Economics at the FTC: Hospital Mergers, Authorized Generic Drugs, and Consumer Credit Markets

$1.2 TR in the pre-crisis year of 2007.[2] Over 1100 merger filings occurred in 2010, and the FTC challenged all or some aspect of 22 transactions.[3]

We examine mergers in a large number of different industries, but one of the most active recently has been hospitals. In this segment we describe the conceptual framework and related empirical analyses that we employ in a typical hospital merger investigation.

2.1 Hospital Merger Analysis

We provide an overview of the basic economic theory and the methods that may be applied in assessing the likely price effects of hospital mergers. While our case analyses rely on numerous sources of information, including documents and interviews, here we discuss only our conceptual framework and our empirical methods.

In addition to the effect on price, the analysis of hospital mergers also requires close attention to likely effects on quality, particularly clinical quality (as it has been defined by the Institute of Medicine and the World Health Organization), as distinct from hospital amenities. As stressed by Town (2011), life and health are very valuable, so even modest improvements in clinical quality may redeem otherwise problematic hospital mergers. For this reason, well-supported claims regarding clinical quality tend to be given more weight than other claims of pro-competitive merger effects. Our methods of evaluating such claims are discussed in detail in Romano & Balan (2011), and so are omitted here in the interest of brevity.

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[2] MergerStat Review, (2011, p. 10). The data represent the dollar value of mergers, acquisitions, and divestitures involving US firms if at least 10% of the equity of a firm is transferred and a value is reported.

[3] FTC Chairman's Annual Report (2011, p. 1). Retrieved from http://www.ftc.gov/os/2011/04/2011ChairmansReport.pdf.

2.2 Bargaining Theory

Prices in commercial hospital markets are generally determined through bilateral bargaining between managed care organiza

Here, n_k denotes the (expected) number of patients covered by the MCO treated at hospital k;[7] $c_k(n_k)$ denotes the (expected) incremental cost of treating n_k patients; denotes the profit-maximizing premium conditional on bargaining outcomes with each of the other hospitals (collectively indexed as $-k$);[8,9] $V \quad p_k, p_{\ k}$ denotes the gross equilibrium payoff (before payments to hospitals) of the MCO under the agreement with hospital k; $V \quad p_{\ k}$ denotes the disagreement payoff of the MCO (before payments to hospitals); and d_{kj} denotes the diversion ratio from hospital k to hospital j.[10] The disagreement payoff of the hospital with respect to that MCO is typically assumed to be zero.[11] The parameter $0,1$ denotes the split of the joint surplus.

The basic principles of competitive effects analysis in this theoretical framework are fundamentally similar to those in standard differentiated products markets in which prices are posted by firms. Changes in the disagreement payoffs of the hospitals or of the MCO, and hence

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[7] For tractability we assume that, conditional on inclusion, n_j does not depend on the negotiated hospital prices. In most instances, we have found that the most common health insurance products significantly limit or eliminate out-

price effects, are increasing in the diversions between the merging hospitals and in their pre-merger bargaining power. If the hospitals are substitutes and bargain separately post-merger, their disagreement payoffs (and, hence, equilibrium prices) rise because each hospital now takes into account the fact that its merger partner will recapture some of the lost volume if it fails to reach an agreement.

If, as is typical, the hospitals instead bargain on an all-or-nothing basis, the disagreement payoff of the MCO will decrease because the cost to the MCO of failing to reach an agreement with the merged hospitals will exceed the sum of the costs of failing to reach an agreement with them separately, again only if the hospitals are substitutes. To see this, recall that the bargaining power of a hospital comes from the diminution in the value of the MCO's network if it is excluded. This diminution is mitigated by the presence of proximate alternatives. When a hospital merges with one of those alternatives and then the merged entity bargains on an all-or-nothing basis, absent an agreement, patients whose first choice was one of the hospitals and whose second choice was the other would be forced to use their third choice instead, which further diminishes the value of the MCO's network. If the hospitals are not substitutes, there are no patients for whom this will be true, so the cost of failing to reach an agreement with both hospitals is equal to the sum of the costs of failing to reach agreements with them separately, and so there will be no effect on price. Hence, in both separate and all-or-nothing bargaining, the magnitude of the price effect depends on the diversions between the merging hospitals.[12]

2.3

payer type, and clinical information such as diagnosis related group (DRG) and diagnosis and procedure codes. We may also utilize data on hospital-specific characteristics. We begin the diversion analysis by estimating a standard

Since preferences on travel time and over hospitals are allowed to vary by condition type and acuity, this approach addresses the "Silent Majority Fallacy" problem discussed in Capps et al. (2001) and Elzinga and Swisher (2011). That is, the choice model, and hence the diversion and merger simulation analyses described below, distinguish between a circumstance in which some patients are observed to travel longer distances because the disutility of travel is relatively low from one in which they are observed to travel longer distances because they have a particularly strong reason to travel (e.g., in order to access services that are not available locally) despite travel costs that are relatively high.

The parameter estimates from the choice model are used generate a full set of fitted choice probabilities. Given the IID Extreme Value assumption, the fitted probability that patient *i* chooses hospital *k* is defined as $prob_{ik} \quad \frac{\exp\{X_{ik}\hat{} \quad Z_k\hat{}\}}{_j \exp\{X_{ij}\hat{} \quad Z_j\hat{}\}}$. Given these probabilities, the predicted diversion ratio from hospital *k* to hospital *l* is

$$d_{kl} \qquad _i prob_{il\backslash k} \qquad _i prob_{il} \quad / \quad _i prob_{ik},$$

where $prob_{il}$ denotes the fitted probability that patient *i* is treated at hospital *l* (with the analogous definition applying to $prob_{ik}$) and $prob_{il\backslash k}$ denotes the fitted probability that patient *i* is treated at hospital *l* under the hypothetical exclusion of hospital *k*.[16,17]

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fixed-effects specification fully captures variation in preferences over quality and other hospital attributes, observed and unobserved, that systematically affect patie

It is well known that if one estimates a conditional logit applying data on relevant individual consumer characteristics, then diversions at the level of the consumer are proportional to that consumer's fitted choice probabilities, but diversions at the product level are not proportional to product level shares. The reason is that information on individual consumers makes it possible to identify variation in valuation of product characteristics across consumers. Hence, the model generates reasonable substitution patterns in that hospitals that are closer in product characteristics space to the hypothetically excluded hospital are predicted to capture a disproportionate (relative to observed shares) share of the diverted patients. See Berry (1994, pp. 246-247).[18]

This simple analysis has the important property that it is largely insensitive to the inclusion of competitively irrelevant geographic areas or hospitals. Unlike share-based concentration measures, it does not require, and in fact has no role for, a geographic market definition. Generally, we start with a broad patient population and a choice set consisting of a broad range of alternative hospitals. However, any claim that these should be made broader still is easily accommodated by simply including data on the additional ZIP codes and/or hospitals in the analysis. In contrast, a share-based concentration measure has the disadvantage of being highly sensitive to geographic market definition.

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d_{kl} $_i prob_{il\backslash k}$ $_i prob_{il}$ / $_i prob_{ik}$ $_i prob_{ik\backslash k}$, where $prob_{il\backslash k}$ and $prob_{ik\backslash k}$ denote the predicted probabilities of *l* and *k* under the hypothetical exclusion of *k*. In these cases, we have found

2.4 Merger Simulation

In this section, we present our approach to merger simulation, which is derived from the above theoretical framework. While our approach can be adapted to either separate or all-or-nothing post-merger bargaining, we present the latter case only since that is the most common.

Solving the first-order condition of the Nash objective function with respect to the equilibrium price (and applying the Envelope Theorem[19]) yields the expression

(1) $$\frac{(\ _k,\ _k)\qquad(\quad)}{\qquad\qquad\qquad\qquad}\quad(1\quad)\frac{(\quad)}{\qquad}\qquad .$$

The expressions in (1) and (2) indicate that in equilibrium the hospital system receives a fraction α of the equilibrium per-patient value that the MCO gains from the system's inclusion in the MCO's network. Comparative statics on (1) and (2) with respect to a small exogenous change in patient preferences that affect the payoffs of the MCO indicate that the system would also receive a fraction α of the additional value generated by the change.

The merger simulation exercise is a least-squares regression based on (1) for independent hospitals and on (2) for multi-hospital systems. We do not have a direct measure of $V(\{p_j\}_{j \in S}, p_{j \notin S}) - V(p_{j \notin S})$. Estimating it for each MCO/hospital system combination by jointly modeling and estimating the oligopoly game played by MCOs and the MCO/hospital bargaining games would be difficult, in part because the time cost would be prohibitively high in the context of a typical antitrust investigation, and also because the data burden placed on MCOs and their customers would be very high. Hence, we seek a proxy variable that can readily be computed using discharge and claims data that are obtained from state agencies and MCOs. Such a proxy should reflect the intuition that the difference in payoffs for the MCO should be determined primarily by the value-added of the hospital or system to the MCO's provider network from the perspective of consumers (i.e., by how much less attractive consumers would find an insurance product that excluded that hospital or system). We use the *willingness-to-pay* (*WTP*) measure that is presented in Town and Vistnes (2001) and Capps et al. (2003), which is specifically constructed to capture this notion of value-added.[22,23]

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[21] The last term in (1) and (2) captures price complementarities between competing hospitals in that they capture the component of the disagreement payoff of the MCO that depends on which hospitals patients will divert to and the prices at those hospitals. The current hospital merger simulation literature does not incorporate these complementarities. Models that ignore them limit the focus of the analysis to the first-order price effects that result directly from the potential elimination of competition between the merging firms, and therefore generally produce smaller merger effects. We are currently expyemitices at 001 T31 Tw 0.0010 T8[S42G4017 Tn

is WT.

Holding constant the number of patients treated at a given system *S*, its *WTP* is larger if there are relatively few proximate alternatives because some patients will be forced to use much less preferred alternatives if *S* is excluded from the MCO's network. Similarly, *WTP* is larger if the component hospitals of *S* are close substitutes for one another because, if system *S* bargains on an all-or nothing basis, the exclusion of the entire system from the MCO's network will also cause some patients to use much less preferred alternatives.

Since *WTP* is a proxy for $V \quad (\{p_j\}_{j \ S}, p_{\ j}) \quad V \quad (p_{\ S})$, and given the relationship defined in (1) and (2), the merger simulation exercise is based on a least-squares regression of case-mix adjusted prices on *WTP* per discharge (*WTP_PD*), rather than *WTP* itself. Since this measure of bargaining power is defined on a per-discharge basis, it does not predict that a large system will have a high price simply because it has a large patient volume.[24] Rather, the extent to which a large system has a large *WTP_PD* is driven by the closeness of substitution between the component hospitals, not its owntsTfspi is]TJents wiume.-1(. Apitals, nl)(e spi) e fewc0.001 Tc 1-0.0009 T4

the MCO’s payoff functions will not necessarily be negligible. Hence, (1) and (2) are first-order

Including variables that are highly correlated with the bargaining power measure, but that in fact act on prices only through the bargaining power measure, as separate regressors can lead to incorrect inference due to collinearity. In addition, it is straightforward to show that if the sample size is small (as is often the case) or if the error variance is high, including these regressors, or other spuriously correlated variables, can produce highly unstable coefficient estimates (even though the least-squares estimator remains, strictly speaking, unbiased) and can significantly reduce the power of hypothesis testing. Hence, in the small sample case, it is particularly important that the specification of the model be carefully guided by theory – particularly in terms of whether and how other explanatory variables should be included.[26] This is in contrast to the hospital choice model discussed earlier, in which the number of observations is usually very large. The small number of observations in the merger simulation regression model (typically less than 200) make this a salient issue.[27]

Direct measures of average cost may or may not be included in the regression. While including tion of the mgres

on *WTP_PD*. Hence, it may be preferable to include proxy variables that indirectly measure the exogenous variation in costs in lieu of the direct cost measure.

Finally, the fact that the dependent variable in the regression model is a case-mix adjusted price may reduce the necessity of including any cost measure. Once prices are case-mix adjusted, the only relevant exogenous cost variation should be limited to the cost of direct healthcare inputs such as supplies or, perhaps, labor inputs. In many instances, there may be little reason to think that input costs will vary significantly across hospitals within a given area on a case-mix adjusted basis.

Given the estimated regression model, it is straightforward to generate a predicted price effect that is consistent with the bargaining model. The relevant question in an all-or-nothing bargaining setting is whether the merged hospitals will be able to extract higher prices from an MCO together than they could, on average, separately. Hence, the model generates a predicted change relative to the volume-weighted average pre-merger price (or predicted "but-for" prices if they are likely to be substantially different). Following Capps et al. (2003), the predicted level effect of a merger between system *S* and hospital *k* relative to the volume-weighted average pre-merger price is given by

$$\hat{} \quad WTP\_PD_{Sk} \quad \frac{n_S}{n_S \quad n_k} WTP\_PD_S \quad \frac{n_k}{n_S \quad n_k} WTP\_PD_k \quad ,$$

where $\hat{}$ denotes the estimated regression coefficient on *WTP_PD*.[28,29] We assume that the relationship between *WTP_PD* and price is unaffected by the change in market structure. This is

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[28] Since *WTP_PD* is a proxy variable for $V \quad p_k, p_{\ k} \quad V \quad p_{\ k} \quad / n_k$, the regression coefficient β captures both the split parameter α and the underlying regression coefficient between *WTP_PD* and $V \quad p_k, p_{\ k} \quad V \quad p_{\ k} \quad / n_k$ which converts *WTP_PD*, measured in "utils", to dollars.

[29]

consistent with assuming that the split parameter in the bargaining model is unaffected by the merger. The predicted effect will be close to zero if either $\widehat{\ }$ is close to zero or the estimated diversions between *S* and *k* are close to zero.[30]

We note that this analysis may also be used to

introduce AGs. AGs are approved by the U.S. Food and Drug Administration (FDA) as brand-name drugs, but are marketed as generic drugs.[32]

The competitive effects of AGs are theoretically ambiguous. Although competition from AGs may contribute to lower generic dr

drug product. The rationale for this prize is that it will encourage generic firms to challenge weak or narrow patents by singling out a specific challenger in an attempt to prevent a free-rider problem.[35] However, the Act does not prohibit an AG from marketing during exclusivity because the AG can rely upon the FDA's approval of the brand.

the prices of generic drugs and the revenues of first-filers both duri

the FDA is used to determine whether a drug faced a patent challenge and the dates of any exclusivity arising from the challenge.40 First-filers are identified in the data as generic firms with positive sales during exclusivity that are not AGs.

First-Filer Revenues During the 180-day Exclusivity Period

The first-filer's revenues that are associated with the 180-day exclusivity period can be affected by the presence of an AG competitor. This effect is estimated by regressing first-filer revenues against drug characteristics and an indicator for whether an AG was introduced. The formal specification is presented as equation (3):

(3) $$f_{dt} = \beta_{ag} ag_{dt} + \beta_{mj} mj_{jdt} + \beta_{agj} agj_{jdt} + \beta_{year} year_{tc} + \beta_{df} df_{months_{dt}} + \beta_{exclusivity\ period} exclusivity\ period_{dt} + \varepsilon_{dt}$$

The impact of AG competition on the proportion of pre-entry brand sales a lone first-filer can expect to earn in revenues during the 180-day exclusivity pe

from the first-filer.[44] Generic prices are normalized by the quantity-weighted pre-entry brand price in the quarter immediately preceding generic entry.

3.2 Estimation Results

The empirical analysis begins with a plot of the mean of normalized revenues for the first filer, the brand drug, the AG, and "other generic firms" over time. These revenues are normalized by pre-entry brand revenues immediately preceding generic entry, which is analogous to the calculation for the dependent variable in the revenues regressions. Figures 1a and 1b plot these measures over time, as stacked area graphs, for markets with and without an AG competitor. Two patterns emerge from these figures. First, the graphs demonstrate that generic products quickly take a large share of the market from the brand, earning between 55-70% of the revenue share during the first six months of entry. Second, the figures reveal that the first-filer and the AG are able to keep most of their share for the duration of the sample. These firms appear to benefit from a "first-mover advantage" that extends well past the end of exclusivity. The average combined contemporaneous revenue share of first-filers and AGs never falls below 50% over the three-year period despite facing three-to-four other competitors, on average, following expiration of the 180-day exclusivity.

The pace at which generic entrants command share and the ability to hold onto that share suggests that the reward from the 180-day exclusivity period is substantial. However, in markets where an AG is present, the figures suggest that the first-filer splits these rewards with the AG. Moreover, the total size of the market, measured as a fraction of pre-entry brand revenues, is smaller in markets where an AG is present than in markets where an AG is not introduced.

The markets that are presented in Figures 1a and 1b represent two sets of drugs: one with and one without an AG. These drugs may differ in characteristics other than whether an AG was introduced, such as the number of eventual generic competitors that are faced in the market. The

[44] All analyses normalize the dependent variable by the relevant pre-entry brand statistic (i.e., prices and revenues). This normalization implies that the decision to consider the unit of analysis to be pills is identical to the decision to consider the unit of analysis

differences in the first-filer revenues across markets may be attributable to these other factors, rather than the AG. The regression models attempt to control for these factors by including drug characteristics such as the therapeutic class and the number of competitors.

The effects of an AG on revenues and prices from the regression models are calculated and presented in Tables 1 and 2, respectively. The results are presented separately during and following exclusivity periods using estimates from un-weighted and sales-weighted regressions. The econometric estimates are largely consistent with the representation of market dynamics that are found in the figures. Table 1 reveals that first-filers facing an AG earn between 40-52% less revenue during exclusivity than do first-filers in markets without an AG. Following exclusivity, the AG effect estimates are also large and economically important. These results are consistent with the shared "first-mover advantage" also seen in Figures 1a-1b. Table 2 suggests that the AG is responsible for 12.8%-13.5% lower wholesale prices during exclusivity. This result is consistent with the smaller overall market observed in the figures. The price effect of the AG following the exclusivity period is statistically insignificant, although the coefficients are negative.

3.3 Incentives to File Paragraph IV Challenges

exclusivity, $\hat{p}_f$, and following it, $\overline{p}_f$, are normalized by brand prices that immediately precede generic entry. Substituting equation (5) into equation (4) and imposing a zero-profit condition on non-exclusive entry allows for the expected profits calibration.[47] The calibration is performed twice, once under the expectation that an AG will not be introduced, and again under the expectation that an AG will be introduced with certainty.[48] In the first calibration (i.e., no AG), the price and revenue values are replaced with the corresponding sample averages for markets that do not contain an AG. In the second calibration (i.e., AG), these averages are discounted by the price and revenue AG effects from the un-weighted regressions.

The values that are used in each set of calibrations are presented in Table 3. Both calibrations use the mean litigation and ANDA submission costs from the subpoenaed responses, which are also reported in Table 3. Marginal costs were approximated by using wholesale pricing data from markets with greater than 10 generic competitors under the theory that prices will fall to a level that is close to marginal costs in these markets. Generic prices average approximately 10% of the pre-entry brand price in these markets with a large number of competitors, so we assume that the marginal cost of producing the drug is 10% of the pre-entry brand price. The analysis is not sensitive to this assumption.[49]

Figure 2 characterizes the win probabilities and market sizes of drugs for which a potential challenger, under the assumptions of the model, would be indifferent between challenging and not. The figure provides separate "break-even" curves for firms that do and do not expect to face an AG. Areas above these curves represent situations where a challenge would be expected to be profitable, and areas below them represent circumstances where the challenge is expected to be

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[47] The zero-profit condition has two functions. It allows us to characterize the set of drugs for which a potential challenger is indifferent between challenging and not. It also implies that expected operating profits of an entrant that comes in after exclusivity must be equal to the filing costs, i.e. $\pi_{non\text{-}excl} = A$.

[48] These assumptions may lead to a finding of a larger deterrence effect than allowing the expectation of facing an AG to depend upon market characteristics.

[49] Consistent with this, a 2004 Morgan Stanley report that analyzed the impact of AG entry on first-filers also assumed pre-generic entry brand profit margins of 90%; see Goodman et al. (2004).

unprofitable. The area between the AG and non-AG curves represents situations where a challenge would be deemed to be profitable only if an AG is not expected to enter. The difference in the win probabilities required to induce a challenge depends on the size of the market.[50]

Figure 2 provides the cumulative sales density for drug markets in the sample to facilitate a characterization of relative market sizes. As can be seen in the figure, the difference between the AG and non-AG win probabilities necessary to induce a challenge can be large in relatively small markets. For example, a generic company considering a challenge in a $15 million market would require a 41% chance of winning to induce a challenge if the potential challenger did not expect an AG. The same challenger would require a win with certainty under the expectation of facing an AG. Over the entire range of market sizes, the ratio of between the break-even win probabilities without and with an AG remains very close to 4:10. However, the absolute AG effect is much smaller in large markets. For example, expectation of AG entry in a $250 million market would only cause the win probability required to induce a challenge to increase from 2% to 5%.

Figure 2 also demonstrates that drug markets that account for the vast majority of sales have low entry thresholds. For example, markets above $130 million in sales would require less than a 10% chance of winning patent litigation to induce a challenge. In these markets that account for the vast majority of sales (85% of sales), weak and narrow patents are likely to be challenged, regardless of whether potential challengers expect to face an AG.

AGs have the potential to deter generic entry into markets that require patent challenges. However, they may also lower generic prices in the markets in which they enter. Although we find evidence that AGs have economically important effects on the revenue incentives of

[50] In Figure 2, the sales for a "market" are aggregate dollar sales of drugs across strengths and therapeutic classes within a dosage form. Many challengers enter into multiple strengths of a dosage form in a patent challenge. $65 million is the median market in the sample, but drug markets that represent more than $400 million in annual sales account for more than half of all sales.

potential challengers, these effects are only likely to deter entry into relatively small drug markets.

4 Consumer Protection

4.1 Homeowners Insurance and Credit based Insurance Scores

premiums written. The Commission requested and obtained policy- and claim-level information on all homeowners insurance policies (except condominium and renters policies) that were in force at each of the nine insurers during mid-2004 through mid-2007: approximately 47 million policies. In addition, the Commission requested data from each insurer on applications and price quotes for prospective customers during a 12-month period from early 2008 through early 2009.

At this point we have extracted a stratified random sample from the insurers' data (over-sampling policies with claims). These data are being combined with credit history information for each policyholder from a credit reporting agency and race and ethnicity data from the Social Security Administration (SSA).

Using the claims data and a standard set of insurance rating variables from the policy data, in addition to credit-based insurance scores, we will run risk models by peril (e.g., fire, wind-hail, theft) to examine the relationship between credit history and the risk that a claim will be filed. Then we will analyze the potential for scores to act as a proxy for race and ethnicity among

is material to creditworthiness? In turn, what proportion of material allegations is confirmed as erroneous by the existing credit reporting dispute process? If a credit report is drawn at random, what is the probability that the report would contain one or more material errors? Further, focusing on consumers and their credit standing, the study will estimate the proportion of American consumers who would encounter one or more material errors across their three credit reports. The study will reveal the main types of errors, their relative frequencies, and the impact of such errors on a consumer's ability to access credit.

A nationwide survey is currently in the field. Given the cost of the sampling procedure and the credit report review process, the target sample size (1000 consumers and 3000 credit reports) is relatively small. That sample should, however, allow us to draw statistically reliable and projectable conclusions regarding the accuracy of credit reports for the population of consumers.[53]

We started with a very large random sample—200,000 individuals—from the population of interest: people with credit histories at the three national credit reporting agencies (i.e., Equifax, Experian, and TransUnion). This broad sample comprises the master list of all potential respondents, including a subgroup of about 28,000 solicited consumers and a further subgroup of 1,000 participants. The individuals on the master list have a distribution of credit scores that is statistically the same, at very refined levels of partition, as the national distribution of scores. As the invitations were sent to the potential participants in progressive waves, the credit scores and the major demographic characteristics of respondents have been analyzed to ensure that the ultimate study participants conform to national norms and are representative of the population.

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[53] Another study of credit report accuracy was recently released by the Policy and Economic Research Council (PERC) for the Consumer Data Industry Association (CDIA), which is the credit reporting industry trade association. That study is modeled in part on the FTC's approach to measuring credit report accuracy. PERC finds that about 19% of reports may contain data errors as judged by the consumer respondents, but that only a small percentage – on the order of 0.5% -- are likely to have a significant adverse impact on a consumer's credit worthiness. The FTC report will contain commentary on the PERC study.

In addition to answering interesting questions about the accuracy of credit reports, the study will evaluate a potential response bias in our sample of participants. We will have access to the credit scores and the redacted credit reports for all non-respondents: the 27,000 solicited consumers (identified only by ID numbers) who did not participate. We will compare respondents to non-respondents on an array of attributes, including credit scores, major demographics (age, gender, regional diversity), and other important categories of credit report information, such as the number of active credit cards, total credit card balances, late payments (30, 60, 90+ days late), number of trade lines currently delinquent, accounts or tradelines that have been sent to collection, reported bankruptcy, liens on property, and the time span of the consumer's file. Conducting a detailed comparison of respondents and non-respondents will allow us to assess rigorously the degree to which the respondents and their credit reports are representative of the population.

5 Conclusion

Health care is one of the most important industries examined by the FTC. Our hospital merger analyses use a wide array of information, with one important component being the rigorous examination of data on the choices of hospitals by patients and prices paid for care by private insurers. That empirical analysis has proven useful in several recent investigations and litigations in the hospital industry. Similarly, empirical work is important in our policy making in the pharmaceutical arena. Our study of the price effects of authorized generics will provide the FTC and other policy-makers with a better understanding of the impact of entry into generic markets by incumbent drug makers. On the consumer protection front, empirical work is also at the forefront of policy development, with ongoing studies including the effects of credit scoring on the price and availability of homeowners insurance, and the accuracy of credit reports and the impact of errors on consumers' ability to obtain credit.

Figures and Tables

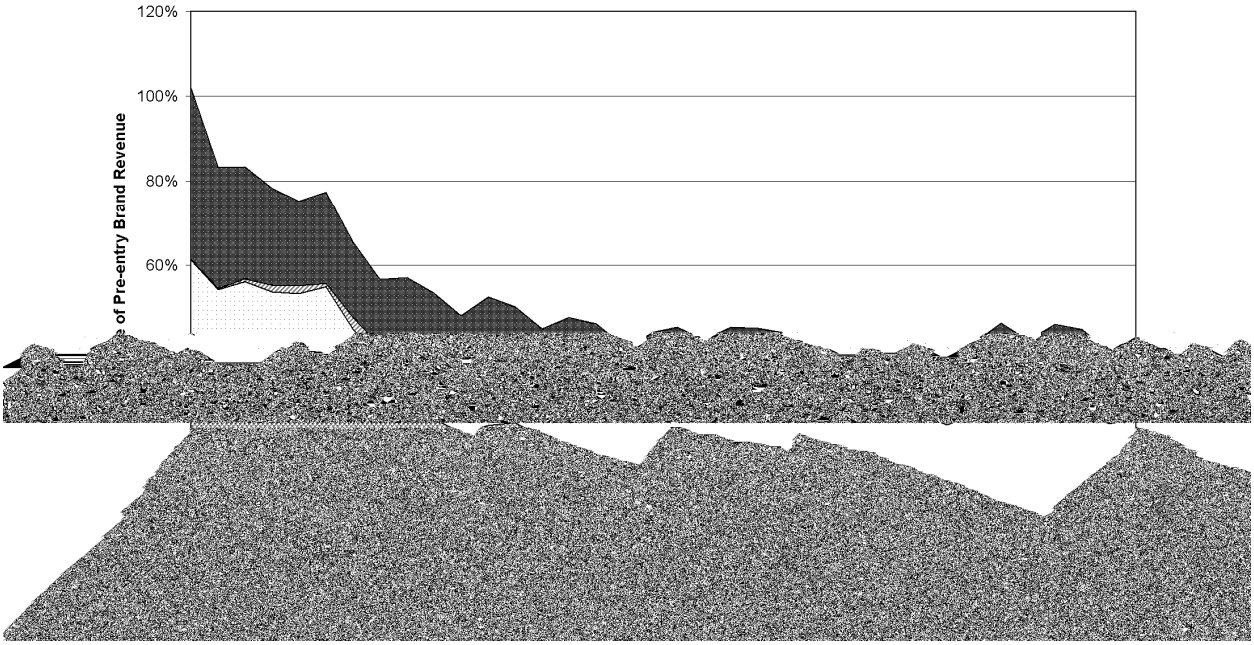

Figure 1a: Average Percent of Pre-Entry Brand Revenue Following Generic Entry by Firm Type in Exclusivity Markets Facing an Authorized Generic

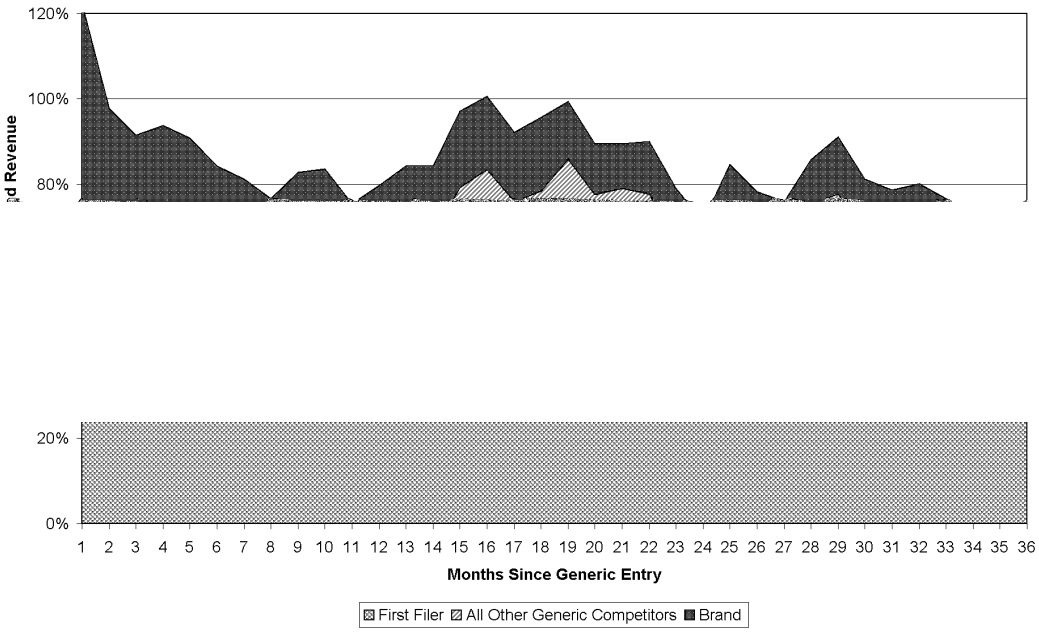

Figure 1b: Average Percent of Pre-Entry Brand Revenue Following Generic Entry by Firm Type in Exclusivity Markets that Do Not Face an Authorized Generic

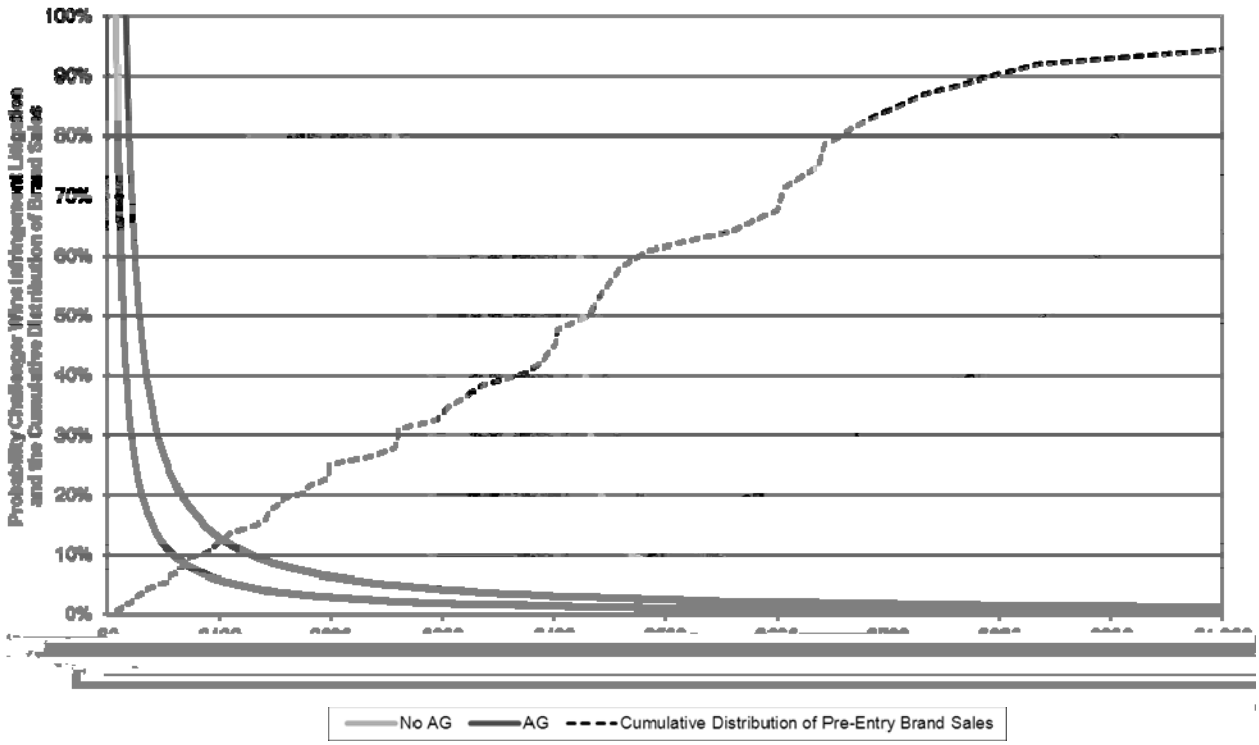

Figure 2: Characterization of Markets that Induce Challenges with and without Expectation of Facing an Authorized Generic Competitor

	Revenues Following 180-day Exclusivity	
	Unweighted	**Sales Weighted**
AG Displaces a Competitor	-52.5%*	-62.3%*

Table 1: The Effect of Authorized Generic Introduction on First-Filer Revenues

	Prices During 180-day Exclusivity	
	Unweighted	**Sales Weighted**
Additional AG Competitor	-12.8%**	-13.5%**
(Standard Error)	(2.8%)	(2.4%)
Mean of Normalized Prices in Markets Facing Only Independent Generics	0.80	0.83
Sample Size	673	673

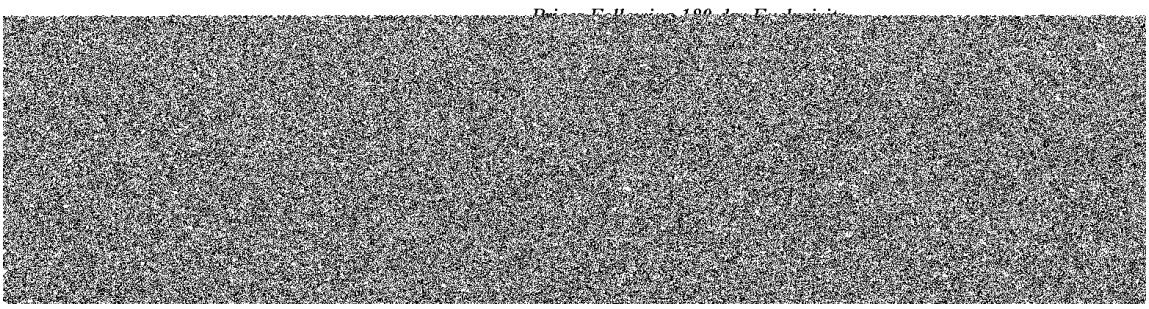

Table 2: The Effect of Authorized Generic Introduction on Generic Wholesale Prices

Model Variable	**Variable Description**	**No AG**	**AG**
L	Litigation Costs	$ 5 million	$ 5 million
A	ANDA Submission Costs	$ 1 million	$ 1 million
		During 180-day Exclusivity	
		No AG	**AG**
$\hat{p}_f$	Mean Generic Price as % Pre-Entry Brand Price	0.80	0.70
$\hat{r}_f$	Mean First-Filer Revenue as % Pre-Entry Brand Revenue	0.70	0.34
		Following 180-day Exclusivity	
		No AG	**AG**

Table 3: The Values Used in The Expected Profits Calibration

Schmalensee, R. (1978). Entry deterrence in the ready-to-eat breakfast cereal industry. *The Bell Journal of Economics*, 9(2), 305-327.
Sorensen, A. T. (2003). Insurer-hospital bargaining: Negotiated discounts in post-deregulation Connecticut. *Journal of Industrial Economics*, 51(4), 469-490.
Town, R. (2011). The effects of US hospital consolidations on hospital quality: A comment. *International Journal of the Economics of Business*, 18(1), 127-131.
Town, R., & Vistnes, G. (2001). Hospital competition in HMO networks. *Journal of Health Economics*, 20(5), 733-753.
Turner, M. A., Varghese, R., & Walker, P. D. (2011). U.S. consumer credit reports: Measuring accuracy and dispute impacts. Policy and Economic Research Council (PERC).