competition Commission recently used LOCI to measure competition as part of its investigation into the private hospital industry in Britain.[8]

To date, there has been limited research on the accuracy of the new screening tools despite their widespread use in antitrust challenges and regulation. Three recent working papers have explored the accuracy of the most-widely used of the new screening tools, Willingness-to-Pay (WTP). Fournier and Gai (2007) find that post-merger WTP changes estimated using pre-merger data are accurate predictors of actual post-merger WTP changes that occurred after two hospital mergers. For one of these mergers, they also find that the price change implied by a WTP-based merger simulation using pre-merger data produced a conservative estimate of the actual post-merger price change. (Data limitations prevented the measurement of the post-merger price change for the second merger in their study.) May (2013) compares the qualitative predictions of WTP changes estimated using pre-merger data against the actual post-merger price changes of two hospital mergers and finds that the merger predicted to have the largest post-merger price increase had the smallest actual price increase of the two mergers. Brand and Balan (2013) conduct a Monte Carlo-like exercise in which they compare the predictions of various merger screens (including WTP) against data produced by a bargaining model of the negotiations between hospitals and health insurance companies and find that diversion ratios, WTP changes, and merger simulation produce accurate predictions of post-merger price changes simulated by the bargaining model. While this finding implies the new hospital merger screening tools are theoretically sound, the evidence from Fournier and Gai (2007) and May (2013) comparing the predictions of the WTP screen against actual post-merger price changes is mixed and limited to a meta-sample of only three mergers. Apart from May (2013) and Fournier and Gai (2007), there has been little research on the accuracy and reliability of WTP, LOCI, diversion ratios, and hospital merger simulation in predicting the price effects of actual hospital mergers.[9]

This paper makes three primary contributions to the literature. First, this paper significantly adds to the sample size of mergers considered by Fournier and Gai (2007) and May (2013), increasing the likelihood of a meaningful evaluation of the accuracy of hospital merger screening tools. Second, the analysis does not assess the accuracy of a particular screen in isolation, but instead compares the predictions of various screening methods. While it is useful

[7] http://www.ftc.gov/enforcement/cases-proceedings/d-9349-111-0102/osf-healthcare-system-rockford-health-system (accessed on September 30, 2014)

[8] See http://www.competition-commission.org.uk/assets/competitioncommission/docs/2012/private-healthcare-market-investigation/ais_app_b_toh_1_annex_2_loci_note_housestyled.pdf (accessed on 3/21/2014)

[9] Ron Kemp, a senior economic officer for the Dutch Authority for Consumers and Markets, has recently compared the post-merger price changes of 12 hospital mergers in the Netherlands (described in Kemp, Kersten, and Severijnen (2012)) with the pre-merger price increase predictions of LOCI. This comparison is described in the April 22, 2015 presentation "Ex-Post Analysis of Dutch Hospital Mergers," available at http://www.oecd.org/daf/competition/workshop-expost-evaluation-competition-enforcement-decisions.htm (accessed on June 2, 2015)

to assess the absolute accuracy of a screening tool, it is more important to evaluate its relative accuracy compared with previous traditional screening methods. Do any of the new screening tools provide information beyond the traditional market-based screening methods that can help more accurately predict the effects of hospital mergers? If so, are some of the new screening tools better than others at providing this additional information?

Finally, one advantage of the new hospital merger screening tools is that most (e.g., diversion ratios, WTP, and LOCI) can be implemented without the traditional exercise of defining product and geographic markets and calculating market shares. However, courts continue to require the definition of a relevant antitrust product and geographic market as part of any merger challenge. In addition to evaluating the relative accuracy of the new screening tools, this paper also evaluates the accuracy of the traditional market power measure, HHI, under various market definitions and share metrics.

All of the screening tools are evaluated by comparing their predictions for each merger to the merger's actual price change. Other potentially important effects of mergers, such as changes in quality or access to care, are not evaluated.

The following section describes the new hospital merger screening tools in more detail, as well as traditional concentration measures used as a benchmark for comparison.

3. Merger Screening Methods

Willingness-to-Pay (WTP)

Willingness-to-Pay (WTP) was developed by Town and Vistnes (2001) and Capps, Dranove, and Satterthwaite (2003) from a bargaining model of the negotiation between a managed care organization (MCO) and a hospital over the contractual price per admission paid by the MCO for its members seeking care at the hospital. Consider MCO k that negotiates with each hospital in the set Φ of hospitals that would provide positive value to k's network of hospitals. We assume there are no impediments to reaching an agreement (e.g., asymmetric information, negotiation deadlines with random communication delays, etc.) if a positive surplus is available, so that, in equilibrium, each hospital in Φ will reach an agreement with k. The focus of the model is on the negotiation between k and hospital j∈Φ, assuming that the outcomes of the negotiations between k and the remaining hospitals Φ_{-j} are taken as given (e.g., because of simultaneous negotiations). Given the vector of hospital prices p = $\{p_i\}_{i\in\Phi}$ negotiated by MCO k and the hospitals in its network, k sets a health insurance premium ρ to maximize profits, taking the premiums and network configurations of its competitors as given (e.g., as in Bertrand health insurance competition). MCO k faces a total membership demand of $X_k(\rho,\rho_{-k},\Phi)$ where ρ_{-k} is the vector of competitor premiums. k chooses ρ to maximize:

$$\pi_k^* = Max_\rho \left\{ \rho X_k - C_k(X_k) - \sum_{h\in\Phi} p_h y_{kh} \right\} \tag{1}$$

where y_{ki} is the number of k's patients treated at hospital i and C_k are k's non-hospital costs. Denote as R_{kj} k's equilibrium profits apart from payments to hospital j (i.e., $R_{kj} = \pi_k^* + p_j y_j$). If we assume that the negotiation between MCO k and hospital j satisfies the axioms of generalized Nash bargaining and we assume, without loss of generality, that hospital j loses all of k's members if it is not part of k's network, then the price that k and j negotiate will solve:

$$Max_{p_j}\left\{\left[R_{kj}(\Phi)-\pi_k^*(\Phi_{-j})-p_j y_{kj}\right]^{(1-\gamma)}\left[p_j y_{kj}-c_j(y_{kj})\right]^{\gamma}\right\} \tag{2}$$

where $c_j(y_{kj})$ are hospital j's costs of serving k's patients and γ is a split parameter reflecting the relative bargaining abilities of the hospital and MCO. If we assume that hospital j's price to k does not affect a member's demand for hospital j, as long as j is in k's network (e.g., k's health plan design is a PPO that charges the same copay for in-network hospitals), then the price that solves (2) is:

$$p_j = \frac{\gamma\left(R_{kj}(\Phi)-\pi_k^*(\Phi_{-j})\right)+(1-\gamma)\left(c_j(y_{kj})\right)}{y_{kj}} \tag{3}$$

As seen in (3), hospital j's market power is proportional to $\left(R_{kj}(\Phi)-\pi_k^*(\Phi_{-j})\right)$, the additional profit k receives from having hospital j in its network. Town and Vistnes (2001) and Capps, Dranove, and Satterthwaite (2003) proxy for $\left(R_{kj}(\Phi)-\pi_k^*(\Phi_{-j})\right)$ with the aggregate consumer surplus hospital j adds to k's network. The change in consumer surplus associated with j's inclusion into k's network is WTP. Assume that, conditional on needing hospitalization, each of k's members have preferences over the hospitals in Φ of the form $U_{hi} = V_{hi} + \epsilon_i$ where V_{hi} is a linear function of hospital characteristics and the stochastic term ε_i is independently and identically distributed according to the extreme value distribution (i.e., the distributional assumption consistent with logit estimation). In this case, WTP for hospital j is defined as the aggregate change in consumer surplus associated with adding hospital j to k's network:

$$\begin{aligned} WTP_{kj} &= \sum_{i\in I_k}\frac{1}{\alpha_i}\left[E[max_{h\epsilon\Phi}(V_{hi}+\epsilon_i)]-E\left[max_{h\epsilon\Phi_{-j}}(V_{hi}+\epsilon_i)\right]\right] \\ &= \sum_{i\epsilon I_k}\frac{1}{\alpha_i}\left[ln\left(\frac{1}{1-s_i^j}\right)\right] \end{aligned} \tag{4}$$

where α_i is the marginal utility of income for patient i and s_i^j is the estimated probability that patient i chooses hospital j. s_i^j are the predicted probabilities associated with the conditional logit estimation of V_{ji}. We cannot directly observe α_i, so WTP is operationalized by ignoring α_i, although it is subsumed within the estimated WTP coefficient of WTP-based merger simulations (described below). Furthermore, individual MCOs usually cannot be observed in the discharge data most commonly used to estimate WTP, so WTP is typically estimated across all commercial MCOs:

$$WTP_j = \sum_i \left[ln\left(\frac{1}{1 - s_i^j}\right)\right] \qquad (5)$$

WTP can be used to analyze the market power created by the merger of two competing hospitals (or hospital systems) by measuring the net change in WTP associated with the combination of the two hospitals (or systems). When used in this way, it is implicitly assumed that the combined hospitals will negotiate in an all-or-nothing manner (i.e., in order to contract with either hospital, the MCO must contract with both). This collective negotiation by multiple competing hospitals worsens the MCO's threat point in (2). For example, consider the merger of two competing hospitals L and M. Before the merger, if the MCO fails to reach an agreement with L, the loss in welfare for the MCO's members may be relatively small with M available as an alternative in the payer's network. Post-merger, if L and M negotiate on an all-or-nothing basis, the loss in welfare if the MCO fails to contract with both hospitals will be greater than the sum of the losses associated with each hospital individually. This is because L and M are competing hospitals, in the sense that some of the MCO's members who prefer L see M as an alternative and vice versa. If there were no members for which this were true, the WTP of L and M would equal the sum of the WTP of L and the WTP of M and there would be no net increase in WTP associated with the merger. In this way, a merger of competing hospitals, along with post-merger all-or-nothing negotiation by the merged hospital system, may lead to a disproportionate worsening of the MCO's threat point, resulting in a price increase. The net change in WTP with the merger can be used as a measure of the worsening of the MCO's threat point.

Diversion Ratios

A merger of competing hospitals can also lead to a price increase even if the hospitals do not negotiate in an all-or-nothing manner and continue to negotiate with the MCO separately. In this case, the merger improves the threat point of the hospital in (2). For example, before the merger, if L fails to reach an agreement with the MCO, some of the MCO's current patients who prefer L will instead seek care at M. Post-merger, when L is negotiating with the MCO, both parties know that failure to reach an agreement will result in less real diversion from L, as those patients who switch to M remain internal to the combined entity. This improved threat point will lead L to be more aggressive in the negotiation, resulting in a higher price despite the lack of all-or-nothing bargaining from L and M. A similar post-merger dynamic exists in M's negotiation with the MCO. This effect of the merger, due to the change in each hospital's threat point, occurs because of the collective ownership of both hospitals, *even* if the negotiations remain separate after the merger.

Whether the post-merger negotiations are collective or separate, both of the merger effects are driven by the potential diversion between the merging hospitals, which is a measure of the substitutability of the hospitals in the eyes of the MCO's members. In other words, the effect of the merger on the negotiated price should be proportional to the number of patients who would switch from a hospital to its merger partner in the event the former is dropped from the MCO's network. Therefore, another measure of the lost competition between two merging hospitals is the diversion ratio: the percentage of the patients treated at a hospital who would go to its merger partner if the former is dropped from the MCO's network. Using the predicted probabilities associated with the conditional logit estimation of V_{ji} and the logit property that diversion is proportional to the probability of selection for each patient type, the diversion ratio from hospital L to hospital M is:

$$d_{LM} = \frac{\sum_i \left(\frac{s_i^L s_i^M}{1 - s_i^L}\right)}{\sum_i s_i^L} \tag{6}$$

This diversion ratio calculation implicitly assumes that no patients would continue to seek treatment at L if it is dropped from the MCO's network. Otherwise, the diversion ratio could be calculated by incorporating the probability that each patient type would stay with his or her preferred hospital if it is dropped from the network.

WTP-Based Merger Simulation

Equation (3) can also be used as the basis of a reduced-form merger simulation. WTP per adjusted discharge WTP_PAD (where the adjustment accounts for variations in acuity across patients) can be used as a proxy for ($\left(R_{kj}(\Phi) - \pi_k^*(\Phi_{-j})\right)/y_{kj}$) in equation (3) and form the basis of a reduced-form econometric model:

$$p_h = \gamma + \beta_1 WTP\_PAD_h + \beta_2 c_h + \beta X_h + \varepsilon_h \tag{7}$$

P_h is the case-mix adjusted price of hospital system h, c_h is the average variable cost of hospital system h, and X_h is a vector of other determinants of price. The coefficient of WTP_PAD is estimated (e.g., via OLS) and then used along with the predicted post-merger change in WTP_PAD to estimate the post-merger price change.

As described in Brand and Garmon (2014), the usefulness of a reduced-form merger simulation may be limited by the data that is available to estimate (7). In most cases, only cross-sectional data is available to estimate (7) and the estimated WTP_PAD coefficient may suffer from omitted variable bias if there are factors related to the hospital/MCO negotiation that cannot be observed or measured. This bias may be compounded in the context of an initial investigation when payer data is not available and only hospital-level price estimates can be calculated. Furthermore, the use of accounting data to measure average variable cost may introduce endogeniety bias as non-profit hospitals with market power may classify some profits as costs. (For instance, see Robinson (2011).)

Logit Competition Index

Gaynor and Vogt (2003) and Antwi, Gaynor, and Vogt (2013) do not use a bargaining model as the basis for their measure of hospital market power, but instead develop a measure from a Bertrand model of hospital price competition in which hospitals simultaneously set price to maximize profit:

$$Max_{p_j}\left[p_j D_j(p) - C_j\left(D_j(p)\right)\right] \tag{8}$$

The first-order necessary condition for profit maximization is:

$$p_j = \frac{\partial C_j}{\partial D_j} - \frac{D_j}{\partial D_j / \partial p_j} \tag{9}$$

Gaynor and Vogt (2003) and Antwi, Gaynor, and Vogt (2013) also assume that patients have preferences over hospitals of the form $U_{hi} = V_{hi} + \epsilon_i$ where V_{hi} is a linear function of hospital characteristics (including price) and the stochastic term ε_i is independently and identically distributed according to the extreme value distribution. With this assumption, the second term on the right-hand side of (9) can be expressed as $1/\alpha\Lambda_j$ where α is the marginal utility of income (assumed constant across all patients) and Λ_j is the Logit Competition Index (LOCI):

$$\Lambda_j = \sum_i \frac{s_i^j}{\sum_i s_i^j}\left(1 - s_i^j\right) \tag{10}$$

Using this model, Antwi, Gaynor, and Vogt (2013) develop a first-order approximation of the price increase associated with the merger of two hospitals. Consider the merger of competing hospitals L and M. The post-merger price increase for hospital L (as a proportion of its pre-merger markup over marginal cost) should be approximately equal to $\left(\Lambda_{LM}/\Lambda_L\Lambda_M\right)$ where Λ_{LM} is a measure of the overlap of M relative to L or "LOCI-Overlap."

$$\Lambda_{LM} = \frac{\sum_i s_i^L s_i^M}{\sum_i s_i^L(1 - s_i^L)} \tag{11}$$

The commercial discharge weighted average of the merging hospitals' LOCI-Overlap price increase estimate is used as the overall price increase estimate of the merger.

Herfindahl-Hirschman Index

For each hospital merger analyzed below, the new merger screening tools (WTP, Diversion Ratios, Merger Simulation, and LOCI) are juxtaposed against the traditional measure of market power used by the antitrust agencies and the courts: the Herfindahl-Hirschman Index (HHI) or the sum of the squared market shares (s_h) for the hospitals in the market (M):

$$HHI_M = \sum_{h \epsilon M} (s_h)^2 \tag{12}$$

The HHI depends on the definition of the product and geographic market M and the method and metric used to calculate the market shares. One significant conceptual benefit of the new tools over the HHI is that none of the new tools require a product or geographic market for calculation, except for restrictions on products and hospitals necessary to make the conditional logit choice model estimation feasible. To expedite comparison, the product market used for all of the screening tools in this paper (including the new tools described above) are services to commercially insured patients with general acute care (GAC) conditions who are treated at short-term, GAC hospitals. This closely matches the "cluster" product market established by the courts in most of the hospital merger challenges over the past 20 years.

Three geographic markets and share calculation methods are used to calculate HHIs. First, as a conservative approximation of the concentration measures used by the courts in the hospital merger challenges of the 1990s, an HHI is calculated based on the Hospital Referral Region (HRR) (defined by the Dartmouth Atlas of Health Care) of the merging hospitals with shares based on the staffed beds of the hospitals located within this HRR. The HRR is used instead of an EH-defined market because the EH procedure will not necessarily produce a unique area for each merger. However, each HRR is roughly similar to a hospital's 90 percent service area, as it is designed to capture the market for high-acuity services. The retrospective hospital competition literature has found that geographic markets of this size are often too large to correctly predict the effects of a hospital merger with an HHI. In addition, this share calculation method suffers from the "all-in-or-all-out" problem. Hospitals within the market are factored into the HHI calculation with their full capacity, even if they are not located near the merging hospitals, and hospitals located outside of the market are not counted at all, even if they serve many of the patients living near the merging hospitals. To rectify these problems, we calculate two alternative HHIs.

The second HHI uses the Hospital Service Area (HSA) (defined by the Dartmouth Atlas) of the acquired hospital and calculates the market shares based on the patients residing in the area, not the hospitals located within the area. The HSA is typically smaller than the HRR and is meant to capture the market for low and medium-acuity cases. Shares are calculated based on the admissions of patients residing in the area, even if they are treated at hospitals outside of the area. Defining the geographic with the HSA is still arbitrary, so the final HHI calculation employs a weighted service area. For each zip code, the share of each hospital is calculated based on the patients who reside in that zip code (regardless of the location of the hospital). Then these shares are weighted based on the importance of the zip code to the merging hospitals (i.e., the weights are the percentage of the combined hospitals' admissions that come from the zip code). The HHI is then calculated as the sum of the squares of the weighted shares. This HHI completely solves the "all-in-or-all-out" problem by including all patients and all hospitals, regardless of location, but doing so in a way that focuses on the area most important to the merging hospitals. This measure is also similar to weighted concentration measures commonly used in the hospital competition literature (e.g., Capps and Dranove (2004)). Appendix A provides an example of each HHI using a simple hypothetical hospital market.

4. Data and Estimation

All of the hospital merger screening methods described above can be implemented with patient-level inpatient discharge data and data on the characteristics of the merging hospitals and potential competitors. The discharge data used for the analysis was provided by the Arkansas Department of Health (2007-2011), the Connecticut Department of Public Health, Office of Health Care Access (2007-2013), the Georgia Hospital Association (2007-2013), the Oklahoma Department of Health (2007-2011), the Pennsylvania Health Care Cost Containment Council (PHC4) (2007-2013), the New York Department of Health (2007-2012), and the company formerly known as Solucient for North Carolina (1997-2002). The data is restricted to patients treated at non-federal, short-term, general acute care (GAC) hospitals. In other words, patients treated at federal hospitals (Veterans Affairs or military), long-term acute care hospitals, rehabilitation hospitals, and psychiatric and substance abuse facilities are excluded. In addition, patients treated at non-federal, short-term GAC hospitals for non-GAC conditions (i.e., rehabilitation, psychiatry, and substance abuse) are excluded. Finally, newborns, patients transferred from other hospitals, and court-ordered admissions are excluded to avoid double-counting patient choices or counting admissions that were mandatory.

Hospital characteristics are taken from the American Hospital Association's (AHA) Annual Survey and the Centers for Medicare and Medicaid Services' (CMS) Healthcare Cost Report Information System (HCRIS). Hospital ownership and changes in ownership are taken from the AHA data and confirmed with background research. The HCRIS and discharge data are used to construct the hospital price estimates as described below. For each merger, the data used to construct the screening tools was that of the calendar year before the year in which the merger was consummated. If the merging hospitals are located near a state border or are located in different states, we use the discharge data of both states to construct the screening tools. Otherwise, only the discharge data from the merging hospitals' state is used.

To focus on mergers of competing hospitals, we include all of the mergers captured in our discharge data between short-term GAC hospitals in the same MSA or adjacent MSAs, as long as we have at least one year of pre-merger discharge and price data and at least one year of post-merger discharge and price data.[10] We also exclude acquisitions of Critical Access Hospitals (CAH) and acquisitions of failing or failed hospitals. The former are excluded because CAHs are small hospitals serving isolated rural areas and, thus, usually do not compete with

[10] For rural mergers, we include all mergers involving hospitals in the same county or adjacent counties. Mergers involving hospitals close to a border of a state for which we do not have discharge data are excluded.

other hospitals.[11] The latter are excluded because merger screens are irrelevant if one of the parties involved in the merger would exit the market absent the merger.[12] Finally, we also exclude cases in which a hospital system acquires multiple hospitals at the same time. The selection criteria result in a sample of 26 mergers: 16 of which occurred between 2007 and 2012 between hospitals in Arkansas, Connecticut, Georgia, New York, Oklahoma, and Pennsylvania and 10 of which occurred between hospitals in North Carolina between 1997 and 2001. The mergers included in our sample are listed in Appendix B, in alphabetical order of the acquired hospital.

The ideal sample to assess the accuracy of a merger screen would be a random selection of mergers that are as likely to trigger the screen as not. However, mergers occurring in a period of active antitrust enforcement are more likely to be those that have or would have passed through the screen. In an era of antitrust enforcement in which the screen is actively used, mergers that the screen would identify as anti-competitive are less likely to occur because they are blocked or deterred. Thus, sampling mergers from such an era will hamper an analyst's ability to fairly assess the accuracy of a screen in predicting post-merger effects, particularly for mergers that the screen identifies as anti-competitive (Carlton (2009)). The North Carolina mergers were added to the sample to ameliorate the bias caused by merger selection during a period of antitrust enforcement. Hospitals merging in North Carolina in 1997-2001 did not possess blanket antitrust immunity. However, hospitals merging in this period likely felt relatively safe from antitrust challenges for two reasons. First, this period was at the tail end of the federal and state hospital antitrust losing streak and before the successful hospital merger challenges of recent years. Second, North Carolina introduced a hospital Certificate of Public Advantage (COPA) regulatory program in 1995 that gave merging hospitals participating in the program antitrust immunity conditional on submitting to state regulation. None of the hospitals in our sample participated in North Carolina's COPA program, but the option to participate, if the merger were challenged by federal or state antitrust authorities, may have reduced the likelihood of an antitrust challenge for these mergers. The sample of recent mergers also includes a merger that was challenged by the FTC, but allowed to proceed by the courts.

Price Measurement

Hospital prices are difficult to measure due to the variety and complexity of services offered. A typical short-term, acute care hospital offers services that support the treatment of patients across a broad range of diagnoses, exhibiting a broad range of severity. The price charged to any particular patient and his or her insurance company can be a function of many factors that affect the cost of treating the patient: the patient's diagnosis, the severity of the

[11] By law, CAHs can have no more than 25 acute care beds and must be at least 35 miles from the next nearest hospital (except in areas of mountainous terrain or other unique circumstances where the hospital is deemed a "necessary provider" despite proximity to another hospital of less than 35 miles).
[12] An earlier draft of this paper included two acquisitions of failing or closed hospitals. Their inclusion would not materially affect the results.

diagnosis, the procedures performed in treating the patient, the manner in which the patient was admitted (e.g., through the emergency room), additional conditions present in the patient when admitted to the hospital (i.e., comorbidities), complications that arise during treatment, etc. To accurately measure the overall hospital price paid by patients with private commercial insurance, one not only needs to accurately measure the payments made by the insurer and patient to the hospital. It is also necessary to properly adjust these payments to account for changes in the diagnoses treated and procedures performed, along with changes in severity, complications, and comorbidities. These latter adjustments are often collectively referred to as "case mix adjustment."

The ideal type of data for hospital price measurement is comprehensive, all-payer claims data that provides detailed information on each patient and treatment episode and the amounts actually paid by (not just the list price charged to) the patient and insurance company for each treatment and procedure. The discharge data described above provides detailed information about each patient stay, but it only includes the total list price for all services, not the amount actually paid. Unfortunately, few states collect all-payer claims data and only two (New Hampshire and Maine) make this data available to researchers and have a panel of hospital claims data stretching back far enough to capture pre and post-merger periods. However, we are aware of no mergers of competing hospitals in New Hampshire or Maine during the time period of their claims data collection. Private collections of claims data available for research either fail to provide a comprehensive collection of commercial insurers or are restricted to make it difficult to identify hospitals and measure their commercial revenues.

Alternatively, some states collect aggregate hospital financial data and make it available to researchers. A few states collect aggregate financial data in sufficient detail to allow estimates of each hospital's commercial price when the data are combined with discharge data. For instance, an estimate of each hospital's average inpatient commercial discount can be calculated from the financial data and applied to the hospital's commercially-insured inpatients listed in the discharge data to estimate the hospital's case-mix adjusted commercial inpatient price. Numerous researchers studying hospital competition have used this approach and Levit, Friedman, and Wong (2013) find that commercial prices calculated with state-level financial data are accurate estimates of commercial prices calculated from private claims data. Unfortunately, the states that collect and disseminate hospital financial data with detail sufficient to accurately estimate commercial inpatient prices are too few to allow the study of more than a handful of hospital mergers.

To estimate hospital prices for a relatively large sample of hospital mergers spread across multiple states and across time, we use financial information in the HCRIS data and the commercial price estimation procedure described in Dafny (2009). Dafny (2009) estimates the case-mix-adjusted commercial price for each hospital using estimates of net inpatient commercial revenue and commercial inpatient discharges derived from HCRIS data and each hospital's case-mix index taken from CMS's Impact Files. Each hospital's estimated price is:

$$P_h = \frac{(IPSC_h + IPIC_h + IPANC_h)\left(1 - \frac{CONTDISC_h}{GROSSREV_h}\right) - MCPRIM_h - MCAP_h}{(DISCH_h - MDISCH_h)CMI_h} \qquad (13)$$

where $IPSC_h$ is the hospital's inpatient routine service charges, $IPIC_h$ is intensive care charges, $IPANC_h$ is inpatient ancillary charges, $CONTDISC_h$ is contractual discounts, $GROSSREV_h$ is gross revenues, $MCPRIM_h$ is the hospital's Medicare primary payer amounts, $MCAP_h$ is the Medicare total amount payable,[13] $DISCH_h$ is the hospital's total inpatient discharges, $MDISCH_h$ is Medicare inpatient discharges, and CMI_h is the hospital's case-mix index (i.e., the average Diagnosis Related Group (DRG) weight for its inpatients). The only change we make to the Dafny (2009) formula in (13) is to substitute the hospital's case-mix index for commercial inpatients calculated from the discharge data for the Impact File case-mix index, which reflects the hospital's Medicare population.

The price estimate in (13) is not an ideal proxy for each hospital's commercial price, as it does not deduct Medicaid revenue and the discount factor applied to inpatient charges reflects inpatient and outpatient discounts. However, our research suggests that, while it is a noisy measure of price, it correlates to commercial price measures calculated with state-level financial data for hospitals with at least 200 commercial patients per year. Using financial data from PHC4 for Pennsylvania short-term, acute care hospitals, we calculated case-mix adjusted commercial inpatient prices and regressed these estimates onto commercial inpatient prices calculating using the Dafny (2009) method described above, while suppressing the constant and restricting the sample to hospitals with at least 200 commercial discharges per year. The resulting estimated coefficient was 0.99 with an R^2 of 0.90. Thus, the commercial price estimate calculated using (13) is likely an unbiased, but somewhat noisy measure of the hospital's actual commercial price and is appropriate to use when studying a relatively large sample of mergers, as in Dafny (2009) and the current analysis, even though it may not be appropriate for the study of a particular merger. However, some merger retrospective studies find that post-merger price changes estimated using HCRIS data are consistent with price changes estimated using detailed claims data. (Haas-Wilson and Garmon (2011))

Post-Merger Price Change Estimation

The merger screens described above are meant to capture the loss of competition associated with a hospital merger. To assess the accuracy of their price predictions, the screens should be compared to the price change associated with the loss of competition from the merger, apart from other changes that occur coincident with the merger. In other words, the screens should be compared to the difference between the post-merger price change and what it would have been absent the merger. Apart from the price measurement issues described above, the former price difference is straightforward to calculate. The latter price difference is impossible to calculate as the merger did, in fact, occur. Thus, following the general difference-in-differences (DID) literature, we select control groups of hospitals to serve as a proxy for the

[13] MCPRIM+MCAP is the total reimbursement to the hospital for Medicare inpatients.

merging hospitals in the counterfactual absent the merger. These control groups should be made up of non-merging hospitals that are similar to the merging hospitals.

Unlike the typical DID comparison of a treatment group with a control group to estimate the effect of treatment, in this case each treatment group—the merged hospitals—is a singleton. For this reason, the standard methods of selecting a control group (e.g., propensity scoring) do not necessarily result in a control group that is similar to the merging hospitals apart from the merger. In addition, a merger may affect nearby non-merging hospitals by lowering the overall level of competition in the market (Dafny (2009)). Thus, the use of nearby hospitals in the control group, which otherwise may be optimal because they face cost and demand conditions similar to the merging hospitals, may bias the estimated price change.

For each merger, the post-merger price change is measured relative to a control group of non-merging hospitals similar in size and cost-structure to the merging hospitals, but outside of their immediate area. Most of the mergers in the sample involve urban, short-term GAC hospitals with more than 100 staffed beds. In these cases, the control group is the set of all non-merging urban short-term GAC hospitals in the same state (but outside of the merging hospitals' MSA) with more than 100 staffed beds. In other cases, the control group is adjusted to match the size and cost structure of the merging hospitals.[14] In all cases, the control groups exclude hospitals specializing in the treatment of children and hospitals with fewer than 200 commercial admissions in the pre or post-merger years. In addition, hospitals outside of the merged hospitals' MSA that are owned by the acquiring hospital system are excluded from the control group and the merging hospitals' price change estimates. We also report results that use an alternate control group in which the size restrictions are relaxed.

The post-merger price change for each merger is calculated using the hospital prices in effect in the first full calendar year after the merger and is measured relative to the prices in effect in the last full calendar year before the merger. Where it is feasible to do so, we also measure the price change using prices in effect two years after the merger to account for lags in the post-merger contracting process between the merged hospitals and insurers (Tenn (2011)). The price change is measured relative to the mean price change across the control group. Thus, the statistical significance of the relative price change can be interpreted as a comparison of the merged hospitals' price change and the distribution of price changes across the control group.[15] The relative price change for each merger is calculated by estimating the following equation using weighted least squares estimation, where the weights are the number of commercial discharges:

[14] For mergers that involve rural hospitals with more than 100 staffed beds, the control group includes all non-merging urban and rural short-term GAC hospitals in the same state with more than 100 staffed beds. In cases in which the merger involves the acquisition of a hospital with fewer than 100 staffed beds, the control group is selected with a smaller bed-size threshold and these thresholds are listed in Appendix B. In all cases, critical access hospitals are excluded from the control group.

[15] The null hypothesis is that the merging parties' price change is equal to the mean price change across the control group. Thus, instead of reporting the standard error of the estimated coefficient, the p-value for the t test comparing the merging parties' price change and the distribution of control price changes is reported.

$$P_{ht} = \alpha + \beta_1 POST_{ht} + \beta_2 POSTM_{ht} + \delta_h + \varepsilon_{ht} \tag{14}$$

where P_{ht} is the log of hospital's commercial price as calculated in (13) above, $POST_{ht}$ is an indicator for the post-merger period (i.e., the year after the merger), $POSTM_{ht}$ is an indicator for the hospitals in the merged entity in the post-merger period, and δ_h are hospital fixed effects. The relative post-merger price change is calculated as:

$$\Delta P = e^{\widehat{\beta_2}} - 1 \tag{15}$$

Choice Model Estimation

The new hospital merger screening tools (e.g., diversion ratios, WTP, and LOCI) are constructed from the predicted probabilities of a conditional logit choice model. We use the estimates from a parametric choice model in which the patient's choice is modeled as a function of hospital characteristics and patient characteristics. The probability that patient i selects hospital j is:

$$s_i^h = \frac{e^{(\gamma Z_{ih} + \beta X_i Y_h + \vartheta X_i Z_{ih})}}{\sum_{j\epsilon H} e^{(\gamma Z_{ij} + \beta X_i Y_j + \vartheta X_i Z_{ij})}} \tag{16}$$

where Z_{ih} are characteristics specific to patient i and hospital h, X_i is a vector of patient characteristics, and Y_h is a vector of hospital characteristics. In other words, patient i's hospital choice is assumed to be a function of hospital characteristics unique to the patient and characteristics common to all patients. Further, patient preferences for these characteristics are allowed to vary across patient types. The patient-specific hospital characteristics Z_{ih} consist of the driving time (under normal traffic conditions) between the center of the patient's zip code and the hospital and the driving time squared.[16] The patient characteristics consist of the patient's DRG weight, a gender indicator, an indicator for emergency room admissions, an indicator for obstetrics, and an indicator for cardiac surgery. The hospital characteristics consist of the hospital's residents and interns per bed (a measure of teaching intensity), a for-profit indicator, an indicator for hospitals that offer obstetrics services, and an indicator for hospitals that offer cardiac surgery.

To test the sensitivity of the merger screens to the choice model type and specification, we also use the predicted probabilities from the semiparametric choice model described in Tenn (2014) in which patient bins are defined iteratively and probabilities are estimated using the observed shares within each bin. As in Tenn (2014), the bins are defined (with a minimum

[16] Driving times are taken from ArcGIS, version 10.

bin size of 25 patients) using the following patient characteristics, in declining order of importance: patient's county, patient's zip code, major diagnostic category (MDC), whether the patient was admitted through the emergency room, whether the service provided was medical or surgical, the severity of the patient's diagnosis (defined with Diagnosis Related Group (DRG) weight quartiles), DRG, age category, and gender. Recent research (Raval, Rosenbaum, and Wilson (2014)) indicates that the Tenn model generally is the most accurate model, of those commonly used, at predicting actual changes in patient choices in response to the removal of a hospital from the patient's options, and that more accurate models tend to predict greater likelihoods of harm when hospitals are substitutes. Thus, the Tenn semiparametric model tends to produce diversion ratios, WTP changes, and LOCI price increase estimates that are larger than those produced using parametric approaches. Therefore, our primary results employ the more conservative parametric merger screens.

Both models are estimated over all of the commercial GAC inpatients in the acquired hospital's HRR in the year prior to the merger. The choice set H is restricted to all hospitals that served at least 0.5% of these patients.[17] The choice of a hospital outside of this set is aggregated into an outside option.[18]

Merger Simulation

The basis for the merger simulation, condition (7), is estimated via a system-level regression of price on WTP_PAD, average variable cost, and other covariates. The dependent variable is the weighted average commercial price (as calculated in (13)) across all of the hospitals in each system in each metropolitan statistical area (MSA) in the year prior to the merger (where the weights are the number of commercial discharges). WTP_PAD is constructed by first estimating the choice model across all of the patients in each MSA in the state in the year prior to the merger using the specifications and choice set selection criteria described above. Each system's WTP is then calculated from the predicted probabilities and divided by the system's aggregate DRG weight to produce the system's WTP_PAD. The system-wide operating cost per adjusted admission (where the adjustment accounts for the hospital's outpatient scale) is used as the proxy for average variable cost. Finally, the other covariates consist of a for-profit indicator (to capture differences in for-profit and non-profit pricing) and MSA indicators (to capture differences in market conditions across MSAs).

The estimated coefficient of WTP_PAD is then used to predict the post-merger price change by applying it to the predicted change in WTP_PAD associated with the merger. The bootstrapped 95 percent confidence intervals of the price change estimate for each merger are listed along with each estimate. Because the estimation of (7) is only carried out for urban

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[17] For two mergers, the HRR is so large that one of the merging hospitals is not included in the choice set using this inclusion criterion. In these cases, the choice model is estimated over all of the commercial GAC patients in the merging hospitals' combined primary service area instead of the HRR.

[18] The coefficient estimates, standard errors, and fit statistics for the estimation of (16) for each merger are listed in Appendix C.

hospital systems in each state, a merger simulation is not conducted for the rural hospital mergers.

5. Results

Ex ante merger screens designed to identify mergers that are likely anti-competitive can be used in one of two ways. First, they can be used to establish a threshold above which the merger is presumed to be anti-competitive, absent extenuating circumstances (e.g., mergers with a change in the screen above X% are likely anti-competitive). We will refer to this as the "threshold" approach. Second, they can be used to make a prediction about the likely effects of a merger (e.g., an X% increase in the screen is associated with a Y% increase in price on average). We will refer to this as the "relationship" approach. The first approach largely differs from the second by making no presumption about mergers below the threshold. We will evaluate the merger screens with both uses in mind. First, are there thresholds of the merger screen above which price increases are likely and price decreases are unlikely? Second, is there a relationship between the merger screen and the post-merger price changes?

Table 1 lists the price change relative to controls for each merger along with each merger screen calculated using pre-merger data. 9 of the 26 mergers resulted in statistically significant price increases larger than the mean increase across the controls, while 2 resulted in statistically significant relative price decreases (i.e., an absolute price decrease or an increase less than the mean increase across the controls).[19] The latter mergers highlight the fact that not all mergers of competing hospitals are anti-competitive and some may lead to lower prices (or smaller price increases than normal) due to, for instance, cost savings resulting from the merger. The mean price change relative to controls across all 26 mergers is 4.7 percent and the median is 5.3 percent.

The first three rows in Table 1 list the traditional post-merger HHI and change in HHI based on the three market definitions and share measures described previously. Following the Federal Trade Commission (FTC) and Department of Justice (DOJ) joint Horizontal Merger Guidelines,[20] mergers resulting in a post-merger HHI of 2500 or more with an HHI increase of 200 or more "will be presumed to be likely to enhance market power." As described in the Guidelines, this presumption is not sufficient to conclude that a merger is likely to substantially lessen competition. However, an antitrust regulator using the HHI as a screen is likely to focus on mergers with a post-merger HHI greater than 2500 and a change greater than 200 for

[19] Statistical significance is measured at the 95% level. It is important to note that a lack of statistical significance does not necessarily imply economic insignificance. For instance, one merger (24) in Table 1 was associated with a 13.2% relative price increase, potentially indicating an anti-competitive merger, but the null hypothesis that this merger's price increase is the same as the mean control price increase cannot be rejected because of the high variance of control price changes. Likewise, two mergers (7 and 15) are associated with relative price decreases exceeding 20%, potentially indicating pro-competitive mergers, but neither is statistically significant because of the high variance of control price changes.

[20] http://www.ftc.gov/sites/default/files/attachments/merger-review/100819hmg.pdf (accessed on 3/27/2014)

further investigation. The mergers that would be flagged under this condition are highlighted in bold in Table 1.

Of the three HHI measures, the HHI calculated using bed shares in the merging parties' HRR is the most likely to produce a false negative. Of the 9 mergers with post-merger price increases, this screen flags only 3. This largely confirms the criticisms of most health economists that the EH-based geographic markets used by the courts in the 1990s (which closely resemble HRR markets) were, in many cases, too large to accurately predict the effect of a hospital merger.

On the other hand, the HHI calculated using discharge shares in the acquired party's HSA is most likely to produce a false positive. This screen flags all but 2 of the 26 mergers as potentially problematic, including both of the mergers with post-merger relative price decreases. The HHI calculated using discharge shares in the merging parties' weighted service area is only slightly better. This screen flags 19 of the 26 mergers as potentially problematic, including both mergers with price decreases.

The new merger screening tools are listed in the bottom rows of Table 1. Also listed in Table 1 is the product of the diversion ratios for each merger. The last row of Table 1 lists the price increase estimates for each merger based on the reduced form WTP-based merger simulation. The change in WTP closely tracks the two other choice-model-based merger screens: the LOCI price change estimate and the diversion ratios. This is not surprising as the WTP change and the LOCI price increase approximation are both largely based on the overlap between the merging hospitals in each patient type, which is also the basis for the diversion ratios. The correlation between the product of the diversion ratios and the WTP change is 0.98. The correlation between the product of the diversion ratios and the LOCI price change estimate is 0.99. Finally, the correlation between the WTP change and the LOCI price increase estimate is also 0.99. Because of the near perfect correlation between the WTP change, LOCI price change estimate, and the product of the diversion ratios, we will focus on the most commonly used of the three, the WTP change.

For each new screen, there are no established thresholds—like the Guidelines' HHI thresholds—above which a merger is presumed problematic. However, WTP was used by the FTC in two recent hospital merger challenges. In the FTC's challenge of Promedica's acquisition of St. Luke's, a projected 13.5% change in WTP was cited by the FTC in its public decision.[21] In the FTC's challenge of the proposed merger between OSF Healthcare and Rockford Health, a WTP change of 19% was cited by FTC staff in its pre-trial brief to the court.[22] In our sample, three mergers have a WTP change exceeding 13.5% and two of these mergers resulted in statistically significant price increases.

[21] http://www.ftc.gov/sites/default/files/documents/cases/2012/06/120625promedicaopinion.pdf , page 49 (Accessed on September 30, 2014)

[22] www.ftc.gov/sites/default/files/documents/cases/2012/04/120404ccpretrialbrief.pdf , page 44 (Accessed on June 9, 2015)

A lower threshold may be more appropriate when using WTP to screen for mergers that warrant further investigation. Graph 1 plots the mean price change for mergers with WTP change values above a certain threshold. At the threshold WTP change of roughly 5%, there is a discrete jump in the mean price change for mergers above this threshold from roughly 5% to more than 10%. (A WTP change threshold of 5% roughly corresponds to a diversion ratio product of 0.0129 and a LOCI price change estimate of 14.4%.)

Table 2 compares the threshold performance of WTP (using the 5% change threshold) to the three HHI screens using the Guidelines' thresholds. Of the four screens, WTP makes the correct prediction (i.e., flags mergers associated with statistically significant price increases and does not flag mergers not associated with statistically significant price increases) most often. In addition, WTP has the lowest incidence of false positives (i.e., flagging a merger as potentially problematic when the merger is not associated with a statistically significant price increase). Furthermore, of the 9 mergers with statistically significant price increases, 5 had a WTP change greater than 5% and both of the mergers with statistically significant price decreases had WTP changes less than 5%. The average price change across mergers with a WTP change greater than 5% was 11.2%, whereas the average price change for mergers with a WTP change less than 5% was 0.7%. For the three HHI screens, the average price change for the flagged mergers is much closer to the overall mean price change of 4.7% and all of the HHI screens flag at least one of the mergers with a statistically significant price decrease as problematic. This suggests that a WTP change threshold of 5% more accurately flags hospital mergers that warrant further investigation than any of the evaluated HHI screens using the traditional Guidelines thresholds.

A closer examination of mergers with relatively large screen values reveals some of the relative advantages and disadvantages of the screening methods. There are 6 mergers with post-merger HHIs of at least 3000 and HHI deltas of at least 500, across all of the geographic markets and share metrics considered. For three of these mergers, the WTP change is also greater than 10% and the average price change across these three is 21%. For the remaining three mergers, the WTP change is less than 5% and the average price change for these is -13%. This highlights that the new screening tools can capture situations in which short-term GAC hospitals are not as competitive as their geographic proximity would suggest because they serve somewhat different populations. In this way, the new screening tools can capture subtleties in product and geographic differentiation that the antitrust market definition exercise cannot capture. This finding also suggests that the relative performance of the HHI screens compared to the new screens would not improve with higher thresholds than in the Guidelines.

Graphs 2 through 8 plot the post-merger price changes against each merger screening tool. For the HHIs, the price change is plotted against the HHI change (i.e., "HHI Delta") with larger dots signifying larger post-merger HHI levels. Hollow dots represent the mergers in North Carolina between 1997 and 2001, while solid dots represent the recent mergers. Table 3 lists the coefficient estimates and fit of the OLS regression of the price change on each merger screen. In each case, there is a great deal of unexplained variation in the price changes. This is not surprising, as the screens are only meant to capture the loss of competition resulting from the merger and not other changes coincident with the merger (e.g., cost savings, management changes, etc.). Still, the new merger screens (diversion ratios, WTP, and LOCI) do a better job of predicting price changes than the HHIs. For the product of the diversion ratios, the WTP change, and the LOCI price change estimate, the relationship between the merger screen and the post-merger price change is positive and statistically significant. By contrast, there is no statistically significant relationship between the post-merger price change and the HHI screens, regardless of the geographic market or share metric employed.

Merger simulation also performs poorly, likely due to the limited data available to identify the relationship between WTP and price and the other limitations of merger simulation described above. With the data available in an initial investigation, one can only measure the commercial price of each hospital and not the price charged to each MCO, which would more closely fit the first order condition in (3). With limited cross-sectional observations, the estimates of the relationship between price and WTP are imprecise, as exhibited by the wide confidence intervals around each estimate in Table 1. While merger simulation may be a useful tool for analyzing a hospital merger with detailed payer data, this suggests that it is not a worthwhile exercise in the initial stages of an investigation when data are limited.

The predictive power of the new merger screens is robust to price changes measured relative to the alternate, less restrictive control group, but the results are not robust to other specification changes and alterations.[23] As seen in graphs 1 through 7, the relationship between the merger screens and the price change is heavily influenced by an outlier, Merger 20. If Merger 20 is excluded, there is no longer a statistically significant relationship between the price change and any merger screen, although the relationships between the price change and the new screens (diversion ratios, WTP change, and LOCI price change estimate) remain positive (but statistically insignificant).

The excessive influence of Merger 20 on the results presents a dilemma for their interpretation. Ideally, one would like to observe additional mergers, like Merger 20, with large values of the merger screens to see if they also result in large price increases. However, in an era of active antitrust enforcement, it is unlikely that such mergers would be proposed, no less consummated. As such, Merger 20 should not be ignored as a simple outlier because it represents what a merger with large merging screening values can produce. On the other hand, mergers such as Merger 20 are likely to trigger any and all merger screens (including the HHI for almost all reasonable geographic markets and share metrics), so the inclusion of Merger 20 may reveal little about the relative advantages or disadvantages of the new screens over traditional methods, particularly for less extreme mergers. It is with the less extreme mergers that screens are more useful to antitrust regulators, to distinguish mergers that are likely innocuous from those that require further investigation.

[23] An expanded version of Table 1 with alternate price changes, control groups, and merger screens is attached in Appendix D.

The estimated relationships between the price changes and the screens for the 1997-2001 North Carolina mergers are similar to the overall sample. The relationships between the new screens and the price changes are each larger than in the overall sample, but are not statistically significant, likely due to the smaller sample size of mergers.

For 17 mergers, data are available to calculate the relative post-merger price change using the second year after the merger. As seen in Graph 9, these price changes are generally of the same sign as the first year price changes, but are more pronounced. For instance, of the 9 mergers with statistically significant price increases after one post-merger year, data are available to calculate relative price increases using a subsequent year for 6 mergers. All 6 have price increases after two years and, for 4 of these mergers, the relative price increase after two years is larger than the relative price increase after one year. However, only 3 of the 6 price increases are statistically significant due to the smaller size of the control group and larger variance of price increases across the control group. (Data are not available to calculate price changes after two years for the two mergers with statistically significant price decreases.) Of the remaining 15 mergers without a statistically significant price change after one year, data is available to calculate a second-year price change for 11. Of these, 3 have statistically significant price increases after two years and 3 have statistically significant price decreases after two years. Overall, the greater variance of second-year price changes weakens the relationship between the price changes and the merger screens, as seen in the third-to-last and second-to-last columns of Table 3, which exclude mergers in which second-year price changes are unavailable.

Finally, as seen in the last column of Table 3, the relationship between the new merger screens and the price changes is not robust to the alternate, semiparametric choice model of Tenn (2014). This is because the screens using the semiparametric model are typically larger than the screens using the parametric model, when there is a difference between the two. For example, Graph 10 plots the semiparametric WTP changes against the parametric WTP changes. For many mergers, the WTP changes produced by the two models are similar, but there are six mergers for which the semiparametric WTP change is much larger (more than 10 percentage points larger) than the parametric WTP change. There are fewer mergers for which the opposite is true and none for which the parametric WTP change exceeds the semiparametric by more than 10 percentage points. Due to this, there is not a statistically significant relationship between the price changes and the semiparametric WTP changes and there are a number of mergers with large semiparametric WTP changes, but without a statistically significant price increase. For instance, of the nine mergers with a semiparametric WTP change greater than 10%, six are not associated with statistically significant price increases and one results in a statistically significant price decrease. This highlights that it is important to avoid reliance on only one choice model specification when using the new tools to screen hospital mergers.

6. Conclusion

Recent research on hospital competition has produced new screening tools that attempt to capture the post-merger pricing incentives of hospitals better than the traditional techniques of concentration measurement. This paper is the first large-scale evaluation of the new screening tools, comparing their predictions to the actual price effects of a relatively large sample of past consummated hospital mergers, using pre-merger data like that readily available in an initial investigation. The results suggest that most of the new hospital merger screening tools (in particular, diversion ratios, WTP, and LOCI) are more accurate at flagging mergers that are potentially anti-competitive than the traditional tools of market definition and concentration measurement. This is because the new tools capture information about the differentiation in hospital markets that the traditional exercise of market definition cannot capture. However, the relationship between the new merger screens and post-merger price changes is not robust to all changes in model specification, highlighting the importance of calculating the new merger screens using multiple choice models and specifications. WTP-based merger simulation performs poorly at predicting post-merger price changes, but this may be due to the limited data available to calibrate the simulation in an initial investigation. Merger simulations may be more accurate when calibrated with detailed health insurance claims data. Finally, for the traditional exercise of market definition and concentration measurement, none of the evaluated geographic market definitions and share metrics was accurate in predicting post-merger price changes. Going forward, better data is needed to more precisely estimate post-merger hospital price changes and more detailed hospital competition models are needed to more accurately predict post-merger price changes.

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Table 1: Post-Merger Price Changes and Screening Tools (Mergers 1-14)
(Standard errors are in parentheses, except as noted)

Merger:		1	2	3	4	5	6	7
Price Change Relative to Controls		6.4%	3.4%	-3.2%	24.8%	16.9%	-4.6%	-21.8%
P-value of t Test: Price Change vs. Mean Control Price Change		0.06	0.74	0.06	0.01	0.00	0.12	0.16
Bed Shares in HRR	Post HHI	951	2285	2002	**2648**	570	1722	**3115**
	HHI Delta	10	416	599	**425**	23	74	**558**
Discharge Shares in HSA	Post HHI	**4656**	**6445**	**6740**	**4662**	**3427**	**6673**	**5797**
	HHI Delta	**812**	**2606**	**2969**	**1802**	**1165**	**3304**	**2490**
Discharge Shares in Weighted Service Area	Post HHI	**4229**	**3674**	**2804**	**3373**	1396	**5415**	**3886**
	HHI Delta	**1724**	**674**	**1293**	**928**	401	**1081**	**1551**
Diversion Ratio	A to B	16.4% (0.2%)	5.3% (0.1%)	8.7% (0.1%)	8.0% (0.1%)	3.5% (0.0%)	10.2% (0.1%)	5.3% (0.1%)
	B to A	15.5% (0.2%)	21.4% (0.1%)	14.8% (0.1%)	17.0% (0.2%)	9.0% (0.0%)	13.0% (0.1%)	10.2% (0.2%)
Product of Diversion Ratios		0.0254	0.0113	0.0129	0.0136	0.0032	0.0133	0.0054
Change in Willingness-to-Pay		8.8% (0.1%)	4.2% (0.1%)	5.8% (0.1%)	5.7% (0.1%)	2.9% (0.0%)	6.8% (0.1%)	3.6% (0.0%)
LOCI Price Change Estimate		21.2% (0.4%)	12.6% (0.1%)	14.5% (0.1%)	14.4% (0.3%)	6.5% (0.0%)	14.8% (0.1%)	8.4% (0.1%)
WTP-Based Merger Simulation	Estimate		1.1%	0.9%	0.1%	1.5%		12.5%
	CI High		11.3%	8.3%	9.5%	5.5%		56.3%
	CI Low		-9.1%	-6.5%	-9.4%	-2.5%		-31.3%

Merger:		8	9	10	11	12	13	14
Price Change Relative to Controls		-5.4%	9.3%	-0.6%	8.9%	-2.6%	19.9%	-15.2%
P-value of t Test: Price Change vs. Mean Control Price Change		0.47	0.02	0.26	0.08	0.40	0.00	0.00
Bed Shares in HRR	Post HHI	1151	589	2084	734	**4285**	1944	**5867**
	HHI Delta	13	42	67	114	**1434**	290	**1329**
Discharge Shares in HSA	Post HHI	**3095**	1421	4572	**3493**	**7523**	**5019**	**7164**
	HHI Delta	**1390**	119	155	**404**	**2623**	**1446**	**3540**
Discharge Shares in Weighted Service Area	Post HHI	1999	876	3803	2180	**4970**	**3165**	**5456**
	HHI Delta	316	80	138	653	**1729**	**1138**	**618**
Diversion Ratio	A to B	1.9% (0.0%)	6.3% (0.0%)	1.0% (0.0%)	20.4% (0.1%)	6.4% (0.1%)	12.1% (0.1%)	5.0% (0.1%)
	B to A	4.4% (0.0%)	11.3% (0.0%)	18.0% (0.1%)	5.2% (0.1%)	27.8% (0.2%)	13.2% (0.1%)	32.6% (0.2%)
Product of Diversion Ratios		0.0008	0.0071	0.0017	0.0106	0.0177	0.0160	0.0163
Change in Willingness-to-Pay		1.4% (0.0%)	4.1% (0.0%)	0.9% (0.0%)	4.1% (0.1%)	4.8% (0.1%)	6.8% (0.1%)	3.5% (0.1%)
LOCI Price Change Estimate		2.9% (0.0%)	9.0% (0.1%)	2.7% (0.0%)	11.5% (0.1%)	15.3% (0.2%)	15.7% (0.2%)	16.9% (0.2%)
WTP-Based Merger Simulation	Estimate	-0.1%	1.5%	0.0%	0.2%	0.9%	0.5%	
	CI High	0.5%	6.3%	3.0%	2.4%	8.4%	5.4%	
	CI Low	-0.7%	-3.3%	-2.9%	-1.9%	-6.6%	-4.3%	

Table 1: Post-Merger Price Changes and Screening Tools (Mergers 15-26)
(Standard errors are in parentheses, except as noted)

Merger:		15	16	17	18	19	20	21
Price Change Relative to Controls		-26.5%	-6.7%	-1.2%	15.6%	30.4%	34.1%	16.1%
P-value of t Test: Price Change vs. Mean Control Price Change		0.17	0.03	0.39	0.00	0.00	0.00	0.00
Bed Shares in HRR	Post HHI	1391	1118	**2825**	845	1792	**8461**	**3199**
	HHI Delta	294	68	**1050**	4	531	**2453**	**987**
Discharge Shares in HSA	Post HHI	**3075**	**7806**	**8464**	**4181**	**5571**	**6615**	**4301**
	HHI Delta	**426**	**1661**	**3355**	**778**	**1912**	**2538**	**1818**
Discharge Shares in Weighted Service Area	Post HHI	1857	**5483**	**4408**	**3172**	**2549**	**5600**	**3756**
	HHI Delta	401	**1148**	**1535**	**594**	**939**	**2117**	**1592**
Diversion Ratio	A to B	5.9% (0.1%)	4.7% (0.1%)	17.5% (0.2%)	1.3% (0.0%)	4.4% (0.0%)	34.2% (0.9%)	20.6% (0.3%)
	B to A	13.3% (0.2%)	16.1% (0.1%)	43.0% (0.2%)	4.3% (0.0%)	21.1% (0.1%)	62.7% (0.7%)	24.9% (0.5%)
Product of Diversion Ratios		0.0079	0.0075	0.0751	0.0006	0.0093	0.2140	0.0512
Change in Willingness-to-Pay		4.2% (0.0%)	3.5% (0.1%)	14.1% (0.2%)	1.0% (0.0%)	3.9% (0.0%)	34.8% (1.2%)	13.6% (0.2%)
LOCI Price Change Estimate		10.4% (0.1%)	9.0% (0.1%)	43.6% (0.4%)	2.2% (0.0%)	10.0% (0.0%)	133.6% (3.9%)	53.2% (0.9%)
WTP-Based Merger Simulation	Estimate	1.0%	-0.4%	0.6%	-2.3%	-0.1%	18.3%	9.9%
	CI High	4.4%	6.8%	18.3%	34.6%	3.6%	66.4%	28.0%
	CI Low	-2.5%	-7.5%	-17.1%	-39.2%	-3.7%	-29.7%	-8.3%

Merger:		22	23	24	25	26
Price Change Relative to Controls		8.2%	-7.7%	13.2%	4.3%	6.3%
P-value of t Test: Price Change vs. Mean Control Price Change		0.10	0.73	0.11	0.06	0.00
Bed Shares in HRR	Post HHI	2382	549	**4024**	**2808**	1977
	HHI Delta	261	17	**1142**	**209**	288
Discharge Shares in HSA	Post HHI	**3624**	**3974**	**6923**	**4096**	**3785**
	HHI Delta	**254**	**1841**	**2578**	**1723**	**655**
Discharge Shares in Weighted Service Area	Post HHI	**3818**	1159	**5316**	**3678**	**2629**
	HHI Delta	**423**	220	**1912**	**1535**	**378**
Diversion Ratio	A to B	4.3% (0.0%)	1.0% (0.0%)	16.5% (0.4%)	7.5% (0.2%)	11.6% (0.1%)
	B to A	21.3% (0.1%)	7.1% (0.0%)	36.1% (0.4%)	10.3% (0.2%)	32.4% (0.1%)
Product of Diversion Ratios		0.0092	0.0007	0.0595	0.0077	0.0376
Change in Willingness-to-Pay		3.6% (0.0%)	1.1% (0.0%)	11.7% (0.3%)	4.7% (0.1%)	9.5% (0.0%)
LOCI Price Change Estimate		10.2% (0.0%)	2.4% (0.0%)	37.4% (0.8%)	10.1% (0.2%)	26.9% (0.1%)
WTP-Based Merger Simulation	Estimate		0.4%	4.3%		-2.6%
	CI High		1.3%	39.7%		3.3%
	CI Low		-0.5%	-31.2%		-8.5%

Table 2: Selection Based on Thresholds

	Correct Prediction	False Positive	Strong False Positive	False Negative	Mean Relative Price Change for Flagged Mergers
HHI (HRR Bed Shares) Guidelines	14	6	1	6	5.8%
HHI (HSA Disch Shares) Guidelines	9	16	2	1	4.7%
HHI (WSA Disch Shares) Guidelines	12	12	2	2	6.7%
Change in WTP > 5%	17	5	0	4	11.2%

Correct Prediction = (Flagged merger as problematic and merger associated with statistically significant relative price increase) or (Did not flag merger as problematic and merger not associated with statistically significant relative price increase)

False Positive = (Flagged merger as problematic and merger not associated with statistically significant relative price increase)

Strong False Positive = (Flagged merger as problematic and merger associated with statistically significant relative price decrease)

False Negative = (Did not flag merger as problematic and merger associated with statistically significant relative price increase)

Guidelines = Horizontal Merger Guidelines thresholds = Post-Merger HHI > 2500 and HHI Delta > 200

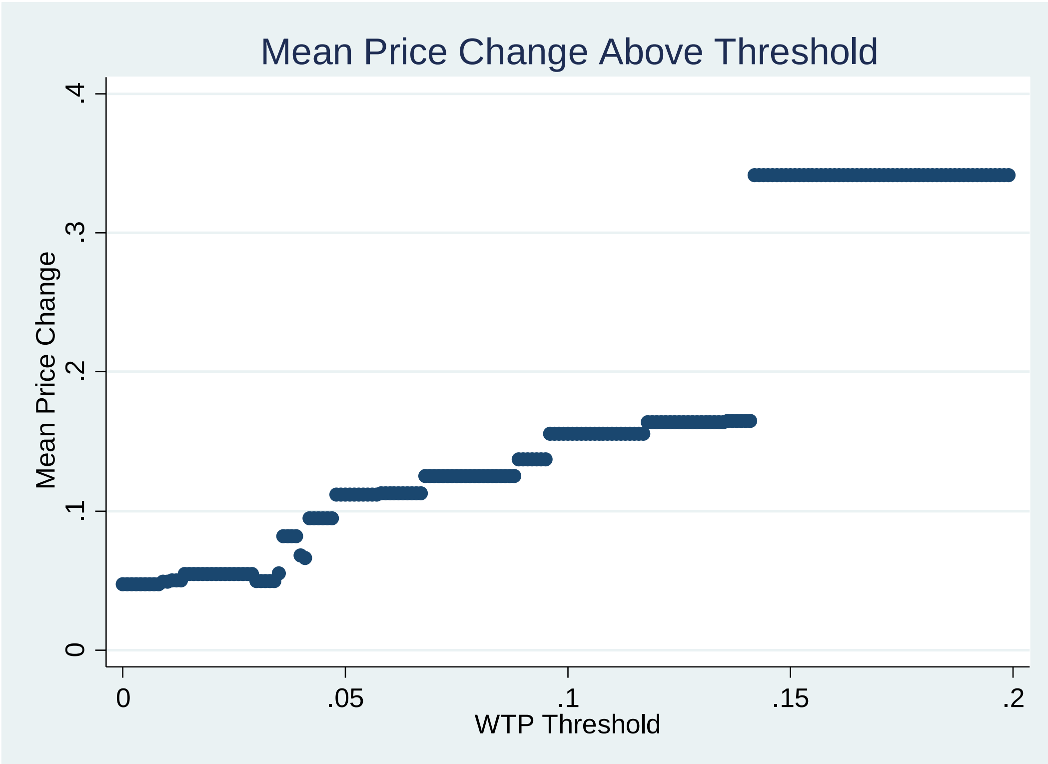
Table 3: Regressions of Price Change on Screening Tools

		Entire Sample (N = 26)		North Carolina (N = 10)		Excluding Merger 20 (N = 25)		Alternate Control Group (N=26)		Alternate (2-Year) Price Change (N=17)		Price Change When Alternate Exists (N=17)		Alternate Choice Model (N=26)	
		Coefficient (SE)	R^2	Coefficient (SE)	R^2	Coefficient (SE)	R^2	Coefficient (SE)	R^2	Coefficient (SE)	R^2	Coefficient (SE)	R^2	Coefficient (SE)	R^2
Bed Shares in HRR	Post HHI	-2.1x10^{-5} (4.8x10^{-5})	0.06	-4.2x10^{-5} (5.4x10^{-5})	0.17	-4.4x10^{-5} (4.6x10^{-5})	0.05	-1.2x10^{-5} (4.9x10^{-5})	0.03	-2.2x10^{-5} (7.4x10^{-5})	0.01	3.5x10^{-5} (4.9x10^{-5})	0.23		
	HHI Delta	1.1x10^{-4} (1.5x10^{-4})		5.2x10^{-5} (1.6x10^{-4})		8.6x10^{-5} (1.4x10^{-4})		7.7x10^{-5} (1.5x10^{-4})		4.0x10^{-5} (2.2x10^{-4})		-1.2x10^{-5} (1.4x10^{-4})			
Discharge Shares in HSA	Post HHI	2.0x10^{-6} (3.1x10^{-5})	0.02	-3.7x10^{-5} (3.7x10^{-5})	0.30	-2.7x10^{-6} (2.8x10^{-5})	0.05	1.9x10^{-5} (3.0x10^{-5})	0.05	-1.6x10^{-7} (4.7x10^{-5})	0.06	3.2x10^{-5} (3.5x10^{-5})	0.06		
	HHI Delta	-2.1x10^{-5} (5.1x10^{-5})		3.3x10^{-6} (4.8x10^{-5})		-2.5x10^{-5} (4.7x10^{-5})		-5.2x10^{-6} (5.1x10^{-5})		-4.1x10^{-5} (7.7x10^{-5})		-5.2x10^{-5} (5.7x10^{-5})			
Discharge Shares in Weighted Service Area	Post HHI	-2.9x10^{-5} (2.8x10^{-5})	0.09	-5.2x10^{-5} (2.9x10^{-5})	0.34	-3.3x10^{-5} (2.7x10^{-5})	0.07	-2.1x10^{-5} (2.9x10^{-5})	0.06	1.9x10^{-5} (4.4x10^{-5})	0.11	-1.1x10^{-7} (3.3x10^{-5})	0.07		
	HHI Delta	9.7x10^{-5} (6.6x10^{-5})		6.8x10^{-5} (5.9x10^{-5})		6.5x10^{-5} (6.4x10^{-5})		8.2x10^{-5} (6.7x10^{-5})		-1.1x10^{-4} (9.6x10^{-5})		4.8x10^{-5} (7.3x10^{-5})			
Diversion Ratio	A to B	0.81* (0.47)	0.19	0.93 (0.53)	0.35	0.62 (0.52)	0.06	0.92* (0.47)	0.19	-0.75 (0.96)	0.07	0.05 (0.62)	0.30	0.05 (0.21)	0.01
	B to A	0.01 (0.27)		-0.15 (0.34)		-0.10 (0.30)		-0.07 (0.27)		0.58 (0.56)		0.46 (0.36		-0.07 (0.17)	
Product of Diversion Ratios		1.46** (0.58)	0.18	2.25 (2.15)	0.12	1.08 (1.48)	0.02	1.31* (0.65)	0.15	0.11 (0.86)	0.00	1.28** (0.54)	0.27	-0.06 (0.18)	0.00
Change in Willingness-to-Pay		0.97** (0.39)	0.20	1.87 (1.09)	0.27	0.79 (0.77)	0.05	0.89** (0.40)	0.17	0.11 (0.56)	0.00	0.83** (0.35)	0.27	0.04 (0.20)	0.00
LOCI Price Change Estimate		0.24** (0.10)	0.19	0.35 (0.38)	0.10	0.19 (0.22)	0.03	0.22** (0.11)	0.16	0.02 (0.14)	0.00	0.22** (0.09)	0.28	-0.02 (0.03)	0.02
WTP-Based Merger Simulation[1]		0.50 (0.70)	0.03	2.73 (2.38)	0.18	-0.88 (0.93)	0.05	0.39 (0.70)	0.02	-0.27 (0.99)	0.01	1.33* (0.71)	0.24	0.003 (0.43)	0.00

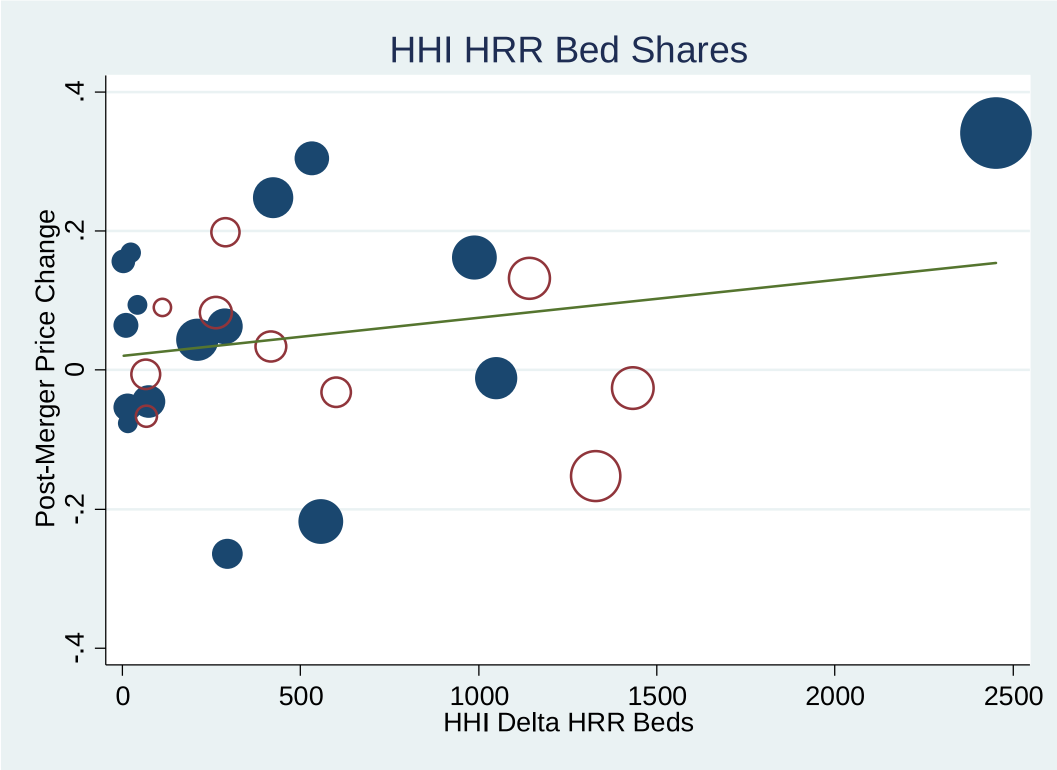
The coefficients are statistically significant at the 99% (***), 95% (**), and 90% (*) levels as indicated.

[1] For the WTP-based merger simulation, the sample size is reduced by 5 to account for rural mergers.

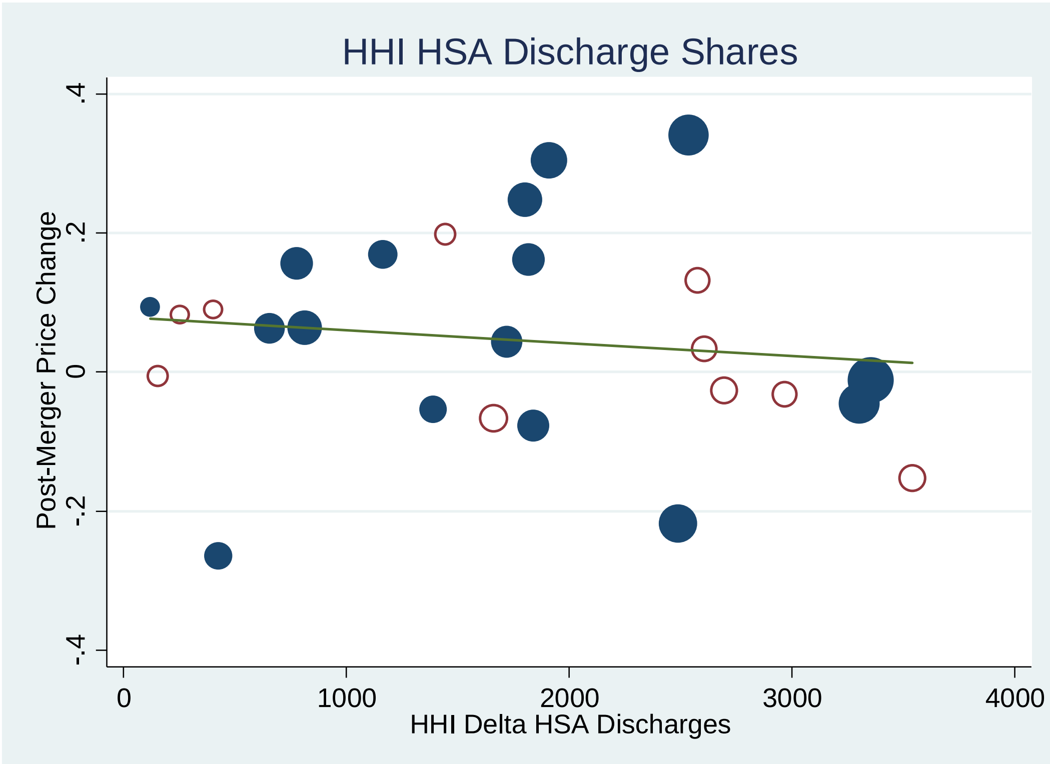
Graph 1: Mean Price Change for Mergers above WTP Threshold



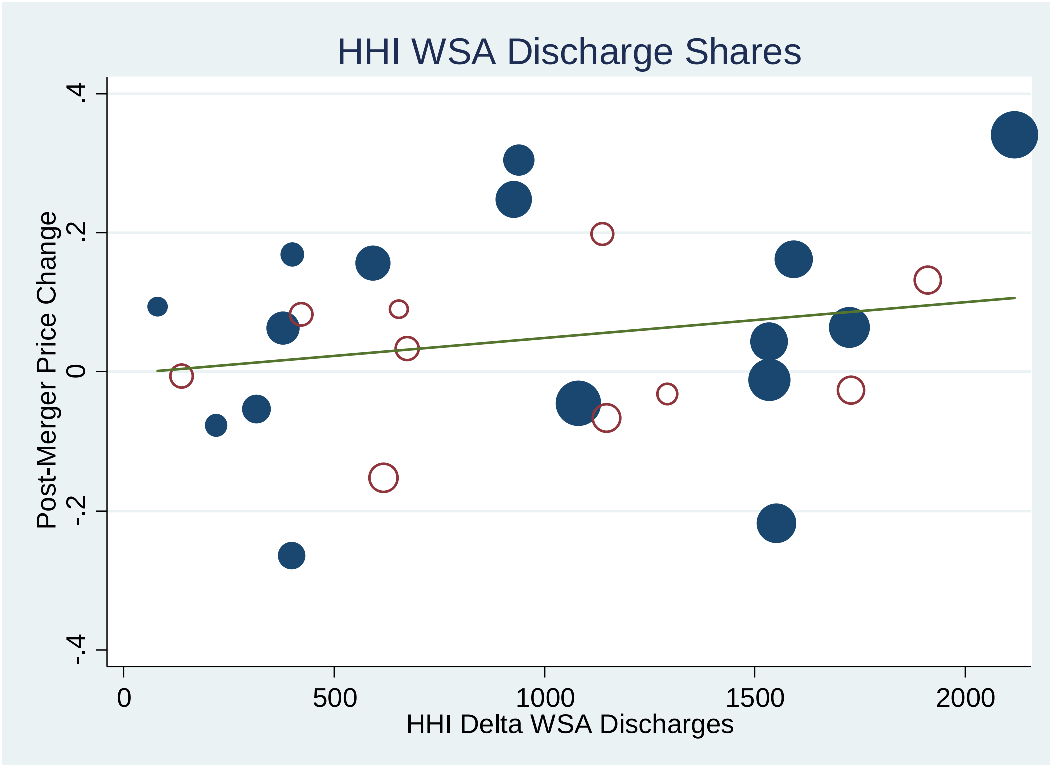
Graph 2: Post-Merger Price Change and HHI Delta (Bed Shares in the HRR)
(Larger dots indicate larger post-merger HHI levels. Hollow dots are North Carolina.)



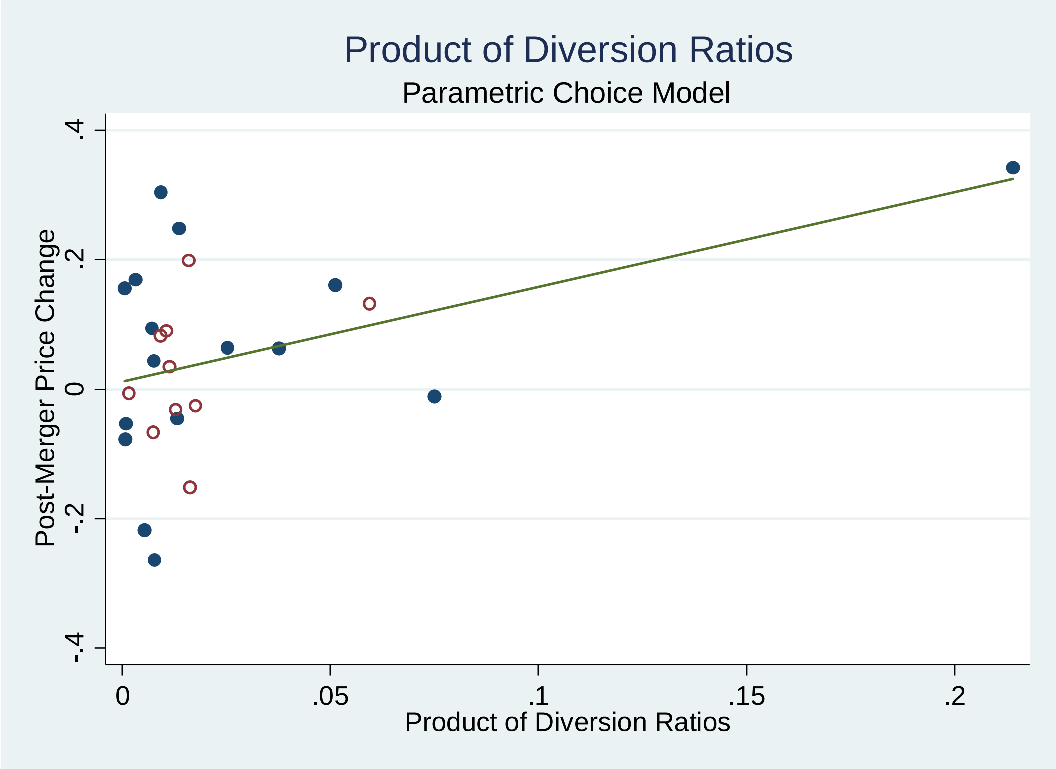
Graph 3: Post-Merger Price Change and HHI Delta (Discharge Shares in the HSA)
(Larger dots indicate larger post-merger HHI levels. Hollow dots are North Carolina.)



Graph 4: Post-Merger Price Change and HHI Delta (Discharge Shares in the Weighted SA)
(Larger dots indicate larger post-merger HHI levels. Hollow dots are North Carolina.)

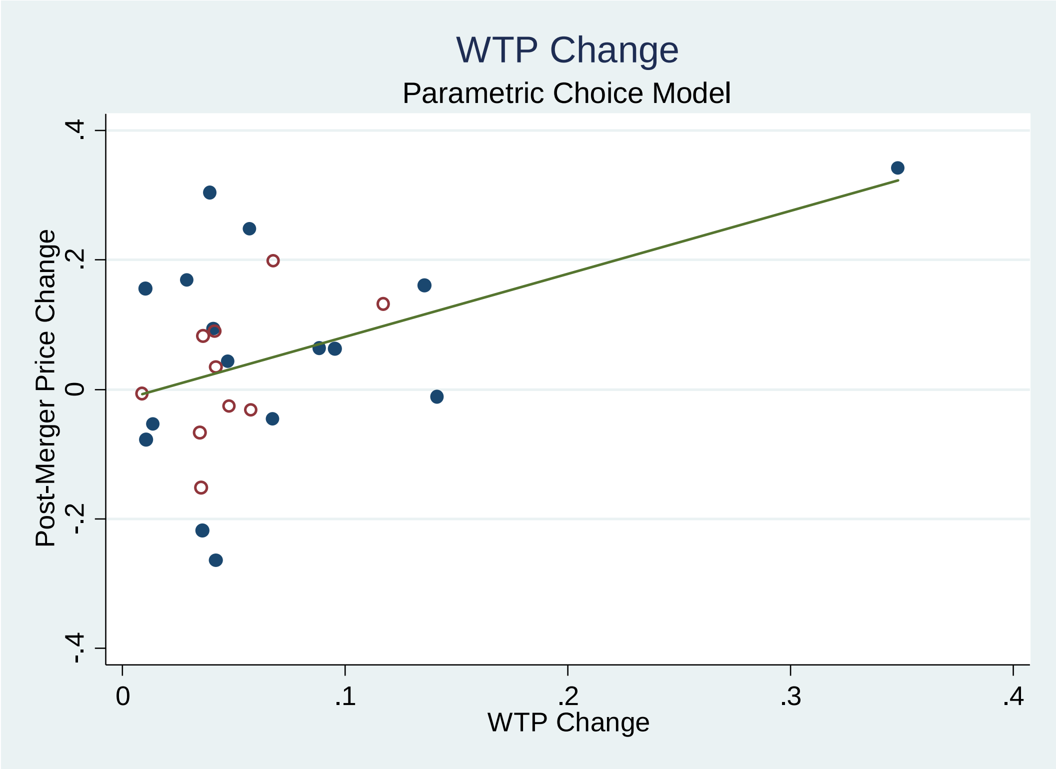


Graph 5: Post-Merger Price Change and the Product of the Diversion Ratios
(Hollow dots are North Carolina.)



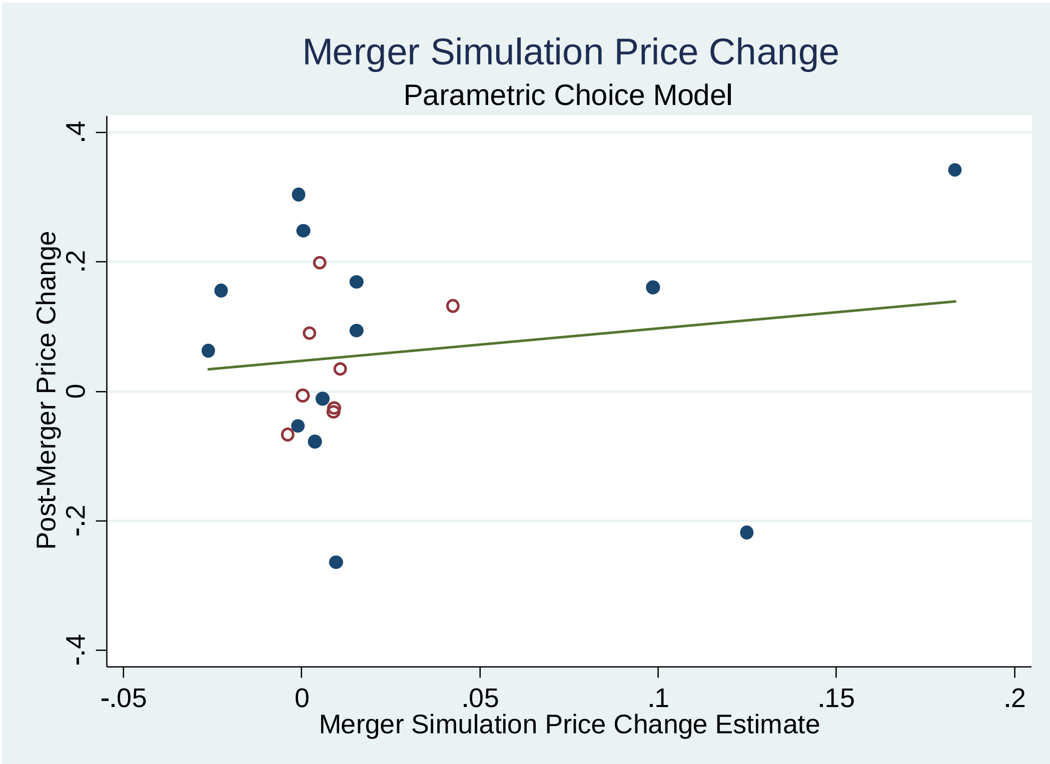
Graph 6: Post-Merger Price Change and WTP Change

(Hollow dots are North Carolina.)

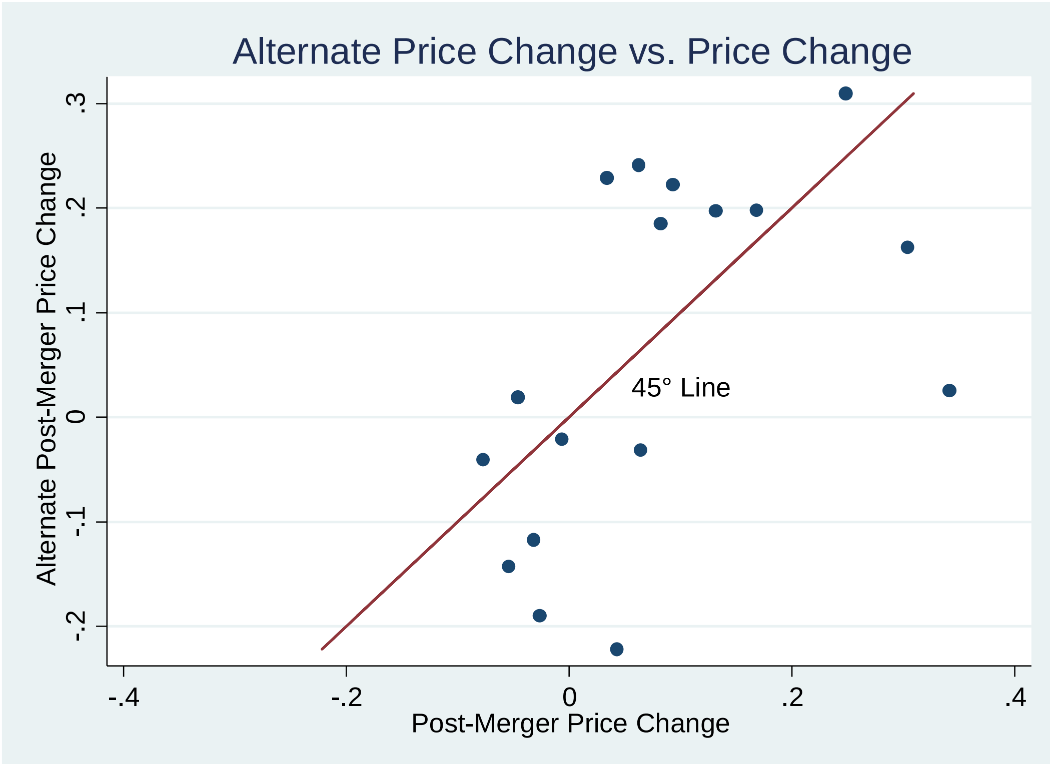


Graph 7: Post-Merger Price Change and LOCI Price Change Estimate
(Hollow dots are North Carolina.)

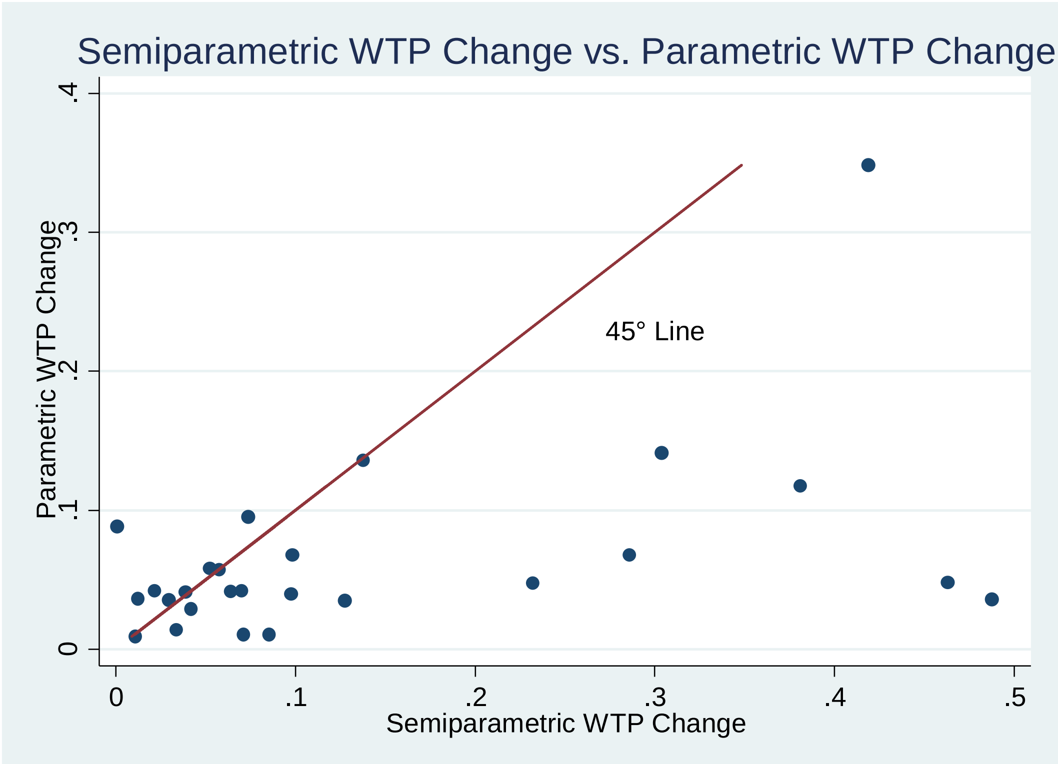
Graph 8: Post-Merger Price Change and WTP-Based Merger Simulation
(Hollow dots are North Carolina.)



Graph 9: Post-Merger Price Change vs. Alternate Second-Year Post-Merger Price Change



Graph 10: Semiparametric WTP Change vs. Parametric WTP Change



Appendix A: Example of HHI Calculations

Consider a hypothetical hospital market in which there are 5 hospitals, each located in one of 5 contiguous areas (e.g., zip codes). The hospitals, locations, and sizes are as follows:

Hospital	Area	Staffed Beds
A	1	100
B	2	150
C	3	50
D	4	200
E	5	250

In each area live 100 patients. The following table lists the patients by their hospital of treatment and their resident location.

Hospital	Area 1 Patients	Area 2 Patients	Area 3 Patients	Area 4 Patients	Area 5 Patients	Total Patients Treated at Hospital
A	40	5	10	10	5	70
B	25	50	15	10	5	105
C	5	5	30	5	5	50
D	10	20	20	60	10	120
E	20	20	25	15	75	155

Consider a proposed merger between hospitals A and B. Suppose A and B's HRR is the combination of areas 1 through 4. Using the first HHI calculation method (bed shares in the HRR), only hospitals A, B, C, and D are in the market with shares of 20% (100/500) for A, 30% (150/500) for B, 10% (50/500) for C, and 40% (200/500) for D. The pre-merger HHI is $(20)^2 + (30)^2 + (10)^2 + (40)^2 = 3{,}000$ with a delta of $2(\text{Share}_A)(\text{Share}_B) = 1{,}200$ for a post-merger HHI of 4,200.

Suppose B's HSA is the combination of areas 1 and 2. Using the second HHI calculation method (discharge shares in the HSA), A has a pre-merger share of 45/200 = 22.5%, B has a pre-merger share of 75/200 = 37.5%, C has a pre-merger share of 10/200 = 5%, D has a pre-merger share of 30/200 = 15%, and E has a pre-merger share of 40/200 =20%. The pre-merger HHI is $(22.5)^2 + (37.5)^2 + (5)^2 + (15)^2 + (20)^2 = 2{,}562.5$ with a delta of $2(\text{Share}_A)(\text{Share}_B) = 1{,}687.5$ for a post-merger HHI of 4,250.

For the third HHI calculation method (discharge shares in the weighted service area), we first have to determine the fraction of the merged entity's business that originates from each area. Of the 175 total patients treated by A and B, 65 (37.1%) come from Area 1, 55 (31.4%) come from Area 2, 25 (14.3%) come from Area 3, 20 (11.4%) come from Area 4, and 10 (5.7%) come from Area 5. A's weighted share is (0.371)(40) + (0.314)(5) + (0.143)(10) + (0.114)(10) + (0.057)(5) = 19.3%. B's weighted share is (0.371)(25) + (0.314)(50) + (0.143)(15) + (0.114)(10) + (0.057)(5) = 28.6%. C's weighted share is (0.371)(5) + (0.314)(5) + (0.143)(30) + (0.114)(5) + (0.057)(5) = 8.6%. D's weighted share is (0.371)(10) + (0.314)(20) + (0.143)(20) + (0.114)(60) + (0.057)(10) = 20.3%. E's weighted share is (0.371)(20) + (0.314)(20) + (0.143)(25) + (0.114)(15) + (0.057)(75) = 23.3%. The pre-merger HHI is $(19.3)^2 + (28.6)^2 + (8.6)^2 + (20.3)^2 + (23.3)^2 = 2{,}215.5$ with a delta of $2(\text{Share}_A)(\text{Share}_B) = 1102$ for a post-merger HHI of 3,317.5.

Appendix B: Sample of Mergers

State Data Used	Control Bed Threshold	MSA	Choice Population	Acquiring System	Primary Hospital in Acquiring System	Acquired Hospital	Consummation Year
NC	100		HRR	Cone Health	Moses Cone Memorial Hospital	Annie Penn Hospital	2001
PA/NY	100		Combined PSA	Upper Allegheny Health System	Olean General Hospital	Bradford Regional Medical Center	2009
NC	100	Wilmington	HRR	New Hanover Regional Medical Center	New Hanover Regional Medical Center	Cape Fear Memorial Hospital	1998
NC	100	Greensboro-Winston-Salem-High Point	HRR	Novant Health	Forsyth Memorial Hospital	Community General Hospital	1998
NY	100	Syracuse	HRR	Upstate University Hospital	Upstate University Hospital	Community-General Hospital of Greater Syracuse	2011
NC	100	Raleigh-Durham-Chapel Hill	HRR	Duke University Health System	Duke University Medical Center	Durham Regional Hospital	1998
NC	100	Hickory-Morganton-Lenoir	Combined PSA	Carolinas Healthcare	Valdese General Hospital	Grace Hospital	2000
AR	0	Hot Springs	HRR	Mercy	St. Joseph's Mercy Health Center	Healthpark Hospital	2010
GA	100	Atlanta-Sandy Springs-Marietta	HRR	Piedmont Healthcare	Piedmont Hospital	Henry Medical Center	2012
NC	100	Greenville & Rocky Mount	HRR	UHS East	Pitt County Memorial Hospital	Heritage Hospital	1999
NC	100	Fayetteville	HRR	Cape Fear Valley Health System	Cape Fear Valley Health System	Highsmith-Rainey Memorial Hospital	1999
CT	100	New Haven-Milford	HRR	Yale New Haven Health System	Yale-New Haven Hospital	Hospital of Saint Raphael	2012
PA	100	Philadelphia-Camden-Wilmington	HRR	Abington Health	Abington Memorial Hospital	Lansdale Hospital	2008
PA	100	Scranton--Wilkes-Barre	HRR	Community Health Systems	Regional Hospital of Scranton	Moses Taylor Hospital	2012
CT	50		HRR	Western Connecticut Health Network	Danbury Hospital	New Milford Hospital	2010
GA	100	Albany	HRR	Phoebe Putney Health System	Phoebe Putney Memorial Hospital	Palmyra Medical Center	2011
GA	100	Atlanta-Sandy Springs-Marietta	HRR	Piedmont Healthcare	Piedmont Hospital	Piedmont Newnan Hospital	2007
NC	50	Charlotte-Gastonia-Rock Hill	HRR	Novant Health	Presbyterian Hospital	Presbyterian Orthopaedic Hospital	1998
NC	100	Raleigh-Durham-Chapel Hill	HRR	University of North Carolina Hospitals	University of North Carolina Hospitals	Rex Healthcare	1999
GA	100	Atlanta-Sandy Springs-Marietta	HRR	Emory Healthcare	Emory University Hospital	Saint Joseph's Hospital of Atlanta	2012
PA	100		HRR	Schuylkill Health System	Pottsville Hospital	Good Samaritan Hospital	2008
AR/OK	0	Fayetteville-Springdale-Rogers	HRR	Community Health Systems	Northwest Medical Center	Siloam Springs Memorial Hospital	2009
NY/PA	100	Elmira	HRR	Arnot Health	Arnot Ogden Medical Center	St. Joseph's Hospital	2011
CT	100	Hartford-West Hartford-East Hartford	HRR	Hartford Healthcare	Hartford Hospital	The Hospital of Central Connecticut	2011
PA	100	Pittsburgh	HRR	UPMC	UPMC Presbyterian Shadyside	Mercy Hospital	2008
NC	100	Greensboro-Winston-Salem-High Point	HRR	Cone Health	Moses Cone Memorial Hospital	Wesley Long Community Hospital	1998

Appendix C: Parametric Choice Model Estimates

Variables: time, timesq, out, csurg_csurg_hosp, weight_csurg_hosp, ob_ob_hosp, female_ob_hosp, female_nicu_hosp, weight_ri_bed, weight_profit, weight_time, weight_timesq, age_60plus_ri_bed, age_60plus_profit, age_60plus_time, age_60plus_timesq, female_ri_bed, female_profit, female_time, female_timesq, emer_ri_bed, emer_profit, emer_time, emer_timesq

<u>Merger 1:</u>

```
Conditional (fixed-effects) logistic regression   Number of obs   =      70129
                                                  LR chi2(24)     =    3418.78
                                                  Prob > chi2     =     0.0000
Log likelihood = -9158.5341                       Pseudo R2       =     0.1573
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	-.0207063	.0021135	-9.80	0.000	-.0248488	-.0165639
timesq	.0000324	.0000125	2.59	0.009	7.91e-06	.0000568
out	.0589588	.0838308	0.70	0.482	-.1053466	.2232642
csurg_csurg~p	3.339535	.6162942	5.42	0.000	2.131621	4.54745
weight_csur~p	-.3124255	.0353074	-8.85	0.000	-.3816267	-.2432243
ob_ob_hosp	2.256242	.3895007	5.79	0.000	1.492835	3.019649
female_ob_h~p	1.631036	.0948196	17.20	0.000	1.445193	1.816879
female_nicu~p	-1.661593	.0859144	-19.34	0.000	-1.829982	-1.493204
weight_ri_bed	.0319543	.07557	0.42	0.672	-.1161601	.1800687
weight_profit	-1.771028	.2863439	-6.18	0.000	-2.332252	-1.209805
weight_time	.0092776	.0008841	10.49	0.000	.0075448	.0110103
weight_timesq	-.0000149	3.86e-06	-3.87	0.000	-.0000225	-7.38e-06
age_60plus_~d	-.9703479	.2804449	-3.46	0.001	-1.52001	-.4206859
age_60plus_~t	-.8618784	.2861557	-3.01	0.003	-1.422733	-.3010236
age_60plus_~e	-.010317	.0020019	-5.15	0.000	-.0142407	-.0063932
age_60plus_~q	.0000666	.000013	5.13	0.000	.0000412	.0000921
female_ri_bed	1.06273	.2327252	4.57	0.000	.6065967	1.518863
female_profit	-.6361106	.1986323	-3.20	0.001	-1.025423	-.2467985
female_time	.0000141	.0018879	0.01	0.994	-.0036862	.0037144
female_timesq	-.0000113	.0000126	-0.90	0.366	-.000036	.0000133
emer_ri_bed	-.5120268	.2411431	-2.12	0.034	-.9846585	-.039395
emer_profit	2.144772	.2469436	8.69	0.000	1.660771	2.628772
emer_time	.0247074	.0024923	9.91	0.000	.0198225	.0295922
emer_timesq	-.0002285	.0000238	-9.60	0.000	-.0002751	-.0001819

Merger 2:

Conditional (fixed-effects) logistic regression

Number of obs	=	455175
LR chi2(24)	=	25522.37
Prob > chi2	=	0.0000
Pseudo R2	=	0.1934

Log likelihood = -53228.84

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0254812	.0011719	21.74	0.000	.0231843	.0277782
timesq	-.0003071	.0000104	-29.61	0.000	-.0003274	-.0002867
out	.1077526	.0503529	2.14	0.032	.0090627	.2064425
csurg_csurg~p	-2.384219	.282347	-8.44	0.000	-2.937609	-1.830829
weight_csur~p	1.231956	.0191442	64.35	0.000	1.194434	1.269478
ob_ob_hosp	1.212991	.1198118	10.12	0.000	.9781646	1.447818
female_ob_h~p	.7256297	.0512408	14.16	0.000	.6251995	.8260598
female_nicu~p	.3638236	.0393335	9.25	0.000	.2867313	.4409159
weight_ri_bed	.4727344	.0383332	12.33	0.000	.3976028	.5478661
weight_profit	.2770175	.0278675	9.94	0.000	.2223982	.3316368
weight_time	-.0064527	.0004591	-14.06	0.000	-.0073524	-.005553
weight_timesq	.0000487	3.01e-06	16.17	0.000	.0000428	.0000546
age_60plus_~d	-.3164012	.1357572	-2.33	0.020	-.5824804	-.0503221
age_60plus_~t	.1021092	.0549652	1.86	0.063	-.0056205	.209839
age_60plus_~e	.0008629	.0015049	0.57	0.566	-.0020866	.0038124
age_60plus_~q	-.0000155	.0000149	-1.04	0.297	-.0000447	.0000137
female_ri_bed	1.080255	.1040778	10.38	0.000	.8762664	1.284244
female_profit	.0188877	.0306306	0.62	0.537	-.0411472	.0789227
female_time	.0076775	.0011634	6.60	0.000	.0053972	.0099578
female_timesq	-.0001816	.0000118	-15.45	0.000	-.0002046	-.0001585
emer_ri_bed	1.327091	.0856996	15.49	0.000	1.159123	1.495059
emer_profit	-.4185035	.038802	-10.79	0.000	-.494554	-.342453
emer_time	.0184108	.0013137	14.01	0.000	.0158359	.0209856
emer_timesq	-.0002908	.0000149	-19.49	0.000	-.00032	-.0002615

Merger 3:

```
Conditional (fixed-effects) logistic regression   Number of obs   =     547740
                                                  LR chi2(24)     =   22015.20
                                                  Prob > chi2     =     0.0000
Log likelihood = -76946.412                       Pseudo R2       =     0.1252
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0248571	.0013046	19.05	0.000	.0223002	.027414
timesq	-.00041	.0000149	-27.55	0.000	-.0004392	-.0003809
out	.120703	.0377843	3.19	0.001	.0466472	.1947589
csurg_csurg~p	.1948685	.1913052	1.02	0.308	-.1800828	.5698199
weight_csur~p	-.3194528	.0161299	-19.80	0.000	-.3510668	-.2878387
ob_ob_hosp	.787157	.096869	8.13	0.000	.5972973	.9770168
female_ob_h~p	.9612413	.0460195	20.89	0.000	.8710447	1.051438
female_nicu~p	.4325316	.0220959	19.58	0.000	.3892244	.4758388
weight_ri_bed	1.190321	.0280756	42.40	0.000	1.135293	1.245348
weight_profit	.0032125	.0317175	0.10	0.919	-.0589528	.0653777
weight_time	.0017384	.0005292	3.28	0.001	.0007012	.0027757
weight_timesq	.0000312	4.60e-06	6.78	0.000	.0000222	.0000402
age_60plus_~d	-.3638137	.0741865	-4.90	0.000	-.5092165	-.2184109
age_60plus_~t	.3208463	.0894011	3.59	0.000	.1456233	.4960693
age_60plus_~e	-.0014554	.0019145	-0.76	0.447	-.0052078	.002297
age_60plus_~q	-2.94e-06	.0000226	-0.13	0.896	-.0000472	.0000413
female_ri_bed	.1522793	.0401636	3.79	0.000	.07356	.2309986
female_profit	.364846	.0431652	8.45	0.000	.2802437	.4494482
female_time	.0006667	.0013423	0.50	0.619	-.0019641	.0032975
female_timesq	-.0001259	.0000163	-7.72	0.000	-.0001579	-.0000939
emer_ri_bed	1.530686	.043905	34.86	0.000	1.444633	1.616738
emer_profit	-2.740461	.1741455	-15.74	0.000	-3.08178	-2.399142
emer_time	.0082895	.0013615	6.09	0.000	.005621	.0109581
emer_timesq	-.0001971	.0000172	-11.46	0.000	-.0002308	-.0001634

Merger 4:

Conditional (fixed-effects) logistic regression

Number of obs	=	117800
LR chi2(24)	=	10734.51
Prob > chi2	=	0.0000
Pseudo R2	=	0.1979

Log likelihood = -21757.2

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	-.0106098	.0016191	-6.55	0.000	-.0137832	-.0074364
timesq	-1.85e-06	8.60e-06	-0.22	0.829	-.0000187	.000015
out	-1.337965	.0819198	-16.33	0.000	-1.498524	-1.177405
csurg_csurg~p	-1.107012	.2753161	-4.02	0.000	-1.646622	-.5674023
weight_csur~p	.7235314	.022116	32.72	0.000	.6801848	.7668781
ob_ob_hosp	1.948528	.2000576	9.74	0.000	1.556422	2.340633
female_ob_h~p	-.732774	.0893354	-8.20	0.000	-.9078682	-.5576798
female_nicu~p	1.167944	.0378403	30.87	0.000	1.093779	1.24211
weight_ri_bed	.2638287	.0659245	4.00	0.000	.1346191	.3930383
weight_profit	-.014941	.0171401	-0.87	0.383	-.048535	.018653
weight_time	.0058896	.0006955	8.47	0.000	.0045264	.0072528
weight_timesq	-.0000229	3.54e-06	-6.46	0.000	-.0000298	-.0000159
age_60plus_~d	-.762705	.297037	-2.57	0.010	-1.344887	-.1805232
age_60plus_~t	-.3370105	.0616811	-5.46	0.000	-.4579032	-.2161178
age_60plus_~e	.0288997	.0022979	12.58	0.000	.024396	.0334035
age_60plus_~q	-.0003733	.0000248	-15.07	0.000	-.0004218	-.0003247
female_ri_bed	-2.483835	.2297084	-10.81	0.000	-2.934055	-2.033614
female_profit	-.0190363	.0453073	-0.42	0.674	-.107837	.0697644
female_time	-.0055609	.0015429	-3.60	0.000	-.0085849	-.0025369
female_timesq	6.97e-06	9.90e-06	0.70	0.481	-.0000124	.0000264
emer_ri_bed	.0223981	.2148964	0.10	0.917	-.398791	.4435873
emer_profit	.5111671	.0439025	11.64	0.000	.4251199	.5972144
emer_time	.0003338	.0014893	0.22	0.823	-.0025852	.0032528
emer_timesq	-.0000551	.0000112	-4.91	0.000	-.000077	-.0000331

Merger 5:

Conditional (fixed-effects) logistic regression

Number of obs	=	4787475
LR chi2(24)	=	148765.64
Prob > chi2	=	0.0000
Pseudo R2	=	0.1530

Log likelihood = -411935.46

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0808996	.0011135	72.65	0.000	.0787171	.0830821
timesq	-.0014291	.0000186	-76.74	0.000	-.0014656	-.0013926
out	1.195367	.0136841	87.35	0.000	1.168547	1.222188
csurg_csurg~p	1.171043	.0837674	13.98	0.000	1.006862	1.335224
weight_csur~p	.3194787	.0040233	79.41	0.000	.3115932	.3273642
ob_ob_hosp	1.442551	.0220735	65.35	0.000	1.399288	1.485815
female_ob_h~p	-.25523	.0135654	-18.81	0.000	-.2818177	-.2286423
female_nicu~p	.6038878	.0105164	57.42	0.000	.5832761	.6244995
weight_ri_bed	.0972985	.0085341	11.40	0.000	.080572	.114025
weight_profit	-.1811828	.0077544	-23.37	0.000	-.1963812	-.1659844
weight_time	-.0030971	.0002874	-10.78	0.000	-.0036604	-.0025338
weight_timesq	.0001034	3.49e-06	29.66	0.000	.0000966	.0001102
age_60plus_~d	-.2854529	.0444958	-6.42	0.000	-.372663	-.1982428
age_60plus_~t	-.239292	.0222923	-10.73	0.000	-.2829841	-.1955998
age_60plus_~e	-.0077753	.001197	-6.50	0.000	-.0101213	-.0054292
age_60plus_~q	.0001755	.0000213	8.23	0.000	.0001337	.0002173
female_ri_bed	-2.171889	.0303672	-71.52	0.000	-2.231408	-2.112371
female_profit	-.6109593	.0124506	-49.07	0.000	-.6353619	-.5865566
female_time	.0387852	.0010678	36.32	0.000	.0366924	.0408781
female_timesq	-.0009515	.0000195	-48.78	0.000	-.0009897	-.0009133
emer_ri_bed	.5063302	.0316598	15.99	0.000	.4442782	.5683822
emer_profit	.1431606	.0149543	9.57	0.000	.1138507	.1724706
emer_time	.0287322	.0011158	25.75	0.000	.0265453	.0309192
emer_timesq	-.0010857	.0000227	-47.91	0.000	-.0011301	-.0010412

Merger 6:

Conditional (fixed-effects) logistic regression   Number of obs = 1019414
LR chi2(20) = 66371.83
Prob > chi2 = 0.0000
Log likelihood = -110043.72   Pseudo R2 = 0.2317

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0497928	.0024957	19.95	0.000	.0449014	.0546843
timesq	-.0018287	.0000543	-33.66	0.000	-.0019352	-.0017222
out	-1.63048	.0482315	-33.81	0.000	-1.725012	-1.535948
csurg_csurg~p	-.7400456	.1115734	-6.63	0.000	-.9587254	-.5213658
weight_csur~p	.3974685	.0087678	45.33	0.000	.3802839	.414653
ob_ob_hosp	.7121899	.0451326	15.78	0.000	.6237315	.8006482
female_ob_h~p	-.3662729	.024997	-14.65	0.000	-.4152661	-.3172797
female_nicu~p	.5024709	.0150909	33.30	0.000	.4728933	.5320484
weight_ri_bed	.1337416	.0113404	11.79	0.000	.1115148	.1559684
weight_time	-.0094268	.0007769	-12.13	0.000	-.0109494	-.0079041
weight_timesq	.0002731	.0000137	19.99	0.000	.0002463	.0002999
age_60plus_~d	-.0440242	.0441939	-1.00	0.319	-.1306427	.0425942
age_60plus_~e	.0195398	.0028427	6.87	0.000	.0139682	.0251115
age_60plus_~q	-.0006988	.0000709	-9.86	0.000	-.0008377	-.0005599
female_ri_bed	.6386492	.0281277	22.71	0.000	.58352	.6937784
female_time	.0079663	.002322	3.43	0.001	.0034153	.0125173
female_timesq	-.00067	.0000552	-12.13	0.000	-.0007783	-.0005618
emer_ri_bed	.969543	.0310112	31.26	0.000	.9087622	1.030324
emer_time	.0773676	.0025928	29.84	0.000	.0722859	.0824494
emer_timesq	-.0032591	.0000725	-44.98	0.000	-.0034011	-.0031171

Merger 7:

Conditional (fixed-effects) logistic regression

Number of obs	= 153935
LR chi2(20)	= 5831.07
Prob > chi2	= 0.0000
Log likelihood = -22739.211 Pseudo R2	= 0.1136

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0223681	.0019956	11.21	0.000	.0184567	.0262795
timesq	-.0002552	.0000185	-13.78	0.000	-.0002915	-.0002189
out	-.4581433	.0671029	-6.83	0.000	-.5896626	-.326624
csurg_csurg~p	2.845534	1.008413	2.82	0.005	.8690813	4.821986
weight_csur~p	.6813315	.0199258	34.19	0.000	.6422777	.7203853
ob_ob_hosp	3.560015	.1873294	19.00	0.000	3.192856	3.927174
female_ob_h~p	-.0009374	.0355334	-0.03	0.979	-.0705816	.0687067
female_nicu~p	-.624647	.0389283	-16.05	0.000	-.700945	-.5483489
weight_ri_bed	-.2458483	.0438681	-5.60	0.000	-.3318282	-.1598684
weight_time	.0006025	.0006321	0.95	0.340	-.0006364	.0018414
weight_timesq	.0000246	4.69e-06	5.24	0.000	.0000154	.0000338
age_60plus_~d	-.7953661	.1821479	-4.37	0.000	-1.152369	-.4383628
age_60plus_~e	.0013633	.0022288	0.61	0.541	-.0030051	.0057318
age_60plus_~q	-.0000541	.0000253	-2.13	0.033	-.0001038	-4.40e-06
female_ri_bed	-1.529223	.1309497	-11.68	0.000	-1.78588	-1.272566
female_time	.0052855	.0018652	2.83	0.005	.0016299	.0089412
female_timesq	-.0000578	.00002	-2.89	0.004	-.0000969	-.0000186
emer_ri_bed	-.5327754	.1433391	-3.72	0.000	-.813715	-.2518359
emer_time	.0048598	.0021565	2.25	0.024	.0006332	.0090864
emer_timesq	-.0002014	.000028	-7.19	0.000	-.0002563	-.0001464

Merger 8:

Conditional (fixed-effects) logistic regression   Number of obs = 5354604
LR chi2(24) = 155823.04
Prob > chi2 = 0.0000
Log likelihood = -455097.5   Pseudo R2 = 0.1462

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.1131372	.0020581	54.97	0.000	.1091035	.117171
timesq	-.0047463	.0000665	-71.37	0.000	-.0048766	-.0046159
out	-.0313478	.0181322	-1.73	0.084	-.0668863	.0041907
csurg_csurg~p	.0289523	.1128692	0.26	0.798	-.1922672	.2501719
weight_csur~p	.3885885	.0056187	69.16	0.000	.377576	.3996009
ob_ob_hosp	1.494284	.0254838	58.64	0.000	1.444337	1.544231
female_ob_h~p	-.1453765	.0161769	-8.99	0.000	-.1770826	-.1136705
female_nicu~p	.5832186	.0147322	39.59	0.000	.5543441	.6120931
weight_ri_bed	.4118884	.0074037	55.63	0.000	.3973775	.4263994
weight_profit	-.1129721	.007445	-15.17	0.000	-.127564	-.0983803
weight_time	-.0109252	.0006768	-16.14	0.000	-.0122516	-.0095987
weight_timesq	.0005499	.0000171	32.19	0.000	.0005164	.0005834
age_60plus_~d	-.1413135	.0255073	-5.54	0.000	-.1913068	-.0913202
age_60plus_~t	-.1566484	.0214674	-7.30	0.000	-.1987237	-.1145731
age_60plus_~e	.0007257	.0021985	0.33	0.741	-.0035833	.0050347
age_60plus_~q	-.0003357	.0000787	-4.26	0.000	-.00049	-.0001814
female_ri_bed	.0390166	.0155624	2.51	0.012	.0085149	.0695184
female_profit	-.3137125	.0130093	-24.11	0.000	-.3392103	-.2882146
female_time	.0140487	.0018418	7.63	0.000	.0104388	.0176586
female_timesq	-.0011315	.0000647	-17.49	0.000	-.0012584	-.0010047
emer_ri_bed	-.2147251	.0172198	-12.47	0.000	-.2484753	-.1809749
emer_profit	-.3896064	.0141355	-27.56	0.000	-.4173115	-.3619012
emer_time	.0117764	.0018989	6.20	0.000	.0080547	.0154981
emer_timesq	-.0027625	.0000711	-38.87	0.000	-.0029018	-.0026232

Merger 9:

Conditional (fixed-effects) logistic regression

Number of obs	= 4787475
LR chi2(24)	= 148754.43
Prob > chi2	= 0.0000
Log likelihood = -411941.07	
Pseudo R2	= 0.1529

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0808955	.0011136	72.64	0.000	.078713	.0830781
timesq	-.001429	.0000186	-76.74	0.000	-.0014655	-.0013925
out	1.195151	.0136842	87.34	0.000	1.16833	1.221972
csurg_csurg~p	1.17218	.083766	13.99	0.000	1.008002	1.336359
weight_csur~p	.3191609	.0040223	79.35	0.000	.3112774	.3270444
ob_ob_hosp	1.442465	.0220737	65.35	0.000	1.399201	1.485728
female_ob_h~p	-.2554584	.0135672	-18.83	0.000	-.2820497	-.2288672
female_nicu~p	.6036681	.0105169	57.40	0.000	.5830553	.6242808
weight_ri_bed	.0977448	.0085307	11.46	0.000	.081025	.1144645
weight_profit	-.1812226	.0077544	-23.37	0.000	-.1964209	-.1660243
weight_time	-.003095	.0002874	-10.77	0.000	-.0036583	-.0025317
weight_timesq	.0001034	3.49e-06	29.65	0.000	.0000966	.0001102
age_60plus_~d	-.2850488	.044514	-6.40	0.000	-.3722946	-.197803
age_60plus_~t	-.2392632	.0222919	-10.73	0.000	-.2829545	-.1955719
age_60plus_~e	-.0077776	.001197	-6.50	0.000	-.0101236	-.0054316
age_60plus_~q	.0001755	.0000213	8.23	0.000	.0001337	.0002173
female_ri_bed	-2.173403	.0304166	-71.45	0.000	-2.233019	-2.113788
female_profit	-.6105435	.0124506	-49.04	0.000	-.6349463	-.5861408
female_time	.0387728	.0010678	36.31	0.000	.0366798	.0408657
female_timesq	-.0009513	.0000195	-48.77	0.000	-.0009896	-.0009131
emer_ri_bed	.508789	.0316684	16.07	0.000	.4467201	.5708579
emer_profit	.143137	.014954	9.57	0.000	.1138277	.1724463
emer_time	.0287311	.0011158	25.75	0.000	.0265441	.0309181
emer_timesq	-.0010857	.0000227	-47.91	0.000	-.0011301	-.0010413

Merger 10:

```
Conditional (fixed-effects) logistic regression   Number of obs   =    1371237
                                                  LR chi2(24)     =   76038.02
                                                  Prob > chi2     =     0.0000
Log likelihood = -148916.02                       Pseudo R2       =     0.2034
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0398794	.0011561	34.50	0.000	.0376136	.0421452
timesq	-.0007229	.0000166	-43.66	0.000	-.0007554	-.0006905
out	.5772439	.0256455	22.51	0.000	.5269796	.6275082
csurg_csurg~p	1.359519	.3843696	3.54	0.000	.6061685	2.11287
weight_csur~p	.6441294	.0090373	71.27	0.000	.6264166	.6618422
ob_ob_hosp	1.511146	.0622646	24.27	0.000	1.38911	1.633182
female_ob_h~p	.5318481	.0280286	18.98	0.000	.4769131	.5867832
female_nicu~p	1.646253	.0143402	114.80	0.000	1.618147	1.674359
weight_ri_bed	.4411812	.0210255	20.98	0.000	.3999719	.4823905
weight_profit	-.1769411	.0168569	-10.50	0.000	-.2099799	-.1439022
weight_time	-.0014051	.0003355	-4.19	0.000	-.0020627	-.0007475
weight_timesq	.0000429	2.55e-06	16.83	0.000	.0000379	.0000479
age_60plus_~d	-.5374025	.104672	-5.13	0.000	-.7425558	-.3322492
age_60plus_~t	.2370973	.0493786	4.80	0.000	.1403171	.3338775
age_60plus_~e	-.0173392	.0014968	-11.58	0.000	-.0202729	-.0144055
age_60plus_~q	.0002763	.0000212	13.03	0.000	.0002348	.0003179
female_ri_bed	-1.090075	.0525445	-20.75	0.000	-1.19306	-.9870892
female_profit	-.5210222	.0271405	-19.20	0.000	-.5742166	-.4678278
female_time	.0003221	.001252	0.26	0.797	-.0021318	.002776
female_timesq	-.0002809	.0000199	-14.14	0.000	-.0003199	-.000242
emer_ri_bed	-.3264046	.0747654	-4.37	0.000	-.4729421	-.1798672
emer_profit	-1.048146	.0432909	-24.21	0.000	-1.132995	-.9632978
emer_time	.0425012	.0017344	24.50	0.000	.0391017	.0459006
emer_timesq	-.0011852	.0000359	-33.00	0.000	-.0012556	-.0011148

Merger 11:

Conditional (fixed-effects) logistic regression

Number of obs	=	1045022
LR chi2(24)	=	64959.25
Prob > chi2	=	0.0000
Pseudo R2	=	0.2212

Log likelihood = -114347.98

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0530634	.0014307	37.09	0.000	.0502592	.0558676
timesq	-.0010168	.0000208	-48.92	0.000	-.0010575	-.0009761
out	-.2037875	.0387253	-5.26	0.000	-.2796876	-.1278874
csurg_csurg~p	.4674674	.3636151	1.29	0.199	-.2452052	1.18014
weight_csur~p	.7327637	.0121952	60.09	0.000	.7088616	.7566659
ob_ob_hosp	1.160995	.0901357	12.88	0.000	.9843328	1.337658
female_ob_h~p	.779399	.0434332	17.94	0.000	.6942715	.8645265
female_nicu~p	1.392805	.0163153	85.37	0.000	1.360827	1.424782
weight_ri_bed	.1586364	.0174183	9.11	0.000	.1244972	.1927756
weight_profit	-.1936148	.0231105	-8.38	0.000	-.2389105	-.1483192
weight_time	-.0078652	.0005583	-14.09	0.000	-.0089594	-.0067711
weight_timesq	.0001365	5.99e-06	22.76	0.000	.0001247	.0001482
age_60plus_~d	-1.090513	.1046679	-10.42	0.000	-1.295658	-.8853678
age_60plus_~t	-.2038372	.0557165	-3.66	0.000	-.3130395	-.094635
age_60plus_~e	-.0000161	.0022106	-0.01	0.994	-.0043488	.0043166
age_60plus_~q	-.0000374	.0000339	-1.10	0.271	-.0001039	.0000291
female_ri_bed	-2.694653	.0450175	-59.86	0.000	-2.782885	-2.60642
female_profit	-.3011149	.0267642	-11.25	0.000	-.3535718	-.2486579
female_time	.016701	.0014773	11.30	0.000	.0138055	.0195965
female_timesq	-.0004263	.0000229	-18.59	0.000	-.0004712	-.0003813
emer_ri_bed	.2985735	.0582727	5.12	0.000	.1843612	.4127858
emer_profit	-.4077479	.0350297	-11.64	0.000	-.4764047	-.339091
emer_time	.0040188	.0015887	2.53	0.011	.000905	.0071325
emer_timesq	-.0002657	.000026	-10.23	0.000	-.0003166	-.0002148

Merger 12:

```
Conditional (fixed-effects) logistic regression   Number of obs   =     311814
                                                  LR chi2(24)     =   23577.46
                                                  Prob > chi2     =     0.0000
Log likelihood = -40178.068                       Pseudo R2       =     0.2269
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0419315	.0024962	16.80	0.000	.037039	.0468239
timesq	-.0009861	.0000421	-23.40	0.000	-.0010687	-.0009035
out	-.5829026	.0585705	-9.95	0.000	-.6976987	-.4681066
csurg_csurg~p	1.463975	.5306371	2.76	0.006	.4239457	2.504005
weight_csur~p	.6288833	.0177991	35.33	0.000	.5939976	.6637689
ob_ob_hosp	2.364834	.1754121	13.48	0.000	2.021033	2.708636
female_ob_h~p	.8479734	.0495835	17.10	0.000	.7507916	.9451552
female_nicu~p	1.851914	.0280653	65.99	0.000	1.796907	1.906921
weight_ri_bed	.1531726	.0263887	5.80	0.000	.1014517	.2048936
weight_profit	-.6515527	.0459511	-14.18	0.000	-.7416152	-.5614903
weight_time	-.007504	.0008102	-9.26	0.000	-.0090921	-.005916
weight_timesq	.0001058	9.93e-06	10.66	0.000	.0000864	.0001253
age_60plus_~d	-.4415618	.1400772	-3.15	0.002	-.716108	-.1670156
age_60plus_~t	.0050995	.0825145	0.06	0.951	-.1566261	.166825
age_60plus_~e	-.0015292	.003513	-0.44	0.663	-.0084146	.0053562
age_60plus_~q	-.0000955	.0000681	-1.40	0.161	-.0002289	.0000379
female_ri_bed	-.745865	.0904779	-8.24	0.000	-.9231984	-.5685315
female_profit	.0033785	.0443017	0.08	0.939	-.0834514	.0902083
female_time	-.0169668	.002673	-6.35	0.000	-.0222058	-.0117279
female_timesq	-.0002628	.0000495	-5.30	0.000	-.0003599	-.0001657
emer_ri_bed	.4602262	.1004594	4.58	0.000	.2633294	.6571229
emer_profit	.3555397	.0538706	6.60	0.000	.2499553	.4611241
emer_time	-.0034821	.0027604	-1.26	0.207	-.0088923	.0019281
emer_timesq	-.0002323	.0000547	-4.25	0.000	-.0003395	-.0001251

Merger 13:

Conditional (fixed-effects) logistic regression	Number of obs	=	96194
	LR chi2(24)	=	9412.41
	Prob > chi2	=	0.0000
Log likelihood = -13426.755	Pseudo R2	=	0.2595

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	-.0408311	.0026332	-15.51	0.000	-.045992	-.0356702
timesq	.0001111	.0000218	5.10	0.000	.0000684	.0001539
out	-1.808546	.0911668	-19.84	0.000	-1.98723	-1.629863
csurg_csurg~p	.0599634	.7388011	0.08	0.935	-1.38806	1.507987
weight_csur~p	.8430761	.0583791	14.44	0.000	.7286552	.957497
ob_ob_hosp	2.641471	.3416028	7.73	0.000	1.971942	3.311
female_ob_h~p	.7203627	.1057248	6.81	0.000	.513146	.9275794
female_nicu~p	-.6334934	.119849	-5.29	0.000	-.868393	-.3985938
weight_ri_bed	1.223505	.1073511	11.40	0.000	1.013101	1.43391
weight_profit	.1924228	.0472669	4.07	0.000	.0997813	.2850644
weight_time	-.0053634	.0016195	-3.31	0.001	-.0085376	-.0021893
weight_timesq	7.69e-06	9.03e-06	0.85	0.394	-1.00e-05	.0000254
age_60plus_~d	.9977235	.4746725	2.10	0.036	.0673825	1.928064
age_60plus_~t	.2156343	.1025631	2.10	0.036	.0146143	.4166543
age_60plus_~e	-.0103045	.0037812	-2.73	0.006	-.0177155	-.0028935
age_60plus_~q	.0000124	.0000349	0.36	0.723	-.0000559	.0000807
female_ri_bed	4.58972	.3849058	11.92	0.000	3.835319	5.344122
female_profit	.419768	.0529732	7.92	0.000	.3159425	.5235936
female_time	-.0069142	.0025509	-2.71	0.007	-.0119139	-.0019146
female_timesq	-.0000795	.0000232	-3.43	0.001	-.0001249	-.0000341
emer_ri_bed	2.119831	.4871105	4.35	0.000	1.165112	3.07455
emer_profit	-.1817059	.0726308	-2.50	0.012	-.3240596	-.0393521
emer_time	-.0117047	.0034557	-3.39	0.001	-.0184777	-.0049317
emer_timesq	-.0002019	.0000587	-3.44	0.001	-.0003169	-.0000868

Merger 14:

Conditional (fixed-effects) logistic regression

Number of obs	= 315885
LR chi2(24)	= 43247.89
Prob > chi2	= 0.0000
Pseudo R2	= 0.3792

Log likelihood = -35404.883

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0478566	.0028508	16.79	0.000	.0422691	.0534441
timesq	-.0013646	.0000499	-27.33	0.000	-.0014624	-.0012667
out	-.1189043	.0497687	-2.39	0.017	-.2164493	-.0213594
csurg_csurg~p	-5.036744	.3840506	-13.11	0.000	-5.78947	-4.284019
weight_csur~p	1.816757	.0267947	67.80	0.000	1.76424	1.869274
ob_ob_hosp	1.695972	.1163595	14.58	0.000	1.467911	1.924032
female_ob_h~p	.9989653	.049684	20.11	0.000	.9015864	1.096344
female_nicu~p	1.546468	.0354876	43.58	0.000	1.476913	1.616022
weight_ri_bed	-.0700692	.0313166	-2.24	0.025	-.1314485	-.0086899
weight_profit	.4766772	.0383645	12.42	0.000	.4014842	.5518701
weight_time	-.0197633	.0011639	-16.98	0.000	-.0220445	-.017482
weight_timesq	.0002654	.0000156	16.98	0.000	.0002347	.000296
age_60plus_~d	-1.130748	.1290512	-8.76	0.000	-1.383684	-.8778127
age_60plus_~t	-.1890167	.072153	-2.62	0.009	-.3304339	-.0475996
age_60plus_~e	.0127196	.0035857	3.55	0.000	.0056918	.0197474
age_60plus_~q	-.0003933	.0000741	-5.31	0.000	-.0005385	-.0002482
female_ri_bed	.150031	.0827911	1.81	0.070	-.0122365	.3122985
female_profit	.0426317	.0446218	0.96	0.339	-.0448253	.1300888
female_time	-.0249735	.0027513	-9.08	0.000	-.0303659	-.0195811
female_timesq	-.0000271	.0000512	-0.53	0.596	-.0001274	.0000732
emer_ri_bed	-.2828284	.0910219	-3.11	0.002	-.4612281	-.1044288
emer_profit	-.6403719	.0563283	-11.37	0.000	-.7507732	-.5299705
emer_time	-.0176816	.002762	-6.40	0.000	-.0230951	-.0122681
emer_timesq	.0001501	.0000537	2.79	0.005	.0000448	.0002555

Merger 15:

Conditional (fixed-effects) logistic regression		
Number of obs	=	507384
LR chi2(20)	=	24994.04
Prob > chi2	=	0.0000
Pseudo R2	=	0.1660

Log likelihood = -62774.139

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0273147	.0015507	17.61	0.000	.0242754	.0303539
timesq	-.000345	.0000167	-20.63	0.000	-.0003778	-.0003122
out	-.7867619	.0555989	-14.15	0.000	-.8957336	-.6777901
csurg_csurg~p	2.680752	.3453366	7.76	0.000	2.003905	3.3576
weight_csur~p	.4594697	.0123115	37.32	0.000	.4353396	.4835998
ob_ob_hosp	1.375817	.0586514	23.46	0.000	1.260862	1.490772
female_ob_h~p	.0128011	.0284911	0.45	0.653	-.0430405	.0686426
female_nicu~p	1.134007	.0201862	56.18	0.000	1.094442	1.173571
weight_ri_bed	.1026872	.0171501	5.99	0.000	.0690737	.1363008
weight_time	-.0018351	.0005545	-3.31	0.001	-.0029219	-.0007482
weight_timesq	.0000358	4.88e-06	7.33	0.000	.0000262	.0000454
age_60plus_~d	-.3826906	.0595202	-6.43	0.000	-.4993481	-.2660331
age_60plus_~e	.0051924	.0016288	3.19	0.001	.002	.0083849
age_60plus_~q	-.0000655	.0000194	-3.38	0.001	-.0001035	-.0000275
female_ri_bed	.2869644	.0427997	6.70	0.000	.2030786	.3708503
female_time	.0046227	.0013736	3.37	0.001	.0019306	.0073148
female_timesq	-.0001614	.000016	-10.08	0.000	-.0001928	-.00013
emer_ri_bed	.9201522	.0412122	22.33	0.000	.8393777	1.000927
emer_time	.0359571	.0017404	20.66	0.000	.0325461	.0393681
emer_timesq	-.0007714	.0000263	-29.37	0.000	-.0008229	-.00072

Merger 16:

Conditional (fixed-effects) logistic regression

Number of obs	=	1045022
LR chi2(24)	=	64959.25
Prob > chi2	=	0.0000
Pseudo R2	=	0.2212

Log likelihood = -114347.98

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0530634	.0014307	37.09	0.000	.0502592	.0558676
timesq	-.0010168	.0000208	-48.92	0.000	-.0010575	-.0009761
out	-.2037875	.0387253	-5.26	0.000	-.2796876	-.1278874
csurg_csurg~p	.4674674	.3636151	1.29	0.199	-.2452052	1.18014
weight_csur~p	.7327637	.0121952	60.09	0.000	.7088616	.7566659
ob_ob_hosp	1.160995	.0901357	12.88	0.000	.9843328	1.337658
female_ob_h~p	.779399	.0434332	17.94	0.000	.6942715	.8645265
female_nicu~p	1.392805	.0163153	85.37	0.000	1.360827	1.424782
weight_ri_bed	.1586364	.0174183	9.11	0.000	.1244972	.1927756
weight_profit	-.1936148	.0231105	-8.38	0.000	-.2389105	-.1483192
weight_time	-.0078652	.0005583	-14.09	0.000	-.0089594	-.0067711
weight_timesq	.0001365	5.99e-06	22.76	0.000	.0001247	.0001482
age_60plus_~d	-1.090513	.1046679	-10.42	0.000	-1.295658	-.8853678
age_60plus_~t	-.2038372	.0557165	-3.66	0.000	-.3130395	-.094635
age_60plus_~e	-.0000161	.0022106	-0.01	0.994	-.0043488	.0043166
age_60plus_~q	-.0000374	.0000339	-1.10	0.271	-.0001039	.0000291
female_ri_bed	-2.694653	.0450175	-59.86	0.000	-2.782885	-2.60642
female_profit	-.3011149	.0267642	-11.25	0.000	-.3535718	-.2486579
female_time	.016701	.0014773	11.30	0.000	.0138055	.0195965
female_timesq	-.0004263	.0000229	-18.59	0.000	-.0004712	-.0003813
emer_ri_bed	.2985735	.0582727	5.12	0.000	.1843612	.4127858
emer_profit	-.4077479	.0350297	-11.64	0.000	-.4764047	-.339091
emer_time	.0040188	.0015887	2.53	0.011	.000905	.0071325
emer_timesq	-.0002657	.000026	-10.23	0.000	-.0003166	-.0002148

Merger 17:

Conditional (fixed-effects) logistic regression

Number of obs	=	862962
LR chi2(17)	=	67149.68
Prob > chi2	=	0.0000
Pseudo R2	=	0.2597

Log likelihood = -95686.941

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0486097	.0022266	21.83	0.000	.0442457	.0529738
timesq	-.0021279	.0000487	-43.65	0.000	-.0022234	-.0020323
out	-.915014	.0376913	-24.28	0.000	-.9888875	-.8411404
csurg_csurg~p	-.608555	.1117969	-5.44	0.000	-.8276729	-.3894371
weight_csur~p	.0543366	.0090708	5.99	0.000	.0365582	.0721149
ob_ob_hosp	.4690573	.0383926	12.22	0.000	.3938092	.5443054
female_ob_h~p	-.2939435	.022443	-13.10	0.000	-.337931	-.249956
female_nicu~p	.0751849	.0174701	4.30	0.000	.0409441	.1094257
weight_ri_bed	1.456066	.0258832	56.26	0.000	1.405336	1.506796
weight_time	-.0066762	.0008553	-7.81	0.000	-.0083526	-.0049999
weight_timesq	.0002374	.0000134	17.71	0.000	.0002112	.0002637
age_60plus_~d	.2758704	.0654961	4.21	0.000	.1475003	.4042404
age_60plus_~e	.0321148	.0030624	10.49	0.000	.0261125	.0381171
age_60plus_~q	-.0010708	.0000749	-14.30	0.000	-.0012176	-.000924
female_ri_bed	2.838178	.0476637	59.55	0.000	2.744758	2.931597
female_time	.0034498	.0024491	1.41	0.159	-.0013503	.0082498
female_timesq	-.000523	.0000573	-9.12	0.000	-.0006354	-.0004107

Merger 18:

Conditional (fixed-effects) logistic regression	Number of obs	=	1375920
	LR chi2(24)	=	47586.48
	Prob > chi2	=	0.0000
Log likelihood = -132199.28	Pseudo R2	=	0.1525

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0482374	.0010057	47.96	0.000	.0462662	.0502086
timesq	-.0004845	.0000103	-46.85	0.000	-.0005048	-.0004643
out	1.310025	.0251154	52.16	0.000	1.2608	1.35925
csurg_csurg~p	.2704662	.1607393	1.68	0.092	-.044577	.5855094
weight_csur~p	.5981241	.0092319	64.79	0.000	.5800299	.6162183
ob_ob_hosp	2.576328	.074376	34.64	0.000	2.430554	2.722103
female_ob_h~p	.2014464	.0188954	10.66	0.000	.1644121	.2384806
female_nicu~p	1.127551	.0149206	75.57	0.000	1.098307	1.156795
weight_ri_bed	.0018552	.002123	0.87	0.382	-.0023058	.0060163
weight_profit	-.0048942	.0089036	-0.55	0.583	-.0223449	.0125564
weight_time	-.0028046	.0003037	-9.23	0.000	-.0033999	-.0022093
weight_timesq	.0000506	2.57e-06	19.67	0.000	.0000455	.0000556
age_60plus_~d	-.0254316	.0092777	-2.74	0.006	-.0436155	-.0072476
age_60plus_~t	.1054284	.0302329	3.49	0.000	.0461729	.1646838
age_60plus_~e	-.0056653	.001077	-5.26	0.000	-.0077762	-.0035544
age_60plus_~q	.0000514	.0000117	4.37	0.000	.0000284	.0000744
female_ri_bed	-.1146753	.0055426	-20.69	0.000	-.1255385	-.1038121
female_profit	-.0035918	.0217105	-0.17	0.869	-.0461436	.03896
female_time	.0003477	.0009894	0.35	0.725	-.0015915	.002287
female_timesq	-.0001306	.000011	-11.91	0.000	-.0001521	-.0001091
emer_ri_bed	.0236051	.0066457	3.55	0.000	.0105798	.0366303
emer_profit	-.587703	.0274958	-21.37	0.000	-.6415938	-.5338122
emer_time	.0300734	.0011996	25.07	0.000	.0277221	.0324246
emer_timesq	-.0005714	.0000162	-35.22	0.000	-.0006032	-.0005396

Merger 19:

Conditional (fixed-effects) logistic regression			
	Number of obs	=	895630
	LR chi2(20)	=	37551.54
	Prob > chi2	=	0.0000
Log likelihood = -111071.82	Pseudo R2	=	0.1446

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0587024	.0020306	28.91	0.000	.0547224	.0626823
timesq	-.0017212	.0000417	-41.29	0.000	-.0018029	-.0016395
out	-.877568	.0429403	-20.44	0.000	-.9617294	-.7934066
csurg_csurg~p	.8229523	.228763	3.60	0.000	.374585	1.27132
weight_csur~p	.7330693	.0091713	79.93	0.000	.7150939	.7510446
ob_ob_hosp	.9503313	.0466666	20.36	0.000	.8588664	1.041796
female_ob_h~p	.2499014	.0246993	10.12	0.000	.2014916	.2983112
female_nicu~p	-.1674747	.0141784	-11.81	0.000	-.1952639	-.1396856
weight_ri_bed	-.0838714	.0115473	-7.26	0.000	-.1065037	-.0612392
weight_profit	-.7197259	.0643331	-11.19	0.000	-.8458166	-.5936353
weight_time	-.0088437	.0007678	-11.52	0.000	-.0103486	-.0073388
weight_timesq	.0002247	.0000132	16.96	0.000	.0001987	.0002506
age_60plus_~d	-.0501452	.0377225	-1.33	0.184	-.1240801	.0237896
age_60plus_~t	-.3592851	.1283102	-2.80	0.005	-.6107684	-.1078018
age_60plus_~e	.0056864	.0025404	2.24	0.025	.0007074	.0106655
age_60plus_~q	-.0002248	.000056	-4.01	0.000	-.0003346	-.0001149
female_ri_bed	.2450234	.0242848	10.09	0.000	.1974261	.2926207
female_profit	.198744	.0803266	2.47	0.013	.0413068	.3561813
female_time	.0167429	.0020957	7.99	0.000	.0126354	.0208503
female_timesq	-.0006143	.0000459	-13.37	0.000	-.0007044	-.0005243

Merger 20:

Conditional (fixed-effects) logistic regression

Number of obs	=	47502
LR chi2(24)	=	6465.43
Prob > chi2	=	0.0000
Pseudo R2	=	0.3610

Log likelihood = -5721.6054

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	-.0121101	.0029536	-4.10	0.000	-.0178991	-.0063211
timesq	-.0000469	.000018	-2.60	0.009	-.0000823	-.0000116
out	.2244664	.081245	2.76	0.006	.065229	.3837037
csurg_csurg~p	1.020552	.6294641	1.62	0.105	-.2131745	2.254279
weight_csur~p	1.118803	.0438863	25.49	0.000	1.032787	1.204818
ob_ob_hosp	2.080637	.1602489	12.98	0.000	1.766555	2.394719
female_ob_h~p	-.0658911	.101754	-0.65	0.517	-.2653252	.133543
female_nicu~p	1.706142	.1264103	13.50	0.000	1.458383	1.953902
weight_ri_bed	-.8912686	.250217	-3.56	0.000	-1.381685	-.4008522
weight_profit	.7646143	.0532345	14.36	0.000	.6602766	.8689519
weight_time	-.0027031	.0011484	-2.35	0.019	-.0049539	-.0004524
weight_timesq	.0000358	6.73e-06	5.32	0.000	.0000226	.000049
age_60plus_~d	.1075359	.8108017	0.13	0.894	-1.481606	1.696678
age_60plus_~t	.3128728	.0971884	3.22	0.001	.1223871	.5033585
age_60plus_~e	.008051	.0034878	2.31	0.021	.001215	.014887
age_60plus_~q	-.0000743	.0000247	-3.00	0.003	-.0001228	-.0000259
female_ri_bed	-5.506454	.8978752	-6.13	0.000	-7.266257	-3.746651
female_profit	.6370926	.0883388	7.21	0.000	.4639516	.8102335
female_time	-.011977	.0029565	-4.05	0.000	-.0177716	-.0061825
female_timesq	.000083	.0000205	4.05	0.000	.0000428	.0001231
emer_ri_bed	1.934863	.6674819	2.90	0.004	.6266225	3.243103
emer_profit	.7860999	.0781855	10.05	0.000	.6328591	.9393407
emer_time	.0164088	.0033917	4.84	0.000	.0097613	.0230563
emer_timesq	-.0002178	.0000281	-7.74	0.000	-.0002729	-.0001626

Merger 21:

Conditional (fixed-effects) logistic regression

Number of obs	=	159564	
LR chi2(24)	=	12870.72	
Prob > chi2	=	0.0000	
Pseudo R2	=	0.2187	

Log likelihood = -22986.514

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	-.0272923	.0019688	-13.86	0.000	-.0311511	-.0234334
timesq	.0000466	.0000136	3.42	0.001	.0000199	.0000734
out	-1.225228	.0521507	-23.49	0.000	-1.327441	-1.123014
csurg_csurg~p	-.5104042	.1674669	-3.05	0.002	-.8386332	-.1821752
weight_csur~p	.1551783	.0155498	9.98	0.000	.1247013	.1856553
ob_ob_hosp	4.673363	.2173026	21.51	0.000	4.247458	5.099269
female_ob_h~p	-1.505958	.0512955	-29.36	0.000	-1.606495	-1.405421
female_nicu~p	2.229571	.0514623	43.32	0.000	2.128706	2.330435
weight_ri_bed	.0834069	.0352081	2.37	0.018	.0144002	.1524136
weight_profit	.0681037	.0181449	3.75	0.000	.0325403	.1036671
weight_time	.0017966	.0006685	2.69	0.007	.0004864	.0031068
weight_timesq	2.14e-06	4.33e-06	0.49	0.621	-6.35e-06	.0000106
age_60plus_~d	-.0058952	.136753	-0.04	0.966	-.2739262	.2621358
age_60plus_~t	.8618376	.0510801	16.87	0.000	.7617224	.9619528
age_60plus_~e	-.0105402	.0019797	-5.32	0.000	-.0144204	-.00666
age_60plus_~q	.0000359	.0000157	2.28	0.022	5.08e-06	.0000667
female_ri_bed	-1.386482	.0973727	-14.24	0.000	-1.577329	-1.195635
female_profit	.2277787	.0484027	4.71	0.000	.1329111	.3226462
female_time	.0057778	.0018406	3.14	0.002	.0021702	.0093853
female_timesq	-.0000748	.0000139	-5.36	0.000	-.0001022	-.0000475
emer_ri_bed	.026632	.1101785	0.24	0.809	-.189314	.242578
emer_profit	.1455877	.0443022	3.29	0.001	.058757	.2324185
emer_time	.0018344	.0017989	1.02	0.308	-.0016915	.0053602
emer_timesq	-.0000399	.0000143	-2.79	0.005	-.000068	-.0000118

Merger 22:

Conditional (fixed-effects) logistic regression

Number of obs	=	775257
LR chi2(24)	=	48673.24
Prob > chi2	=	0.0000
Pseudo R2	=	0.2165

Log likelihood = -88058.017

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0505792	.0017116	29.55	0.000	.0472245	.0539339
timesq	-.0010184	.0000286	-35.56	0.000	-.0010746	-.0009623
out	.2021321	.0333214	6.07	0.000	.1368233	.2674409
csurg_csurg~p	-2.321157	.2236257	-10.38	0.000	-2.759455	-1.882859
weight_csur~p	1.167675	.0141991	82.24	0.000	1.139846	1.195505
ob_ob_hosp	2.854836	.0820711	34.78	0.000	2.693979	3.015692
female_ob_h~p	.0163725	.0243494	0.67	0.501	-.0313515	.0640964
female_nicu~p	.9389596	.0199921	46.97	0.000	.8997758	.9781433
weight_ri_bed	.2367105	.0167065	14.17	0.000	.2039663	.2694547
weight_profit	-.0457354	.039533	-1.16	0.247	-.1232187	.0317479
weight_time	-.0099503	.0005881	-16.92	0.000	-.0111029	-.0087976
weight_timesq	.0001516	6.65e-06	22.80	0.000	.0001385	.0001646
age_60plus_~d	-.2818101	.0705365	-4.00	0.000	-.420059	-.1435611
age_60plus_~t	-.4197042	.088203	-4.76	0.000	-.5925788	-.2468296
age_60plus_~e	-.0101758	.0021408	-4.75	0.000	-.0143717	-.00598
age_60plus_~q	.0001081	.0000386	2.80	0.005	.0000325	.0001836
female_ri_bed	-1.342644	.0628488	-21.36	0.000	-1.465826	-1.219463
female_profit	-.2465618	.0453413	-5.44	0.000	-.3354291	-.1576945
female_time	.0265167	.0019123	13.87	0.000	.0227685	.0302648
female_timesq	-.0009155	.0000375	-24.44	0.000	-.000989	-.0008421
emer_ri_bed	.4904486	.0522126	9.39	0.000	.3881138	.5927833
emer_profit	-.4521282	.059848	-7.55	0.000	-.5694281	-.3348282
emer_time	.0441066	.0023475	18.79	0.000	.0395056	.0487077
emer_timesq	-.0013381	.0000523	-25.59	0.000	-.0014406	-.0012356

Merger 23:

Conditional (fixed-effects) logistic regression

Number of obs	= 6750738
LR chi2(24)	= 196931.67
Prob > chi2	= 0.0000
Pseudo R2	= 0.1524

Log likelihood = -547754.98

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0831074	.0009048	91.85	0.000	.081334	.0848809
timesq	-.001408	.0000147	-96.01	0.000	-.0014367	-.0013792
out	1.166658	.0118973	98.06	0.000	1.14334	1.189976
csurg_csurg~p	.8482727	.0639438	13.27	0.000	.7229452	.9736002
weight_csur~p	.3918779	.0039704	98.70	0.000	.3840961	.3996597
ob_ob_hosp	1.156771	.0142617	81.11	0.000	1.128819	1.184724
female_ob_h~p	-.6749707	.0111009	-60.80	0.000	-.6967281	-.6532132
female_nicu~p	1.062437	.0096301	110.32	0.000	1.043563	1.081312
weight_ri_bed	.1444792	.0079255	18.23	0.000	.1289456	.1600128
weight_profit	-.2186753	.0074746	-29.26	0.000	-.2333252	-.2040254
weight_time	-.0023573	.0002663	-8.85	0.000	-.0028792	-.0018353
weight_timesq	.0000965	2.77e-06	34.86	0.000	.0000911	.000102
age_60plus_~d	-.8860695	.0484508	-18.29	0.000	-.9810313	-.7911076
age_60plus_~t	-.2713718	.0212095	-12.79	0.000	-.3129416	-.2298019
age_60plus_~e	-.0147804	.0010227	-14.45	0.000	-.0167848	-.012776
age_60plus_~q	.0003071	.0000176	17.43	0.000	.0002725	.0003416
female_ri_bed	-2.56134	.0283856	-90.23	0.000	-2.616975	-2.505706
female_profit	-.3166918	.0107165	-29.55	0.000	-.3376958	-.2956878
female_time	.0271025	.0008922	30.38	0.000	.0253538	.0288512
female_timesq	-.0007546	.0000159	-47.47	0.000	-.0007857	-.0007234
emer_ri_bed	-.9793849	.0384049	-25.50	0.000	-1.054657	-.9041127
emer_profit	.2738236	.014019	19.53	0.000	.2463469	.3013004
emer_time	.0530042	.0010471	50.62	0.000	.050952	.0550564
emer_timesq	-.0016163	.0000223	-72.48	0.000	-.00166	-.0015726

Merger 24:

Conditional (fixed-effects) logistic regression

Number of obs =	101023
LR chi2(24) =	9593.03
Prob > chi2 =	0.0000
Pseudo R2 =	0.2406

Log likelihood = -15135.707

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	-.0057185	.0019829	-2.88	0.004	-.0096049	-.0018321
timesq	-.0000268	.0000123	-2.17	0.030	-.0000509	-2.61e-06
out	-.4120377	.0680748	-6.05	0.000	-.5454618	-.2786136
csurg_csurg~p	-1.081595	.4336371	-2.49	0.013	-1.931508	-.2316814
weight_csur~p	1.04864	.0348549	30.09	0.000	.9803261	1.116955
ob_ob_hosp	2.718323	.2661182	10.21	0.000	2.196741	3.239905
female_ob_h~p	.4818698	.0653693	7.37	0.000	.3537484	.6099913
female_nicu~p	.2962816	.0599247	4.94	0.000	.1788313	.4137319
weight_ri_bed	.4350934	.1117918	3.89	0.000	.2159856	.6542013
weight_profit	.4043707	.0439113	9.21	0.000	.3183062	.4904353
weight_time	-.0064492	.0009771	-6.60	0.000	-.0083643	-.0045341
weight_timesq	.000034	5.80e-06	5.86	0.000	.0000226	.0000453
age_60plus_~d	5.649241	.4872341	11.59	0.000	4.694279	6.604202
age_60plus_~t	-.3162018	.0931875	-3.39	0.001	-.498846	-.1335576
age_60plus_~e	.0260326	.0025135	10.36	0.000	.0211063	.030959
age_60plus_~q	-.0004161	.0000268	-15.52	0.000	-.0004687	-.0003635
female_ri_bed	3.145448	.2983892	10.54	0.000	2.560616	3.73028
female_profit	.2328162	.0572957	4.06	0.000	.1205188	.3451136
female_time	.0008291	.0019264	0.43	0.667	-.0029467	.0046048
female_timesq	-.0001421	.0000161	-8.85	0.000	-.0001735	-.0001106
emer_ri_bed	2.43328	.3431852	7.09	0.000	1.760649	3.10591
emer_profit	.0087084	.0638781	0.14	0.892	-.1164904	.1339073
emer_time	.0017128	.0018575	0.92	0.356	-.0019277	.0053534
emer_timesq	-.0001328	.0000172	-7.72	0.000	-.0001665	-.0000991

Merger 25:

Conditional (fixed-effects) logistic regression

Number of obs	=	384048
LR chi2(24)	=	18579.66
Prob > chi2	=	0.0000
Pseudo R2	=	0.1506

Log likelihood = -52379.14

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0728209	.0024806	29.36	0.000	.0679589	.0776828
timesq	-.0016819	.000044	-38.26	0.000	-.001768	-.0015957
out	.5234127	.0362938	14.42	0.000	.452278	.5945473
csurg_csurg~p	.896296	.285381	3.14	0.002	.3369594	1.455633
weight_csur~p	.1975591	.0137519	14.37	0.000	.1706057	.2245124
ob_ob_hosp	1.153398	.0795951	14.49	0.000	.9973949	1.309402
female_ob_h~p	.2299177	.0434807	5.29	0.000	.1446972	.3151383
female_nicu~p	-.1663309	.0237048	-7.02	0.000	-.2127916	-.1198703
weight_ri_bed	.2793975	.0189737	14.73	0.000	.2422097	.3165852
weight_profit	-.455601	.0266957	-17.07	0.000	-.5079237	-.4032784
weight_time	-.0012363	.0006601	-1.87	0.061	-.0025301	.0000576
weight_timesq	.0000952	7.43e-06	12.82	0.000	.0000807	.0001098
age_60plus_~d	.1777924	.0873467	2.04	0.042	.0065959	.3489889
age_60plus_~t	-.2545328	.0551548	-4.61	0.000	-.3626343	-.1464314
age_60plus_~e	.0339593	.0033232	10.22	0.000	.027446	.0404726
age_60plus_~q	-.0008351	.0000684	-12.20	0.000	-.0009693	-.000701
female_ri_bed	.5177536	.0503712	10.28	0.000	.4190279	.6164792
female_profit	-.1522417	.0335525	-4.54	0.000	-.2180033	-.0864801
female_time	.0237093	.0026055	9.10	0.000	.0186025	.0288161
female_timesq	-.0006528	.0000503	-12.98	0.000	-.0007514	-.0005542
emer_ri_bed	-.2559687	.0771266	-3.32	0.001	-.407134	-.1048034
emer_profit	1.37191	.0385331	35.60	0.000	1.296387	1.447434
emer_time	-.0092818	.0027831	-3.34	0.001	-.0147366	-.0038271
emer_timesq	.0000777	.0000566	1.37	0.170	-.0000333	.0001886

Merger 26:

Conditional (fixed-effects) logistic regression

Number of obs	=	3394272
LR chi2(20)	=	80759.66
Prob > chi2	=	0.0000
Pseudo R2	=	0.1098

Log likelihood = -327234.24

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
time	.0454193	.0011418	39.78	0.000	.0431815	.0476572
timesq	-.0008923	.0000189	-47.13	0.000	-.0009294	-.0008552
out	.3014288	.0195831	15.39	0.000	.2630466	.339811
csurg_csurg~p	-.528618	.0673776	-7.85	0.000	-.6606757	-.3965603
weight_csur~p	.5058113	.0048498	104.29	0.000	.4963058	.5153168
ob_ob_hosp	1.909541	.0231283	82.56	0.000	1.864211	1.954872
female_ob_h~p	-.2786756	.0117525	-23.71	0.000	-.3017102	-.2556411
female_nicu~p	.4704584	.0132303	35.56	0.000	.4445274	.4963894
weight_ri_bed	.8661893	.0112795	76.79	0.000	.8440818	.8882968
weight_time	-.0102757	.0003596	-28.57	0.000	-.0109806	-.0095709
weight_timesq	.0001871	3.95e-06	47.36	0.000	.0001793	.0001948
age_60plus_~d	-1.19702	.0367224	-32.60	0.000	-1.268995	-1.125046
age_60plus_~e	-.0123136	.0012682	-9.71	0.000	-.0147993	-.0098279
age_60plus_~q	.0000419	.0000237	1.77	0.077	-4.51e-06	.0000884
female_ri_bed	.1667141	.0268216	6.22	0.000	.1141446	.2192836
female_time	.0126654	.0011421	11.09	0.000	.0104268	.0149039
female_timesq	-.0004131	.0000212	-19.52	0.000	-.0004546	-.0003717
emer_ri_bed	.5492681	.026153	21.00	0.000	.4980091	.6005271
emer_time	.0250921	.0012658	19.82	0.000	.0226112	.0275729
emer_timesq	-.001127	.0000268	-42.03	0.000	-.0011795	-.0010744

Appendix D: Expanded Table 1

merger	pchange1	tt_pvalue	pchange_alt1	alt_tt_pvalue	pchange2	pchange_alt2	hhi_hrr_post	hhi_hrr_delta	hhi_hsa_post
1	0.064226666	0.06254905	-0.031738345	0.674651942	0.07159018	-0.015860217	951.4073154	10.00319489	4655.621913
2	0.033822797	0.740306734	0.228677744	5.44407E-06	0.095831216	0.309527506	2285.126978	416.0706369	6444.769479
3	-0.031780382	0.055797718	-0.117337158	0.016201053	-0.037862024	-0.109980876	2002.110891	599.452297	6740.395552
4	0.248319283	0.006275311	0.309629632	0.005191387	0.265523789	0.340225416	2647.990038	424.7312463	4662.163129
5	0.16883739	0.001752492	0.197741633	0.013201084	0.143882134	0.164703683	569.690749	22.64789477	3427.334173
6	-0.045800123	0.122364514	0.019073077	0.891322113	-0.046629494	0.017502379	1721.785281	73.72077263	6673.105241
7	-0.217678357	0.162927308			-0.192946558		3115.349945	557.5073964	5796.689991
8	-0.05370317	0.47191204	-0.143173277	0.456006581	-0.058123266	-0.150580266	1151.005901	13.49335672	3094.634089
9	0.093445201	0.016497503	0.2219311	3.70814E-05	0.056268213	0.143791342	589.3060746	42.26322037	1420.929619
10	-0.006112189	0.259991593	-0.021111164	0.419714946	0.05687596	0.058889682	2084.271411	66.82685117	4571.6466
11	0.089444506	0.084643162			0.157821081		734.2456271	113.6864316	3492.660032
12	-0.026244293	0.395537828	-0.190075343	0.031301351	-0.024812938	-0.139465566	4285.332957	1434.432597	7522.799383
13	0.198845574	0.00048428			0.305527611		1943.835563	289.5440033	5018.81458
14	-0.151909796	0.001635851			-0.155440355		5866.813655	1328.611604	7164.304013
15	-0.264560885	0.171866971			-0.232682436		1391.112918	294.0178247	3075.297864
16	-0.066820434	0.025431283			0.005083424		1117.711021	67.61159315	7806.345472
17	-0.011629682	0.39060333			0.010617713		2824.835688	1049.811305	8464.465819
18	0.155635028	0.00343703			0.14410037		845.1846664	3.792958357	4180.562128
19	0.304361007	4.53148E-05	0.161927279	0.085016686	0.291124076	0.155560949	1791.570241	531.0677115	5570.961856
20	0.341478679	3.66965E-13	0.025081255	0.751808581	0.326081375	0.017248772	8461.435098	2453.050255	6614.627781
21	0.161279329	4.48294E-16			0.180625127		3198.641504	987.1923252	4300.698049
22	0.082265297	0.103202533	0.184683686	1.16285E-07	0.094298381	0.170173429	2381.63916	261.3187653	3624.459777
23	-0.077099723	0.733641935	-0.040800084	0.49289909	-0.125310725	-0.104368396	548.961794	16.61415876	3973.7927
24	0.131683844	0.107864229	0.197266828	0.026478229	0.071543895	0.150802671	4023.605824	1141.913243	6923.295226
25	0.043449077	0.059750895	-0.221985147	0.002400476	0.041418825	-0.224969758	2808.193188	209.3094365	4096.045654
26	0.062936666	0.001015859	0.240875012	0.072946441	0.056773049	0.23174061	1977.179944	287.7863133	3784.629371

Appendix D: Expanded Table 1

merger	hhi_hsa_delta	hhi_wsa_post	hhi_wsa_delta	prod_div_bin	divb_bin	divb_bin_se	diva_bin	diva_bin_se	wtp_change_bin
1	811.9284562	4228.517224	1724.403505	3.2194E-06	0.001639473	0.003011598	0.00196368	0.003009569	0.000652353
2	2605.684387	3673.875177	674.3895424	0.036542615	0.520171272	0.037405899	0.070251121	0.009104389	0.021687387
3	2968.795304	2803.989856	1292.629892	0.015327865	0.117190418	0.007023923	0.13079452	0.011021719	0.052381261
4	1801.515112	3372.652747	928.2925937	0.017689884	0.433439509	0.029896357	0.040812809	0.003704247	0.057735162
5	1164.947247	1395.859087	400.9494814	0.006370245	0.213557845	0.00712507	0.029829131	0.001221834	0.041951379
6	3304.09715	5415.435899	1080.640926	0.11171441	0.711084523	0.016730479	0.157104264	0.009540676	0.098414894
7	2490.42201	3885.52342	1550.938559	0.406437667	0.755078046	0.014106189	0.538272394	0.017024519	0.48766567
8	1390.145571	1999.47035	316.41598	0.010718714	0.309820623	0.011112378	0.034596515	0.001759389	0.033604403
9	119.4724633	875.5053252	80.26633909	0.006673543	0.132007921	0.00423064	0.050554109	0.001743397	0.038648011
10	155.3654099	3803.033316	137.675764	0.002621184	0.215918825	0.011526512	0.012139674	0.000837245	0.011111027
11	403.6469543	2179.666065	653.2545877	0.024951996	0.085763941	0.00344566	0.29093807	0.008722824	0.064067327
12	2695.422416	4970.014533	1729.211911	0.488267733	0.81021173	0.006203227	0.602642143	0.008479607	0.463089616
13	1445.525035	3165.170231	1137.517271	0.132734228	0.363419946	0.021831631	0.365236498	0.017558809	0.285924052
14	3540.278197	5455.712737	618.0730429	0.03239552	0.578123091	0.022635518	0.056035679	0.003928936	0.029585271
15	426.4127506	1857.478113	400.6043909	0.016410278	0.165525474	0.00602753	0.0991405	0.004037021	0.070219787
16	1660.844641	5482.524664	1147.865157	0.414796586	0.817138768	0.010684849	0.50762074	0.017914333	0.127586408
17	3354.80638	4407.855822	1534.881093	0.378524711	0.733043149	0.00566465	0.516374393	0.006370216	0.303792328
18	777.9340184	3172.038695	593.7498546	0.045078284	0.425932371	0.017691353	0.105834369	0.007674184	0.085290547
19	1911.72093	2548.805431	939.3961992	0.032906834	0.338545323	0.009607461	0.097200675	0.00277785	0.097462753
20	2537.746204	5599.828218	2116.508487	0.373148574	0.813365518	0.0116708	0.458771076	0.016552852	0.418765858
21	1818.065506	3756.321342	1592.16105	0.085737287	0.289453552	0.012452983	0.296203955	0.007883906	0.137707619
22	253.9950456	3818.075456	422.7507068	0.00080523	0.195722618	0.011162014	0.00411414	0.000534863	0.012423933
23	1840.693003	1159.144608	219.9642199	0.006209803	0.390838127	0.012436207	0.015888426	0.000892684	0.071061062
24	2577.617207	5316.431822	1911.653166	0.466626269	0.823850865	0.00977999	0.566396528	0.015727534	0.381257132
25	1722.647581	3678.114056	1534.703458	0.15214744	0.499567818	0.016319747	0.304558129	0.015297049	0.232183297
26	655.147888	2628.69836	377.8717566	0.024198928	0.442350469	0.004703766	0.054705329	0.0015643	0.073538605

Appendix D: Expanded Table 1

merger	wtp_change_bin_se	loci_pchange_bin	loci_pchange_bin_se	simpi_bin_est	simpi_bin_high	simpi_bin_low	prod_div_cr	divb_cr
1	0.001229208	0.078919431	0.13110005				0.025407242	0.155381894
2	0.020820564	0.920041006	0.083333212	0.003074918	0.011733652	-0.005583815	0.011341258	0.214339549
3	0.00845105	1.929311225	0.09303428	0.294089229	0.81234855	-0.224170092	0.012893277	0.147619167
4	0.013050623	0.331157401	0.023206886	0.040396664	0.189099731	-0.108306403	0.013608291	0.169907621
5	0.003812957	0.190199988	0.006054951	0.024734583	0.075937402	-0.026468235	0.003154643	0.089983886
6	0.025114501	1.459415631	0.077435453				0.013267814	0.129536434
7	0.064404716	2.720604838	0.107850995	0.195288106	0.549635668	-0.159059455	0.005358707	0.101829311
8	0.002401235	0.15991276	0.006505179	0.006449244	0.012460631	0.000437857	0.00083936	0.044054459
9	0.004395832	0.090706399	0.00260227	-0.007723436	0.0095364	-0.024983271	0.007143705	0.113032508
10	0.00088921	0.057169763	0.003369304	-0.006297831	0.00719815	-0.019793813	0.001717207	0.179759924
11	0.003631679	0.271342706	0.009108039	0.022483704	0.085796089	-0.040828682	0.010608883	0.052095511
12	0.042305197	2.089670074	0.03461552	0.200662604	0.554280673	-0.152955464	0.017713821	0.277878007
13	0.037834951	0.973111302	0.048837355	0.128424649	0.490058616	-0.233209317	0.015972679	0.132418661
14	0.007573323	1.539717498	0.070914932				0.016348342	0.326088477
15	0.003784051	0.22220352	0.007934494	0.015785836	0.04484686	-0.013275188	0.007864843	0.132865746
16	0.052046927	2.054014595	0.083308061	0.002717208	0.018036733	-0.012602316	0.007489712	0.160608774
17	0.0459034	1.403867206	0.019991609	0.08203219	0.187282865	-0.023218486	0.075102226	0.429889068
18	0.00816328	0.358752356	0.024475451	0.015236683	0.084275405	-0.05380204	0.000585625	0.043392223
19	0.005193574	0.432189433	0.011806572	0.091888713	0.192716283	-0.008938857	0.009342785	0.210551372
20	0.076119813	2.582246921	0.110225936	0.139904931	0.425717351	-0.145907488	0.213974512	0.626509932
21	0.015199371	1.044078868	0.031244879	0.127168874	0.223457338	0.03088041	0.051160768	0.248872779
22	0.00093338	0.249004115	0.015847183				0.009242404	0.212768647
23	0.011592929	0.160986313	0.006002201	0.0382224	0.087727971	-0.011283171	0.000719866	0.070956157
24	0.06376668	2.093160691	0.066367033	0.128793169	0.355759183	-0.098172846	0.059496983	0.361017882
25	0.029119855	1.185665753	0.046125573				0.007726017	0.103498181
26	0.007907924	0.294361122	0.005499374	0.017287766	0.035368116	-0.000792583	0.03764994	0.324165534

Appendix D: Expanded Table 1

merger	divb_cr_se	diva_cr	diva_cr_se	wtp_change_cr	wtp_change_cr_se	loci_pchange_cr	loci_pchange_cr_se	simpi_cr_est
1	0.002168795	0.16351482	0.002341522	0.088479776	0.001344528	0.21245072	0.003572296	
2	0.001459574	0.052912575	0.000794287	0.041808108	0.000597675	0.125788385	0.001480666	0.010895168
3	0.000916854	0.087341486	0.001154144	0.057775749	0.00058808	0.145110729	0.001289619	0.008907696
4	0.002348765	0.080092296	0.000940032	0.057134611	0.000884912	0.143500488	0.002908458	0.000543508
5	0.000259245	0.035057861	0.000117194	0.029058077	8.12305E-05	0.065442498	0.000183387	0.015324174
6	0.001289561	0.102425348	0.000836671	0.067502611	0.000654706	0.148446992	0.001375136	
7	0.002022373	0.052624402	0.000715571	0.035943217	0.000393322	0.0836638	0.00109754	0.124941736
8	0.000165152	0.019052773	0.000134334	0.013693627	7.35385E-05	0.029109167	0.000121667	-0.001055905
9	0.000489221	0.063200445	0.000346581	0.04078732	0.000209524	0.09008236	0.000425168	0.015376794
10	0.001435757	0.00955278	0.000198934	0.008982844	0.000167966	0.02721972	0.000347357	0.000354837
11	0.000724076	0.203642946	0.001319521	0.041426812	0.000539664	0.115122754	0.000870207	0.00231311
12	0.001782619	0.063746756	0.000833392	0.047947886	0.00061971	0.152738033	0.001532802	0.009045935
13	0.001229663	0.120622567	0.001076363	0.067739434	0.000620985	0.157057105	0.001612406	0.005175453
14	0.001525411	0.05013468	0.000681538	0.035433019	0.000507044	0.169141061	0.00200582	
15	0.00176514	0.059193911	0.000558077	0.041984214	0.000384396	0.103777107	0.001261294	0.009686719
16	0.001054046	0.046633271	0.000760708	0.034893872	0.000541046	0.090416696	0.001031051	-0.003795433
17	0.001737683	0.17470141	0.001912856	0.141277376	0.001620288	0.435625952	0.003814559	0.005854462
18	0.000294231	0.013496093	0.000177254	0.010389303	0.000102312	0.021892594	0.000126924	-0.02259776
19	0.000852264	0.044372947	0.00033704	0.039396663	0.000251369	0.099938288	0.000439148	-0.000752397
20	0.007066666	0.34153411	0.009399135	0.348424815	0.012093062	1.336257027	0.039367167	0.183313531
21	0.004612041	0.205569963	0.003112866	0.135717829	0.002483332	0.531719752	0.009361795	0.098602723
22	0.001131716	0.043438748	0.000255452	0.036220495	0.000174833	0.101846383	0.000468995	
23	0.000131022	0.010145229	5.61191E-05	0.010545351	4.85079E-05	0.024324686	6.67759E-05	0.003712751
24	0.004486368	0.164803423	0.004466166	0.117170372	0.003463985	0.373691541	0.007856221	0.042533938
25	0.001692552	0.074648823	0.001761293	0.047493279	0.000989732	0.100902804	0.001968347	
26	0.000943099	0.116144179	0.000548516	0.095477695	0.000351396	0.268631797	0.001011788	-0.026094153

Appendix D: Expanded Table 1

merger	simpi_cr_high	simpi_cr_low	nc
1			Recent Mergers
2	0.113118975	-0.091328638	NC Mergers
3	0.083077849	-0.065262457	NC Mergers
4	0.094778138	-0.093691122	Recent Mergers
5	0.055290802	-0.024642454	Recent Mergers
6			Recent Mergers
7	0.562673636	-0.312790165	Recent Mergers
8	0.005010308	-0.007122119	Recent Mergers
9	0.063270282	-0.032516694	Recent Mergers
10	0.029538993	-0.028829319	NC Mergers
11	0.024015837	-0.019389618	NC Mergers
12	0.084367137	-0.066275267	NC Mergers
13	0.053734092	-0.043383186	NC Mergers
14			NC Mergers
15	0.044265315	-0.024891878	Recent Mergers
16	0.067568151	-0.075159016	NC Mergers
17	0.182726851	-0.171017928	Recent Mergers
18	0.346362616	-0.391558135	Recent Mergers
19	0.035595375	-0.03710017	Recent Mergers
20	0.664074824	-0.297447762	Recent Mergers
21	0.280290509	-0.083085064	Recent Mergers
22			NC Mergers
23	0.012577419	-0.005151918	Recent Mergers
24	0.396693832	-0.311625956	NC Mergers
25			Recent Mergers
26	0.033030467	-0.085218773	Recent Mergers