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Measuring the Welfare Effect of Entry in Differentiated Product Markets: The Case of Medicare HMOs

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School of Economics Discussion Paper: 2008/01

ISSN 1323-8949
ISBN 978 0 7334 2595 0

Measuring the Welfare Effect of Entry in Differentiated Product Markets: The Case of Medicare HMOs

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December 20, 2007

Abstract

Should governments subsidize entry to promote competition? In general, theory models cannot determine whether entry under the free-entry condition is socially excessive, optimal, or insufficient. In this paper I propose an empirical framework to evaluate welfare consequences of policy intervention through entry in differentiated product markets, with a case study of the US Medicare HMO market. In endogenizing firms' entry-exit decision, a technical breakthrough is to explicitly incorporate firm heterogeneity by employing a sequential move game. This enables us to exploit detailed firm level data and makes policy simulations relevant. I find no evidence of socially excessive entry. The government may achieve higher social welfare by expanding the program.

[1]I am thankful to Leemore Dafny, David Dranove, Michael Mazzeo, Aviv Nevo, and Robert Porter for guidance. Discussions with Raquel Bernal and Rosa Matzkin were also helpful. I am also thankful to the CMS staff for kindly providing the data files and answering my inquiries. Support from the Center for the Study of Industrial Organization is gratefully acknowledged. E-mail: s.maruyama@unsw.edu.au.

1 Introduction

Should governments subsidize entry to promote competition? Advocates of market competition often claim more deregulation and liberalization of markets. On the other hand, not many argue that competition is so welfare enhancing that governments should intervene further to bring about more entrants and intensify competition. Actually, from the social welfare point of view, it is not straightforward to conclude whether additional entry generates positive or negative welfare impact.

The theory literature of industrial organization finds that free entry does not guarantee the socially optimum number of entrants. As discussed in Spence (1976) and Mankiw and Whinston (1986), in the homogeneous product setting, free entry can lead to socially excessive entry. Additional entry would expand consumer surplus with lower prices, but, at the same time, it reduces the market shares of other firms ("business stealing") and leads to an inefficient replication of fixed costs. In differentiated product markets, however, the direction of bias is unclear, because consumers' appreciation of variety from entry causes a trade-off. Consider, for example, a price subsidy to attract more entry in order to promote competition. New entrants enhance consumer surplus through more intensive competition — lower prices, better product quality, and more variety. On the other hand, new entry lowers social welfare by duplicative set-up costs and "business stealing" from incumbents. In addition, the price subsidy causes market distortion. It is an empirical task to quantify these effects and to determine if the government can achieve higher social welfare by encouraging or discouraging entry.

In spite of its policy importance, this empirical issue has not been well explored. In this paper I propose an empirical framework to evaluate welfare consequences of policy intervention through entry, using the national data of the US Medicare HMO market for the years 2003 and 2004. By endogenizing firms' entry-exit decision, the framework enables evaluating not only welfare consequences of direct intervention in the number of entrants but also welfare impacts of policy changes through entry. To make policy simulations even more relevant, my model incorporates product differentiation and firm heterogeneity.

In most real world cases, neither products nor firms are homogeneous. When analyzing welfare consequences of entry, the resulting welfare distributions and policy implications are more meaningful with the heterogeneity we actually observe, e.g. whether a new entrant in a market is a large chain firm or a small not-for-profit one and whether it offers generic minimal service or highly differentiated tailor-made service. Nevertheless, previous empirical analyses of entry assume limited or no firm heterogeneity due to analytical limitations. A technical breakthrough proposed in my empirical framework is to explicitly incorporate firm heterogeneity into the welfare analysis by employing a sequential move game. This progress has a significant implication for the application of empirical entry models. That is, unlike the previous analyses, I can exploit detailed firm level data and draw relevant policy implications from various policy simulations. For example, performing a welfare simulation of subsidies, taxes, entry regulations, or other competition policies and evaluating its welfare impact through entry is beyond the scope of previous models.

The US Medicare HMO market is one of the most fruitful applications, because the products are highly differentiated and there is a large scope for government intervention in regard to entry. The US Medicare is the federal entitlement program that provides comprehensive health insurance coverage to individuals age 65 and older and certain disabled people (hereafter "Medicare eligibles"). Currently Medicare features private health insurance plans in addition to a government-administered fee-for-service plan (hereafter "traditional Medicare plan"). Most of the private plans are HMOs (Health Maintenance Organizations, explanation provided in the data section). HMO plans make their entry-exit and price decisions in each county annually, by taking into consideration the responses of the demand side and competing firms. Medicare eligibles make their choice between the government plan and the private plan(s) available in their county, considering each plan's monthly premium, if any, and insurance coverage, e.g. whether it covers prescription drugs.

Government payments to Medicare HMOs have been an intense policy debate. While private plans are allowed to charge some monthly premiums, which I use as a price in the demand estimation, their main source of revenue is the per enrollee government payment, which can be regarded as a price subsidy. The rate of the government payment is fixed ex ante and varies across counties (but not across plans within a county). Since the rate of the payment directly affects price cost margin of HMOs, the government can utilize the payment rate to influence the number of competing HMOs, the quality and coverage of their services, the size of the Medicare HMO program, and, as the final target, the distribution of social welfare. Though the socially optimal level of the payment rate has always been an intense policy debate, there has never been an empirical study to evaluate welfare consequences of payment rate changes through entry.

My empirical strategy is as follows. All estimations are at the plan-county-year level. I first estimate a discrete choice demand model of the Medicare health insurance market. The consumer surplus is calculated using these results. Second, by using the estimated demand parameters and assumptions on firms' price-setting behavior, I back out the health plans' marginal costs. Third, because the entry game is played not only by the observed firms but also firms that choose not to enter and do not appear in the data, the pool of potentially entering HMOs is created. Then I estimate HMO profit functions with a sequential move entry game that guarantees a unique pure-strategy equilibrium. The observed market structure and the inclusion of the demand model into the framework allow me to identify the level of fixed and variable profits, despite the lack of cost information. Finally, I perform counterfactual simulations, where all the consumers and HMOs re-optimize their decisions on plan choice, price, and entry-exit in response to an exogenous change, which gives me a new market equilibrium. Since my data set has only a couple of time points and dealing with agents' detailed heterogeneity is still a considerable challenge for dynamic modeling, I follow the customary approach in the empirical entry literature and employ no scope of dynamics.

As the main result of the research, I find no evidence of socially excessive entry, which suggests that the consumer efficiency gain from having more variety and competition matches or maybe even outweighs the social inefficiency from duplicative set-up costs of firms. This suggests that the government should keep at least this level of entry. Though net social welfare is not quite responsive to the level of entry, the indicated changes in welfare distribution caused by entry are notable. In addition, the payment simulation suggests that the government may achieve higher social welfare by expanding the program. I also find that the national welfare gain of having private health insurance plans in Medicare is around ten billion dollars a year in 2003 and 2004, which is overall consistent with the preceding study by Town and Liu (2003).

2 Empirical Entry Literature

The study I follow most closely is Berry and Waldfogel (1999), one of few studies that apply the empirical entry literature to welfare analysis. They model the broadcasting industry as a homogeneous product market,[2] and quantify social inefficiency from free entry. Dutta (2005) advances their work to the differentiated product case. Her study of the pharmaceutical industry in India performs counterfactual simulations of entry and finds no evidence of excessive entry. Her empirical framework is similar to mine, except that her estimation still heavily relies on the assumption on certain firm homogeneity. I build on these studies by incorporating full firm heterogeneity.

In the long history of the empirical entry literature, firm heterogeneity has not been

[2] In their framework, listeners' demand for broadcasting is modeled as a discrete choice demand, but the industry's primary output, advertisement, is treated as homogeneous product.

fully incorporated in entry models for several reasons. How to deal with multiple equilibria is one of the largest issues in this literature. To guarantee certain equilibrium properties the researchers have specified the econometric setting in a very restrictive way such as homogenous product markets, symmetric games, simple reduced-form profit functions, and an infinite pool of homogeneous potential entrants. Computational burden is another difficulty in this literature, as the introduction of firm heterogeneity requires a researcher to estimate large asymmetric game models.

Facing these difficulties, various approaches are proposed. Berry (1992) avoids this problem by introducing firm heterogeneity into the fixed cost part, thus, keeping his game symmetric. Berry and Waldfogel (1999) and Town and Liu (2003) follow the same approach. Dutta (2005) incorporates firm heterogeneity by categorizing firms into three types, but, within each type, firms are symmetric. Mazzeo (2002) models firm heterogeneity as endogenous choice of location and product types. Seim (2001, 2004) proposes the use of incomplete information setting to alleviate computational burden. Ciliberto and Tamer (2004) pursue a more flexible model of firm heterogeneity and identities, by not making point identifying assumptions on equilibrium selection. All of these studies, however, still use reduced-form profit function and/or certain symmetry assumptions in entry games, which is a restriction, especially when a researcher's goal is welfare simulations. By employing a sequential move game and avoiding multiple equilibria, my model makes it possible that HMOs have different cost structures and product characteristics across markets.

Another key feature of my model is structural combination of the demand and supply sides, which brings a significant advantage – counterfactual simulations by extrapolation. It enables a researcher to analyze how a policy change affects entry and exit, market competition and, in turn, social welfare in each section of the entire market. I am not the first to nest demand into an entry model. Reiss and Spiller (1989) estimate the demand and supply of airline services simultaneously, but for carefully selected small homogenous product markets.

Berry and Waldfogel (1999) explicitly model profit functions with price and quantity and allowing firms to vary across fixed costs. Another study along this line is Town and Liu (2003). They quantify the welfare impact of Medicare HMOs, by combining structural models of demand and entry. Though they model the market as a differentiated product market, their supply side model does not fully incorporate firm heterogeneity and detailed entry simulations are beyond their scope.

3 Data

Medicare is administered by the Centers for Medicare and Medicaid Services (hereafter CMS) and the main body of the data set comes from the CMS. The three main data sources are the following: (1) the Enrollment data at the county-plan level, (2) the Monthly Report data, and (3) the Plan Benefit Package data (PBP data) (For the detailed discussion and description of the data, see Maruyama 2007).

3.1 The Unit of Observation

The unit of observation is a plan-county-year. I follow the CMS in considering the county the market definition. The time points I use are the years 2003 and 2004.[3] These years are relatively stable and suitable for this research because, before this period, the market experienced a huge exodus of HMOs and this period is sufficiently before the implementation of the Medicare Prescription Drug Improvement and Modernization Act in 2006, while these years observe considerable entry and exit across counties within Medicare.

In the CMS data files, there is a clear distinction between *organization*, *plan* (or *contract*, as the CMS sometimes calls it), and *product* (or plan, as the CMS sometimes calls it).

[3] Information from the year 2002 is also used to identify incumbents in creating the pool of potential entrants.

Table 1: The Number of HMO Plans and their Market Share in 2004

	Number of plans	Enrollment	Share
HMO (Health Maintenance Organizations)	145	4,684,304	85%
PPO (Preferred Provider Organizations)	41	119,110	2%
Other Medicare+Choice types	70	266,247	5%
Other prepaid plan types	44	428,833	8%
Total prepaid plans	300	5,498,494	100%
Entire Medicare eligibles		42,992,077	

Source: Medicare Managed Care Contract Report and the Enrollment data

The *organization* is the governing body: for example Pacificare, Aetna, Humana, etc. In the Medicare program, each organization may enter into one or more *plans* (or *contracts*). Each of these plans is assigned a unique contract number by the CMS. In addition, each plan can offer more than one *product* — that is, a particular benefit package with unique benefits, copays, premiums and service counties. I focus this study on the plan level analysis, because many important variables such as county enrollment are reported at the plan level.[4] Product level information is aggregated to the plan level in each county, by choosing the product with the largest enrollment as the representative product. For ambiguous cases, I average the variables across products, but such cases are rare.

3.2 The Sample Population

Under the current Medicare program, several types of private health plans are eligible to participate.[5] Among others, HMOs (Health Maintenance Organizations) are dominant players. An HMO forms its network of health provides to enhance its purchasing power and to restrict and manage the flow of its patients. A Medicare HMO receives a monthly payment

[4] Also the plan level analysis works favorably in reconciling the demand and supply side models. While HMOs are likely to maximize their profits at the plan or organization level, for the demand side, the product level analysis may be more reasonable because consumers are more likely to choose a product than a plan or an organization.

[5] Currently, the private part of the program is referred to as the Medicare Advantage (formerly Medicare+Choice) program and private health plans are referred to as Medicare Advantage plans.

for each enrollee from the CMS and, in return, it is responsible for providing all covered services and takes full financial responsibility for the actual costs generated. Because of these patient management device and financial incentive, Medicare HMOs are supposed to be more efficient than the government fee-for-service insurance plan.

Table 1 shows that HMOs' enrollment share within the private health plans is 85 % in 2004. While I use most plan types in the demand estimation, I focus my supply side model on HMOs because the other types' profit structure may differ from HMOs' and their shares are small. I estimate profits only for HMOs, and throughout this research, the presence of the non-HMO types is treated as exogenous.

I choose the observations used in this research as follows.

Omitted Plan Types With various types of private Medicare plans, I exclude the plan types that are regarded as not open to regular Medicare beneficiaries, such as PACE (Program of All-Inclusive Care for the Elderly) plans and long-term care Demonstration plans. Dropping these different type plans excludes only 3% of the entire private plan enrollment.

Choosing *Operating Plans* Next, at the plan-county-year level, I select *operating plans*. In the CMS Enrollment data files, individual members are assigned to counties according to the reported residence. This implies that for many counties there are an unrealistically high number of health plans with very low enrollment. I include a plan-county observation in the data set as a valid observation if it satisfies both of the following: (1) it is in a plan's official service counties under its contract to the government and (2) it has at least 50 members.[6]

A very small number of observations with missing values are also dropped. Then, I recalculate the market size by subtracting the dropped observations' enrollment from the original

[6] I set this threshold higher than the previous studies to make the data more stable; Town and Liu [2003], for example, define the operating HMOs in a county as HMOs with at least 12 members if the county has fewer than 5,000 eligibles and 35 members otherwise.

numbers of Medicare eligibles. This completes the data set for the demand estimation.

Creating Potential Entrants In my supply side model, all the potentially operating plans play a one-shot entry game each year. The pool of potential entrants consists of the operating HMOs observed in the data and *hypothetical potential entrants* that I add to the data set.

I limit my entry model to entrants that are operating in other areas in the same state or the same MSA.[7] This means I exclude: a) entrants from outside the state or MSA and b) brand-new entrants from the commercial sector. The potential bias due to this exclusion, however, seems to be minimal as a first order approximation. First, no entry from outside the state or MSA is observed during my sample periods. Second, although each Medicare HMO plan has its main entity in the commercial sector, not much brand-new entry from the commercial sector occurs during my sample periods. For 2004, for example, out of 1,020 plan-county-year observations in the data set, only five plans are brand-new.

The pool of potential entrants consists of the following six types: (1) plans that actually operate in the county in the year, (2) plans that operate in the same MSA in the year, (3) plans that operate in the same state in the year, (4) plans that operate in the county in the previous year, (5) plans that operate in the same MSA in the previous year, and (6) plans that operate in the same state in the previous year. Thus, in the supply estimation, observations that qualify as one of (2) to (6) but not (1) are created and included as "hypothetical entrants".[8][9] The plan level characteristics of the newly created potential entrants are the same as the original plan. For the product level characteristics, I pick the product with the

[7] There exist multi-state MSAs. Entry from outside the state but in the same MSA is considered.

[8] Thus, the term, hypothetical potential entrants, is a concept different from incumbency. A hypothetical potential entrant that operates in the previous year but not this year plays the entry game as an incumbent.

[9] As a result, the supply data set has many counties with one or more hypothetical entrants but with no observed entrant. These counties are kept in the sample so as to avoid unwanted selection bias and make use of information value from the fact that no entry occurs.

Table 2: The Sample Size

	2003	2004	Total
Demand data set			
Number of plans	196	207	207
Number of plans (HMO)	133	138	138
Number of counties	829	938	948
Number of plan-counties	1,478	1,811	3,289
Number of plan-counties (HMO)	997	1,094	2,091
Entry estimation data set			
Number of HMO plans	133	138	138
Number of counties	2,574	2,501	2,630
Number of plan-counties	9,617	9,927	19,544

largest enrollment under the plan as the representative product.

3.3 Variables, Sample Size, and Summary Statics

The PBP data set has a great amount of detailed information about the additional benefits a product offers. To summarize this information, I perform a factor analysis. Based on the results, I aggregate relevant benefit variables into six benefit composite variables: drug, education, physicals, peripheral1, peripheral2, and screenings (see Maruyama 2007 for the detailed discussion). The payment rate data in the original CMS data sets is the standardized, payment base in each county. The actual payment for a particular enrollee is determined by certain formulae which take demographic and risk factors into consideration. In this study, I use not the payment base but the average of actual payments in the county calculated by using demographic and risk factor information.

Table 2 shows the sample size for the demand and supply estimation. Table 3 shows descriptive statistics of selected variables. The minimum of payment rates is negative because, since 2003, the premium can be "negative" in the form of a premium rebate. A comparison of the average and standard deviation of monthly premiums and payment rates indicates that the payment from the government is the primary source of revenues, but private plans

Table 3: Descriptive Statistics of Selected Variables

	Average	(2003)	(2004)	Std.dev.	Min	Max
Plan enrollees	3,060	3,339	2,833	7,715	50	142,050
Plan market share	0.063	0.066	0.061	0.070	0.0002	0.447
Monthly premium	51.3	58.9	45.0	47.5	−62.6	189.0
Payment rate	549.4	530.7	564.7	91.1	296.7	1067.5
benefit: drug	0.61	0.55	0.65	0.48	0.00	1.00

The number of observations: 3289 plan-county-years. Monthly premium and payment rate are in dollars.

take various strategies in regard to their premiums.

Table 4 shows the distribution of observations and the average numbers of market size, payment rates, and monthly premiums by the number of observed entrants in a county. The majority of observations are from concentrated markets. The table suggests that counties with larger demands and/or higher payment rates attract more private plans. Also, the more competitive a county is, the lower premiums they charge.

Table 4: Sample Distribution, Average Market Size, Average Premiums, and Average Payment Rates by the Number of Plans in Each County: 2004

Number of operating plans in a county	Number of plan-counties: demand data	supply data	Average number of: eligibles	payment rates	premiums
0		5,386			
1	497	1,860	13,583	527.6	59.4
2	456	1,167	32,183	536.9	40.8
3	339	635	47,116	582.2	40.8
4	184	367	58,611	574.7	38.5
5	130	180	65,552	579.3	46.7
6	84	146	130,593	598.3	29.4
7	21	40	234,969	700.6	12.8
8	24	41	157,267	760.3	0.7
9	36	56	261,881	725.2	−0.2
10	40	49	513,123	698.3	−1.2
Total	1,811	9,927		544.1	43.8

Table 5 explains the variables used in this study. After the names and definitions of the variables in the first two columns, the next three columns indicate in which estimation of demand, supply, or marginal cost a variable is used. Summary statistics follow.

4 Econometric Specifications

4.1 The Demand

My demand model follows Town and Liu (2003) closely, using market share data with the nested Logit model (Berry 1994's approach) for welfare analysis. A Medicare beneficiary chooses a Medicare plan every year by comparing the utility from each plan available in his county and picking the plan with the highest utility. Utility is derived from health plan characteristics such as premiums, benefits, and so on. Here are some notations:

M : Year-markets (year-counties), $m = 1, ..., M$

J : Private Medicare plans, $j = 1, ..., J_m$

If $j = 0$, it means the traditional Medicare plan (the outside option).

I_m : Medicare beneficiaries, $i = 1, \ldots, I_m$.

Beneficiary i's utility from plan j in year-market m is denoted as

$$
\begin{aligned}
u_{ijm} &= w'_{jm}\beta - \alpha p_{jm} + \xi_j + \xi_{MSA} + \Delta\xi_{jm} + \varepsilon_{ijm} \\
&\equiv \delta_{jm} + \Delta\xi_{jm} + \varepsilon_{ijm},
\end{aligned} \tag{1}
$$

where w_{jm} is a vector of observed plan characteristics, p_{jm} is the premium, ε_{ijm} is a nested Logit error, and $\xi_j + \xi_{MSA} + \Delta\xi_{jm}$ is a scalar contribution of the plan characteristics and demand shocks unobserved by the econometrician. δ_{jm} is the mean utility. Without loss of generality, the error term is normalized as $E[\varepsilon_{ijm}] = 0$. Thus a beneficiary's *expected utility*, $E[u_{im}]$, increases with better benefits, lower premiums, and more choices. To alleviate the endogeneity problem discussed below, I apply fixed effects to plans and selected MSAs,

Table 5: Definitions of Variables, Estimations Used (Demand, Supply, and Marginal Cost), and Summary Statistics

Variable Name	Definition	D	S	MC	Obs	Mean	Std. dev.	Min	Max
(i) Plan or plan-year level variables (the numbers of plan and plan-year observations: 207 and 403)									
no experience	=1 if a plan has no experience in Medicare before	X	X	X	403	0.11	0.31	0	1
experience year	Years in business since the first Medicare enrollee	X	X	X	403	8.18	6.44	0	27
nonprofit	Dummy variable: not-for-profit organizations		X	X	207	0.34	0.47	0	1
national chain	Dummy variable: national chains		X	X	207	0.29	0.46	0	1
group model	=1 if the plan is a group model HMO (The omitted category is "network, mixed, and other models".)		X	X	207	0.47	0.50	0	1
staff model	=1 if the plan is a staff model HMO		X	X	207	0.07	0.25	0	1
IPA model	=1 if the plan is an IPA model HMO		X	X	207	0.43	0.50	0	1
entire enrollees	Total enrollees of the plan over its entire service areas (in 1,000)			X	403	25,313	57,033	52	648,281
DEMO plan	Dummy variable: DEMO plans			X	207	0.15	0.36	0	1
cost plan	Dummy variable: cost contract HMOs			X	207	0.13	0.33	0	1
cost missing	Dummy variable: cost contract HMOs with missing data			X	207	0.05	0.22	0	1
PPO plan	Dummy variable: PPO plans			X	207	0.17	0.38	0	1
PFFS plan	Dummy variable: PFFS plans			X	207	0.02	0.15	0	1
PSO plan	Dummy variable: PSO plans			X	207	0.01	0.12	0	1
POS	Dummy variable: HMOPOS			X	207	0.03	0.17	0	1
(ii) Plan-county level variables (the number of plan-county-year observations: 3,289)									
s_{jm}	Plan j's market share in market m	X			3,289	0.06	0.07	0.00	0.45
$\ln s_{j \mid \text{private}, m}$	"Within-group share" in log	X			3,289	-1.21	1.44	-7.55	0.00
monthly premium	Monthly premium in $ (Medicare premium not included)	X		X	3,289	51.3	47.5	-62.6	189.0
# product in plan	The number of products the plan offers in the market	X		X	3,289	2.16	1.28	1	10
benefit: drug	Dummy variable: supplemental benefits in outpatient prescription drugs	X			3,289	0.61	0.48	0	1
benefit: education	Composite score: supplemental benefits in health education/welness	X			3,289	0.36	0.27	0	0.9
benefit: physicals	Composite score: supplemental benefits in routine physicals	X			3,289	0.51	0.21	0	1
benefit: peripheral1	Composite score: supplemental benefits in preventive and comprehensive dental, chiropractic, and acupuncture	X			3,289	0.10	0.18	0	1
benefit: peripheral2	Composite score: supplemental benefits in eye exams, eye wear, hearing exams, and hearing aids	X			3,289	0.48	0.29	0	1
benefit: screenings	Composite score: supplemental benefits in screenings (mammography, colorectal, prostate cancer, pap smears, and pelvic exams)	X			3,289	0.20	0.26	0	1
avg # competitor	Average number of competitors in the other markets served by the plan	IV			3,289	1.75	1.69	0	9
competitor: npo	The number of competing NPO plans in the market	IV			3,289	0.70	1.13	0	5
competitor: chain	The number of competing national-chain plans in the market	IV			3,289	0.71	1.08	0	5
competitor: IPA	The number of competing IPA model plans	IV			3,289	0.97	1.30	0	6
competitor: group	The number of competing group model plans	IV			3,289	0.74	0.99	0	4
competitor: staff	The number of competing staff model plans	IV			3,289	0.11	0.34	0	2
(iii) County or county-year level variables (the numbers of county and county-year observations: 948 and 1,767)									
s_{0m}	The market share of the traditional Medicare plan	X			1,767	0.88	0.11	0.50	1.00
payment rate	CMS monthly payment rate per enrollee for parts A and B		X		1,767	527.5	80.5	296.7	1,067.5
FFS per capita cost	Average fee-for-service monthly cost per enrollee				1,767	519.7	118.8	214.9	1,217.3
Std FFS per capita cost	FFS per capita cost standardized by demographic factor		X	X	1,767	552.8	131.0	203.6	1,262.2
per capita # hospital	The number of hospitals per 10,000 residents in 2001	IV	X	X	948	0.27	0.36	0.00	5.12
per capita # hospital bed	The number of hospital beds per 1,000 residents in 2001	IV	X	X	948	3.18	4.58	0.00	87.50
per capita # medical doctor	The number of general practice M.D.s per 1,000 residents in 2001	IV	X	X	948	0.33	0.19	0.00	1.54
HMO penetration rate 98	Estimated (HMO enrollment / total population) in 1998	X		X	948	0.22	0.17	0.00	0.96
eligibles	Medicare eligibles (in 1,000)			X	1,767	32,939	64,364	370	1,046,829
county: no hospital	Dummy variable for counties with no hospital	IV	X	X	1,767	0.16	0.36	0	1
MSA	Dummy variable for counties in an MSA		X		948	0.55	0.50	0	1
county: small	County dummy: 3,000 < number of eligibles < 6,000		X		1,767	0.19	0.39	0	1
county: medium	County dummy: 6,000 < number of eligibles < 15,000		X		1,767	0.28	0.45	0	1
county: large	County dummy: 15,000 < number of eligibles < 50,000		X		1,767	0.25	0.44	0	1
county: extra large	County dummy: 50,000 < number of eligibles < 150,000		X		1,767	0.14	0.35	0	1
county: huge	County dummy: 150,000 < number of eligibles		X		1,767	0.04	0.19	0	1
year: 2004	Year dummy variable for 2004	X	X	X	1,767	0.53	0.50	0	1
demo factor	Demographic factors (e.g. age, sex, institutional status, and Medicaid status) to adjust the payment rate (the higher, the more costly)			X	1,767	0.95	0.04	0.82	1.11
demo factor HMO	Demographic factors for HMO enrollees			X	1,767	0.93	0.09	0.73	1.66
risk factor HMO	Risk factors for HMO enrollee (e.g. disease group, community factors, and institutional factors) to adjust the payment rate			X	1,767	0.86	0.12	0.52	1.53
medigap premium	Monthly Medigap premium in $			X	1,767	137.4	38.4	70.1	231.8
hospital expenditure	Total reported facility expenditures (short term general hospitals) (not only Medicare) per 1,000 residents in $1,000 in the county			X	1,767	1.06	2.06	0.00	51.97
inpatient days	Total Medicare inpatient days (short term hospitals) in 1,000 days			X	1,767	67,939	157,012	0	2,351,152

"IV" means the variable used in the estimation as an instrument. For the summary statistics, Non-HMO observations are included. The "hypothetical potenti entrants" used in the supply estimation are not included. The six benefit variables from "benefit: drug" to "benefit: screenings" are the quality composite variables made by aggregating the detailed characteristics information in the PBP data set, based on the results of the factor analysis (Maruyama [2007]).

which are represented by $\xi_j + \xi_{MSA}$.[10] Thus, $\Delta\xi_{jm}$ is the first-differenced demand shock. I normalize the utility from the traditional Medicare plan as: $u_{i0m} = \varepsilon_{i0m}$. This normalization does not affect the welfare calculation, because consumer surplus in my study measures the utility gain from enrolling in private Medicare plans relative to traditional Medicare.

Following previous studies, I assume a nested Logit error. The group structure is the private plan group against the traditional Medicare plan. Thus, my assumption allows substitution among private plans to differ from substitution between private plans and the traditional Medicare plan. The market share of plan j is derived as:

$$
\begin{aligned}
s_{jm} &= s_{j|\text{private},m} \cdot s_{\text{private}|m} \\
&= \frac{\exp\left(\frac{1}{1-\sigma}\delta_{jm}\right)}{D_m^{\sigma} \cdot \left[1 + D_m^{(1-\sigma)}\right]},
\end{aligned}
\tag{2}
$$

where σ represents the similarity within the private plan group, and

$$
D_m \equiv \sum_{k|\text{private},m} \exp\left(\frac{1}{1-\sigma}\delta_{km}\right).
$$

The correlation within a group is possible through σ. As σ goes to one, the within-group correlation becomes one, and when $\sigma = 0$, this model is reduced to the multinomial Logit model. When the market share data is used, this model can be estimated by transforming to a linear form as follows (see Berry 1994):

$$
\ln s_{jm} - \ln s_{0m} = w'_{jm}\beta - \alpha p_{jm} + \xi_j + \xi_{MSA} + \sigma \ln s_{j|\text{private},m} + \Delta\xi_{jm} \tag{3}
$$

for $j = 1, ..., J_m$. In estimation, I use the instrumental variable method to deal with the potentially endogenous variables in (3) — the monthly premium, p_{jm}, and the within-group

[10] County fixed effect dummies are not used because many counties appear in the data set with only one observation. By the same token, I apply MSA fixed effects only to MSAs with at least ten observations.

share, $\ln(s_{j|\text{private},m})$; these two variables may be correlated with the plan demand shock, $\Delta\xi_{jm}$. As I use the fixed-effect approach, the identification of parameters comes from within-plan and within-MSA changes in the instruments.

I construct instruments using three strategies. The first set of instruments is the per resident numbers of hospitals, hospital beds, and general practice medical doctors, and a county dummy variable for counties with no hospital. These variables are valid instruments because they affect the plans' relative bargaining power with providers, and thus their cost structure and the number of competitors. Second, I use the characteristics of competing plans in a county. This approach is traditional in the literature on product-differentiated market demand (e.g. Bresnahan 1987, Berry 1994).[11] This is valid if competitors' entry-exit decisions and changes in product characteristics are uncorrelated with changes in $\Delta\xi_{jm}$. Specifically, I choose indicator variables for not-for-profit ownership, chain affiliation, and HMO network types (IPA, Group, and Staff models), as instruments, which are supposed to be relatively fixed and predetermined. Third, I use the average number of competitors in the other markets in which the plan operates. This use of the panel structure of data is a strategy similar to that of Hausman (1997) and Nevo (2001). Private Medicare plans typically set premiums not for individual counties but for each product, so the plan premium in a county is likely to be correlated with the competitive environment in the plan's other service counties. $\Delta\xi_{jm}$ is specific to the market, so it is likely to be uncorrelated with this instrument.[12] In the end, I have ten instruments for two endogenous variables. The first stage regression is reported in Appendix A. For both p_{jm} and $\ln(s_{j|\text{private},m})$, the F-statistics reject the joint hypothesis that the coefficients on the instruments are all zero.

[11] Dafny and Dranove (2005) also use this approach in the demand estimation of Medicare HMOs.

[12] The argument here does not contradict with the assumption that each plan chooses its premiums at the county level. Since a product must have the same premium in all the counties it covers, a plan sets its (average) premium in each county by setting up additional products and/or adjusting the service areas each product covers. To the extent that an additional product requires some set-up costs and the county-level profit-maximization assumption holds only as an approximation, the Hausman type instrument is valid.

4.2 HMO's Behavioral Model

4.2.1 The Game Specification

In each market, there are J_m^{pot} potentially operating HMO plans. Each county can accommodate zero, one, or more than one HMO plan. At the beginning of each year, all the potential entrants in each market play the following game. The game consists of two parts, a sequential move entry game and a simultaneous-move price setting game. Only HMOs that choose "enter" play the price setting game. If a plan chooses "not enter", it receives zero profit from the county. The plan characteristics are exogenously fixed in this study.

The game is assumed to be a public information game, because private information models with publicly observable heterogeneity are relatively difficult to be estimated. The number of potential entrants, plan characteristics, random shocks in profits, and other information are all commonly known by all players. The only information unknown to all the plans when they make decisions is the random shock in the demand, $\Delta\xi_{jm}$. This technical assumption is necessary to keep the estimation consistent and well-behaved, because the values of $\Delta\xi_{jm}$ cannot be obtained for the hypothetical entrants. This assumption is not unrealistic as long as the fixed effects capture some of the plan characteristics observed by the plan but not the econometrician and there exist demand shocks HMOs cannot predict ex ante.

I employ a sequential move entry game. This guarantees the existence of a unique subgame perfect Nash equilibrium, even for large asymmetric games.[13] In the sequential game, I assume the decision order as follows. Among all the potential entrants in a market, the incumbents move first. Incumbents make decisions in the order of the following incumbency

[13] There is no guarantee that this assumption will be realistic, but a simultaneous game is no less *a priori* than a sequential game. Mazzeo (2002) estimates his model under several game structure assumptions. Einav (2003) endogenizes the order of decisions. These papers suggest that differences from employing different game settings are relatively small. For simultaneous move games of complete information, there have been recent developments of the estimation method, such as Bajari et al. (2007), while the estimation of a sequential move game has not been well studied.

classes: (1) previous year presence in the county, (2) previous year presence in the same MSA, and (3) previous year presence in the same state. Within the same incumbency class, HMOs make decisions in the order of their entire enrollment size. If larger incumbents have to announce their service area changes earlier, this assumption is more likely.

I use the subgame perfect pure strategy Nash equilibrium (SPNE) concept. An SPNE in a county is obtained when: (1) all entering firms are profitable with their optimized prices, and (2) all firms that do not enter expect non-positive profits from entry. Each HMO's entry-exit strategy in county m is represented by a binary variable, y_{jm}, which takes "0" if plan j does not enter and "1" if enters. A market configuration is denoted as y_m, which is a vector that stacks $(y_{1m}, ..., y_{J^m m})$ and the equilibrium solution, y_m^*, can be calculated by the backward induction algorithm.

4.2.2 The Profit Function

I assume the profit to be additively separable across counties, so each plan's profit maximizing decisions can be reduced to a county level optimization problem. I assume the following local profit function for plan j in county m:

$$\begin{aligned} (4) \qquad \pi_{jm}(x_{\cdot m}, z_{jm}, \varepsilon_{jm}, y_m; \gamma) &= [p_{jm}(x_{\cdot m}, y_m) + \text{Payment Rate}_m - MC_{jm}] \\ &\quad \cdot q_{jm}\left(p_{\cdot m}(x_{\cdot m}, y_m), x_{\cdot m}, y_m\right) + z_{jm}\gamma + \varepsilon_{jm} \\ &\equiv VP_{jm}(x_{\cdot m}, y_m) + z_{jm}\gamma + \varepsilon_{jm}, \end{aligned}$$

where the square bracket part is marginal profits and $q_{jm}()$ is the demand. $p_{\cdot m}$ is $(p_{1m}, ..., p_{J^m m})'$, $x_{\cdot m}$ is $(x_{1m}, ..., x_{J^m m})'$, x_{jm} is the set of predetermined observables and fixed effects in the demand function, namely $(w_{jm}, \xi_j, \xi_{MSA})$, and *payment rate* means the government per enrollee payment rate. z_{jm} is the independent variables that explain the fixed part of the profits, γ is a parameter vector to be estimated, and ε_{jm} is idiosyncratic shocks to plan j in market m, observed by all the firms ex-ante, but unobserved by the econometrician.[14] $VP_{jm}()$ denotes variable profits. HMOs are assumed to incur fixed costs at the county level, which is the sum of the last two terms. For the explanatory variables, z_{jm}, I choose market-specific variables and relatively exogenous or predetermined plan-specific variables, such as non-profit status, chain affiliation, and years of experience. I exclude variables that are likely to be correlated with ε_{jm}, such as benefit coverages, regarding this specification as a reduced form.

Before estimating the entry model, I estimate marginal costs. The estimation of marginal costs for the firms that actually enter relies on the first order condition of the price-setting game. The first order condition in market m can be written as

$$s_{jm}(p_{\cdot m}, x_{\cdot m}, y_m) + (p_{jm} + \text{Payment Rate}_m - MC_{jm})\frac{\partial s_{jm}}{\partial p_{jm}} = 0, \tag{5}$$

for $j = 1, ..., J_m^{enter}$, where J_m^{enter} is the number of actual entrants in county m. This equation can be solved for MC_{jm} by writing[15]

$$p_{jm} + \text{Payment Rate}_m - MC_{jm} = -\left(\frac{\partial s_{jm}}{\partial p_{jm}}\right)^{-1} \cdot s_{jm} = \frac{1-\sigma}{\alpha\left(1 - \sigma s_{j|\text{private},m} - (1-\sigma)s_{jm}\right)}. \tag{6}$$

To calculate MC_{jm} by using (6), I use fitted shares for s_{jm} and $s_{j|\text{private},m}$, instead of observed shares, under the assumption that $\Delta\xi_{jm}$ is unknown to plans when they make decisions.[16]

For hypothetical entrants, the lack of observed p_{jm} and s_{jm} requires MC_{jm} to be ex-

[14] I also implicitly assume the additive separability across plans for an organization. Some HMOs offer more than one plan in an area, but incorporating the economies of scale and scope is beyond the scope of this article. Likewise, the strategic dynamic optimization is beyond the static approach of this article. Market specific error terms and fixed effects I use may alleviate the biases from these issues.

[15] While plans can charge "negative" premiums in the form of a Medicare premium rebate since 2003, only 0.5% of the plan-county observations charge negative premiums in my data and 30.0% charge zero premiums. This mass point at zero premiums may reflect administrative costs of charging non-zero premiums. As long as this censoring occurs symmetrically around zero, the bias is considered to be modest, if any.

[16] Including $\Delta\xi_{jm}$ changes the mean of MC_{jm} by just 0.2%, so the potential bias of this behavioral assumption is negligible.

trapolated. I obtain MC_{jm} by a reduced-form linear OLS regression, in which I choose independent variables that are likely to be exogenous or predetermined, such as non-profit status, chain affiliation, and market characteristics variables, as listed in Table 5. The result is reported in Appendix A.

4.3 The Estimation Algorithm

I specify the components unobserved to the econometrician as

$$\varepsilon_{jm} = I_m^{\lambda} \cdot \left(\omega\eta_{jm} + \rho\eta_m\right), \tag{7}$$

where I_m is the market size and ω, ρ, and λ are parameters to be estimated. η_{jm} and η_m are distributed i.i.d. standard normal across plans and markets and assumed to be independent of $z_{\cdot m}$. The correlation of the unobservable ε_{jm} across plans in a given market is then ρ^2. As the market size varies significantly, λ and I_m are used to control the variance of the error term.

I employ the maximum likelihood estimation. Denote the observed market configuration as y_m^o. The maximum likelihood problem can be written as

$$\widehat{\theta}_{ML} = \arg\max_{\theta} \left\{ \frac{1}{M} \sum_{m=1}^{M} \ln \Pr\left[y_m^o = y_m^*(x_{\cdot m}, z_{\cdot m}; \theta)\right] \right\}, \tag{8}$$

where θ is the vector of model parameters, $(\gamma, \omega, \rho, \lambda)$, and y_m^* is the predicted market configuration given $(x_{\cdot m}, z_{\cdot m}, \theta, \varepsilon_{jm})$ that can be solved uniquely by backward induction.

The probability in the likelihood, however, does not have an analytical form solution due to multidimensional integrals, so I use the maximum simulated likelihood method. To make the estimation of the large game computationally feasible, I propose a modification of the GHK (Geweke-Hajivassiliou-Keane) simulator, one of the smooth recursive conditioning simulators, in the maximum simulated likelihood method.[17] This simulator provides a differentiable, unbiased estimator of likelihood with smaller variance than the crude frequency simulator. The original GHK simulator allows interactions across j through the disturbance structure, but not strategic interactions across j. In Appendix B, I modify the simulator to fit my model, by claiming the simulator can be harmonized with sequential move games by exploiting its recursive conditioning structure.

To solve the game and obtain y_m^* in each likelihood evaluation, the (partial) equilibrium prices and quantities, $p_{\cdot m}$ and $q_{\cdot m}$, need to be available for any market configuration, y_m, to determine the payoffs. First I calculate $p_{\cdot m}$ by solving the system of the first order conditions in the price-setting game, (5). Given the estimated demand parameters, (α, β, σ), and the values of $MC_{\cdot m}, x_{\cdot m}$, Payment Rate$_m$, and y_m, there are J_m^{enter} equations and J_m^{enter} unknowns. Due to the numerical feature of the discrete choice model, however, the price function, $p_{jm}(x_{\cdot m}, y_m)$, does not have a closed form solution. I solve the equation system for p_{jm} by the following numerical algorithm. The first order condition, (5), can be written as:

$$p_{jm} = -s_{jm}\left(p_{\cdot m}, x_{\cdot m}\right) \cdot \left(\frac{\partial s_{jm}\left(p_{\cdot m}, x_{\cdot m}\right)}{\partial p_{jm}}\right)^{-1} - \text{Payment Rate}_m + MC_{jm},$$

for $j = 1, ..., J_m^{enter}$. The following numerical iteration gives the numerical solution for p_{jm}.

$$p_{jm}^{t+1} = -s_{jm}\left(p_{\cdot m}^{t}, x_{\cdot m}\right) \cdot \left(\frac{\partial s_{jm}\left(p_{\cdot m}^{t}, x_{\cdot m}\right)}{\partial p_{jm}}\right)^{-1} - \text{Payment Rate}_m + MC_{jm}, \tag{9}$$

for $j = 1, ..., J_m^{enter}$ and $t = 0, 1, 2, ...$ For the initial values of p_{jm}^t, the observed values of p_{jm} are used. It turns out that this numerical iteration converges in an acceptable amount of time.[18] After $p_{\cdot m}$ is calculated, I can use the estimated demand equation to calculate $q_{\cdot m}$.

[17] For a starting point for the GHK simulator and related methods, see Contoyannis, et al. (2004).

[18] The demand shock, $\Delta\xi_{jm}$, is consistently excluded from all of these calculations. If I use MC_{jm} calculated with $\Delta\xi_{jm}$, the performance of this numerical iteration is sometimes poor.

4.4 Welfare Measures and Simulations

The net welfare gain of having private plans in Medicare is given by

$$
\begin{aligned}
\text{(10)} \qquad \Delta W &= (CS_{w/\text{PrivatePlans}} - CS_{w/o\text{PrivatePlans}}) - \\
&\quad (G_{w/\text{PrivatePlans}} - G_{w/o\text{PrivatePlans}}) + \text{private plan profits},
\end{aligned}
$$

where CS_x denotes the aggregated consumer surplus attributable to program x, and G_x denotes government expenditures. I use HMO profits instead of the profits of all private plans, as discussed above. Following McFadden (1981), annual expected consumer surplus can be derived as:

$$
\begin{aligned}
\text{(11)} \qquad \Delta CS_m &\equiv (CS_{w/\text{PrivatePlans}} - CS_{w/o\text{PrivatePlans}}) \\
&= I_m \cdot \frac{12}{\widehat{\alpha}}(1-\widehat{\sigma}) \ln \left[\sum_{j=0}^{J_m^{ent}} \exp \left(\frac{\widehat{\delta}_{jm} + \Delta\xi_{jm}}{1-\widehat{\sigma}} \right) \right].
\end{aligned}
$$

The wealth effect is assumed to be zero. In the data set, all the premiums and payment rates are defined on a monthly basis, so the calculated surplus is multiplied by twelve.

Counterfactual simulations use the same framework as above. The only difference is that I exclude $\Delta\xi_{jm}$ from all calculations in the simulations, because $\Delta\xi_{jm}$ can be calculated only for observed entrants. Due to the convexity of the function in the square bracket in (11), consumer surplus is understated without $\Delta\xi_{jm}$. By the same token, the predicted number of HMO enrollees, government gain, and HMO profits, are also understated. In the simulations, we should focus on the change in numbers, not the level.

Not only beneficiaries and suppliers but also the government may enjoy the welfare gain from the program. This gain comes from per-enrollee cost difference between per-enrollee payments to private plans and expected per capita costs in the traditional Medicare plan that the government would have to pay without private Medicare plans. Thus if the government payment rate is lower than the expected fee-for-service cost in a county, the government expect more gain from more members transferring from traditional Medicare to Medicare HMOs. I calculate $G_{w/o\text{PrivatePlans}}$ by using demographic data and average fee-for-service cost of traditional Medicare. I discount the average cost data by 8.0% to take into account favorable selection, a widely acknowledged phenomenon that Medicare beneficiaries who choose to join an HMO are systematically healthier than beneficiaries who choose to remain in the same fee-for-service sector even after adjusting for the demographic characteristics included in Medicare's HMO payment methodology (e.g. Mello, et al. 2003). GAO (2000) concludes Medicare HMO enrollees are 11.7% less costly than the other Medicare eligibles on average. I use 8.0% instead, because (1) the Medicare HMO market is shrinking since GAO (2000)'s data years, while the main source of the cost difference is new HMO joiners, (2) the cost difference for new enrollees is also gets smaller over years (GAO 2000), and (3) after 1998, the government has gradually introduced a new payment methodology with more detailed risk adjustments. If 8.0% is misspecified by, for example, 1%, the net social welfare gain is affected by 2 to 5%. Thus, welfare simulation results and policy implications are robust overall.

5 Results

5.1 Parameter Estimation

Table 6 shows the results of the demand estimation. The significant coefficient on $\ln s_{j|\text{private},m}$ implies that the imposed grouping structure is relevant. The results indicate that consumers are attracted by plans with lower premiums, more benefits (except for education benefits), more options ("# products in plan"), and longer experience of business in Medicare.

Table 6: Nested Logit Demand with Fixed Effects

Dependent variable:	Nested Logit			
$\ln(s_{jm}) - \ln(s_{0m})$	without IV		with IV	
$\ln\ s_{j\vert\text{private},m}$	0.639	(.014)	0.348	(.055)
monthly premium	−0.0022	(.0008)	−0.0105	(.0057)
benefit: drug	0.203	(.062)	0.338	(.182)
benefit: education	−0.139	(.150)	−0.296	(.182)
benefit: physicals	0.457	(.149)	0.419	(.167)
benefit: peripheral1	0.351	(.195)	0.551	(.236)
benefit: peripheral2	0.069	(.113)	0.096	(.124)
benefit: screenings	0.370	(.196)	0.517	(.232)
# products in plan	0.112	(.021)	0.163	(.027)
no experience	−0.364	(.077)	−0.389	(.107)
ln experience year	0.720	(.195)	0.794	(.236)
HMO penet rate 98	1.802	(.137)	1.255	(.194)
year: 2004	0.118	(.040)	−0.253	(.075)
constant	−4.277	(.288)	−4.955	(.411)
Adjusted R^2	0.831		0.797	

The number of observations: 3,289. Standard errors are in parentheses.

Medicare HMOs have more popularity in the counties where HMOs are more common in the commercial sector. Table 7 reports price elasticities, marginal costs, and per-capita consumer surplus. The conventional price elasticity is not defined, because charging a non-positive premium is a common practice. Table 7 shows two alternative measures of price sensitivity — the semi-elasticity, $\eta_{jm} \equiv (\partial s_{jm}/\partial p_{jm}) \cdot (1/s_{jm})$ and the price elasticity from producers' point of view, $\eta_{jm} \cdot (p_{jm} + \text{Payment Rate}_m)$.[19] The latter elasticity is well-defined because premiums are much smaller than payment rates. With values less than −1.0, the estimated elasticity does not contradict with the profit-maximizing firm assumption. The table also shows that the elderly people in counties with at least one Medicare HMO are enjoying about monthly \$50 consumer surplus on average, regardless of whether he joins a private plan or the traditional Medicare plan. As discussed in the model section, I calculate these values in two ways, depending on whether I include $\Delta\xi_{jm}$ or not, i.e. whether I use

[19] If the semi-elasticity is −0.02, a \$1 increase in the premium is expected to reduce the enrollment by 2%.

observed market share or fitted market share. When $\Delta\xi_{jm}$ is in the calculation, the obtained values will be closer to the reality, but the values calculated without $\Delta\xi_{jm}$ are necessary for the counterfactual simulations. The table shows that this does not make a difference in the estimated elasticities, but does affect consumer surplus.

Table 7: Price Semi-Elasticity, Marginal Costs, and Consumer Surplus

	# obs	Mean	Std. dev.	Min	Max
Own-price semi-elasticity (in 100%)					
with $\Delta\xi_{jm}$	3,289	−0.0124	0.0026	−0.0161	−0.0058
w/o $\Delta\xi_{jm}$	3,289	−0.0124	0.0026	−0.0161	−0.0075
Own-price elasticity for private plans (in %)					
with $\Delta\xi_{jm}$	3,289	−7.529	2.246	−17.452	−2.841
w/o $\Delta\xi_{jm}$	3,289	−7.575	2.167	−16.583	−2.952
Marginal costs (monthly in $)					
w/o $\Delta\xi_{jm}$	3,289	517.6	103.0	196.2	1146.3
Consumer surplus (per capita, monthly in $)					
with $\Delta\xi_{jm}$	1,767	53.2	80.3	0.02	512.8
w/o $\Delta\xi_{jm}$	1,767	41.1	64.4	0.09	396.3

Table 8 shows the results of the entry estimation. The estimated coefficients represent each variable's contribution to fixed profits. The result suggests that a newcomer in Medicare incurs significant setup costs in each county, but the length of business in Medicare is irrelevant. The result that for-profit and chain plans face higher fixed costs seems not straightforward. What is explained by this model is not the accounting profits but the economic profits that lead a plan to entry decision. If for-profit chain plans have a tendency to re-optimize their market area more frequently than nonprofit local chains, it may explain these results. The negative coefficient on standardized per capita fee-for-service costs indicates that a plan incurs additional fixed costs and/or is reluctant to operate in a county where utilization of medical care is relatively high. Per capita medical care infrastructure variables are included to control the costs of organizing and maintaining the provider network. The results indicate a plan incurs the highest cost when there is only one hospital in the county, the case where the plan's bargaining power is weakest. The larger the county is, the higher fixed costs a plan incurs. On the other hand, being in an MSA is favorable to HMO plans, probably because health providers' bargaining power is weaker compared to isolated cities, or maybe because the coefficient captures some economy of scale, which is beyond the scope of my supply side model. The estimated parameters, ω and ρ, indicate that plan-county-specific shocks, η_{jm}, account for 60% of the variance of fixed cost errors and county-specific shocks, η_m, for 40%. The significantly estimated value of λ rejects the null hypothesis of homoskedasticity.

Table 8: Entry Estimation

Dependent variable: County level fixed profits in $1,000,000		
no experience	−1.252	(.250)
experience year	0.006	(.006)
nonprofit	0.159	(.044)
national chain	−0.505	(.067)
group model	0.568	(.088)
IPA model	0.166	(.099)
staff model	0.069	(.126)
Std FFS per capita cost	−0.002	(.0002)
per capita # hospital	0.228	(.035)
per capita # hospital bed	0.001	(.004)
per capita # medical doctor	0.114	(.062)
county: no hospital	0.937	(.080)
MSA	0.321	(.079)
county: small	−0.554	(.070)
county: medium	−1.462	(.096)
county: large	−4.430	(.218)
county: extra large	−7.334	(.771)
county: huge	−12.124	(4.85)
year: 2004	0.091	(.031)
constant	−1.158	(.076)
ω (plan-county-specific error)	0.267	(.024)
ρ (county-specific error)	0.216	(.018)
λ (heteroskedasticity)	0.859	(.019)

The number of markets: 5,075. The number of potential entrants: 19,544.
Standard errors are in parentheses. The number of simulation draws: 40.

5.2 Welfare Analysis and Simulations

Table 9 summarizes the calculated net social welfare gain of the Medicare HMO program. Adding the above three welfare components results in the net welfare gain, 9.04 billion dollars in 2003 and 10.27 billion in 2004. The majority of the gain comes from producer surplus, while the government is losing money.[20]

Table 9: Welfare Results

	2003	2004	2000 (Town&Liu)
Consumer surplus	2,806	2,862	4,061
	(1,362)	(1,366)	
HMO profits	7,751	8,027	8,757
	(210)	(243)	
Net government gain	−1,119	−371	N/A
CMS payment to private plans			
	34,147	37,825	41,726
Expected FFS payment without private plans			
	33,028	37,454	N/A
Net social welfare gain	9,044	10,267	N/A
Consumer surplus w/o $\Delta\xi_{jm}$	2,262	2,476	
HMO profits w/o $\Delta\xi_{jm}$	7,357	7,777	
Net government gain w/o $\Delta\xi_{jm}$	−1,133	−307	
Net social welfare gain w/o $\Delta\xi_{jm}$	8,486	9,947	

Annual, in millions of dollars. Standard errors shown in parentheses are calculated by Monte Carlo simulation over simulation draws and parameters.

My estimates are all smaller than the 2000 numbers by Town and Liu (2003) shown in the last column. A drastic decrease in the number of participating HMOs and enrollees between these years may explain the differences. The decrease in producer surplus is smaller than the decreases in the others, possibly because the actual payments had gradually increased on average since 1998 (GAO 2000). Overstatement of producer surplus may be another ex-

[20] The table also shows the numbers calculated without $\Delta\xi_{jm}$. Whether I use fitted market share or predicted market share affects HMO profits and government gain as well through a change in enrollment.

planation. While firms make their entry decision considering their long-run payoff, my entry model, as well as Town and Liu's, assumes firms only consider current year payoffs. Under a certain stationarity assumption of the market, this simplification should be fine, but, after huge exodus of HMOs around 2001, it is likely remaining firms are systematically optimistic for their future profits, which leads to upward bias of current-year producer surplus. The assumption of additive separability across counties might also be a source of bias.

In the following, I perform counterfactual simulations to demonstrate the potential of endogenizing the entry-exit decisions of firms. The structural estimation strategy combined with welfare analysis and full firm heterogeneity enables the following various counterfactual simulations. Some biases may arise from the fact I endogenize the entry-exit decision but not the decision on plan characteristics, so the result numbers have limitations and should be carefully interpreted for policy suggestions.

Payment Rate Simulations I perform welfare simulations with four different payment rates. In the simulations, a change of the payment rate first affects the cost structure of HMOs, and then they re-optimize their entry-exit and price decisions by taking the demand and the rivals' response into consideration, which leads to a new equilibrium. Based on the recalculated market shares, the welfare components are recalculated.

Tables 10 and 11 show the results with four different payment rates in 2003 and 2004, respectively. Uniformly raising the payment rate by 25 or 50 dollars leads to a decrease in the average premium and increases in the enrollment and entrants. In turn, this increases consumer surplus, producer surplus, and the government deficit. Among the five different payment rates, the maximum social welfare gain is achieved with +$25 in both years. Table 12 shows where new HMO entry occurs when the payment rate is raised by 50 dollars in 2004. While entry is observed in all county types, its probability is lower in more concentrated counties.

Table 10: Payment Rate Simulation: 2003

Payment rate:	−$50	−$25	±$0	+$25	+$50
Consumer surplus	1,038	1,518	2,262	3,610	5,247
HMO profits	6,160	6,698	7,357	8,148	9,186
Net government gain	1,000	181	−1,133	−3,204	−6,172
CMS payment to HMO	17,719	23,203	30,626	41,965	54,211
Expected FFS payment	18,719	23,385	29,493	38,761	48,039
Net social welfare gain	8,198	8,397	8,486	8,555	8,261
Enrollment (total)	2,786,815	3,488,045	4,417,637	5,760,803	7,167,725
Enrollment (HMO)	2,323,225	3,058,945	4,028,858	5,410,492	6,854,673
# of plan-mkt (total)	1,320	1,387	1,478	1,564	1,662
# of plan-mkt (HMO)	839	906	997	1,083	1,181
Avg premium (HMO)	97.71	73.43	49.23	27.35	5.76

All welfare measures are in millions of dollars, calculated without $\Delta\xi_{jm}$.

Decomposing Welfare Changes Further counterfactual simulations give another insight into how payment rate changes affect social welfare. I decompose net social welfare changes into three components: entry effect, market power effect, and subsidy effect. Entry effect, the welfare impact through HMOs' entry-exit response, can be confirmed by turning the entry-exit response on and off in a payment simulation. HMOs' market power might be a possible source of social inefficiency. To clarify this point, the average premium changes when the payment rate is raised by 50 dollars are shown in Table 13 by the type of county. The second column shows the results without entry, and the third column shows the results with simulated entry. Each plan sets its premium according to the first order condition, (6), depending on its market power. The result shows that, while monopolists "bank" about 10% of the payment rate change through increased price-cost margins, when there are nine entrants, most of the payment rate increase goes to consumers through premium reduction.[21]

[21] Concerning pass-through behavior of a firm with a cost advantage, see Besanko, et al. (2001).

Table 11: Payment Rate Simulation: 2004

Payment rate:	$-$\$50	$-$\$25	±\$0	+\$25	+\$50
Consumer surplus	1,143	1,671	2,476	3,589	5,121
HMO profits	6,492	7,067	7,777	8,689	9,786
Net government gain	1,695	950	−307	−2,237	−5,022
CMS payments	20,777	27,064	35,401	45,817	58,388
Expected FFS payment	22,472	28,013	35,094	43,581	53,366
Net social welfare gain	9,330	9,688	9,947	10,041	9,885
Enrollment (total)	3,054,761	3,813,610	4,795,493	5,952,749	7,304,955
Enrollment (HMO)	2,457,181	3,270,073	4,309,146	5,516,147	6,918,159
# of plan-mkt (total)	1,637	1,712	1,811	1,895	1,990
# of plan-mkt (HMO)	920	995	1,094	1,178	1,273
Avg premium (HMO)	84.97	60.61	36.50	14.59	−6.99

All welfare measures are in millions of dollars, calculated without $\Delta\xi_{jm}$.

The last column of the table shows the average payment rate changes by incumbents that face new entrants. The more concentrated the market is, the larger premium reduction the market experiences from entry.

Subsidizing too much is another possible source of potential dead weight loss, as the per-enrollee payment from the government to HMOs can be seen as price subsidy. After the welfare impact of entry is quantified, I decompose the residual into market power effect and subsidy effect, by using the following experimental simulation: (1) there is no additional entry and (2) each firm passes all the incremental payment along to its enrollees through premium reduction.[22][23]

The results of the decomposition are shown in Table 14. The second column shows the

[22] I do not assume HMO's price cost margins are zero; I assume there is no room for them to exploit their market power for the \$50 payment rate increase.

[23] In this decomposition, cross term effects are included in entry effect, that is, entry effect here includes not only pure entry effect but also market power and subsidy effect for new entrants. In any case, the difference in the results is negligibly small.

Table 12: Where New Entry Occurs when Payment Rate Raised by $50: 2004

Initial number of HMO plans in a county	Number of markets	Number of entry occurrence	Ratio
0	1918	110.2	5.7%
1	362	34.9	9.6%
2	181	19.1	10.5%
3	49	7.5	15.2%
4	27	3.0	10.9%
5	3	0.5	17.7%
6	2	0.6	28.5%
7	3	1.3	42.3%
8	5	1.6	31.4%
9	3	0.4	13.3%
Total	2,553	178.9	7.0%

Average over simulation draws. Non-HMO plans are not included.

Table 13: Average Incumbent Premium Changes when Payments Raised by $50: 2004

Initial number of HMO plans in a county	Average over all plans		Average over plans facing new entry
	w/o entry	with entry	
1	−44.12	−46.37	−69.92
2	−46.80	−47.64	−55.45
3	−47.53	−48.20	−52.39
4	−48.15	−48.40	−51.06
5	−48.11	−48.64	−50.53
6	−48.94	−49.61	−51.67
7	−49.11	−49.78	−52.22
8	−49.23	−49.74	−51.30
9	−49.26	−49.41	−50.47

Average over plans and simulation draws.

Table 14: Welfare Change Decomposition: 2004

		Total effect	Subsidy effect	Market power	Entry effect
2004	Total welfare	+90.1	+132.7	−13.0	−25.5
+\$25	Cons surplus	+1,112.4	+949.9	−85.6	+248.1
	Prod surplus	+911.8	+954.0	+27.0	−69.2
	Gov savings	−1,930.1	−1,771.3	+45.5	−204.4
	Enrollment	+1,207,001	+942,134	−81,704	+346,571
	Premium	−21.91	−25.00	+1.69	+1.32
2004	Total welfare	−61.6	+77.5	+8.6	−147.6
+\$50	Cons surplus	+2,644.5	+2,223.6	−233.5	+654.4
	Prod surplus	+2,009.1	+2,031.6	+78.2	−100.8
	Gov savings	−4,715.2	−4,177.8	+163.8	−701.2
	Enrollment	+2,609,013	+2,004,772	−191,360	+795,601
	Premium	−43.49	−50.00	+3.62	+2.81

All welfare figures are in millions of dollars.

net welfare changes from the payment rate increase. The remaining three columns show the three effects, which sum up to the total effect. For both +\$25 and +\$50 cases, subsidy and entry effects significantly increase consumer surplus by lowering premiums and providing more choices. The market power effect is relatively small.[24] The net welfare impacts of these three effects are different between the two cases. The subsidy effect is positive in both cases, but larger in the \$25 case. On the contrary, the entry effect is negative in both cases, but larger in the \$50 case. As a result, increasing payment rates by 25 dollars has a positive net welfare impact because of the large subsidy effect, while increasing payment rates by 50 dollars has a negative net welfare impact because the negative entry effect dominates. Beyond this level of payment rates, per enrollee government spending is huge and entry of HMOs harms social welfare.

[24] The reason the market power effect on government gain is positive is that, at this level of payment rates, it is beneficial for the government to have fewer HMO enrollees even if it is due to HMOs' price-cost margins. For the same reason, entry effect increases government deficits. The entry effect on premiums is positive because some entry occurs in counties without incumbents, which results in high, monopoly premiums.

Simulating Entry Is the entry level excessive? To answer this question, I perform entry simulations. Changing the level of entry is not straightforward because the simulation result may depend on which plan to be included. To choose which plan I use the results in the previous payment simulations, by employing four market configurations that result from four different payment levels. For example, increasing payment rates by 25 dollars in 2004 results in 84 more entrants, which I add to the actual observations and recalculate welfare components without changing payment rates.

Tables 15 and 16 show the results for 2003 and 2004, respectively. In general, additional entry increases HMO enrollment and consumer surplus but harms HMO profits and the government budget. In 2003, 86 more entrants lead to a higher social welfare gain. Additional consumer surplus brought by new entry exceeds other negative impacts. In 2004, the actual entry level is likely to be close to the optimum. Thus, the result shows no evidence of excessive entry. At the current level of entry, the consumer efficiency gain from having more entrants matches or maybe even outweighs the social inefficiency from duplicative set-up costs of firms. Also, though net social welfare is not quite responsive to the level of entry, the implied changes in welfare distribution from entry is significant.

6 Concluding Remarks

In this paper I develop an econometric model to examine welfare consequences of policy change through entry, with a case study of the US Medicare HMO market. The explicit treatment of firm heterogeneity is the technical breakthrough of this paper. It enables us to exploit detailed firm level data and makes policy simulations relevant, which is beyond the scope of previous studies. As the main result of the research, I find no evidence of excessive entry in terms of social welfare, which suggests that the government should keep at least this level of entry. Also, the government may achieve higher social welfare by expanding the

Table 15: Entry Simulation: 2003

HMO entry:	-158	-91	± 0	$+86$	$+184$
Consumer surplus	1,912	2,064	2,262	2,682	2,933
HMO profits	7,411	7,422	7,357	7,120	6,818
Net government gain	−992	−1,016	−1,133	−1,262	−1,377
CMS payments	27,178	28,679	30,626	34,385	36,819
Expected FFS payment	26,255	27,664	29,493	33,123	35,442
Net social welfare gain	8,400	8,470	8,486	8,540	8,373
Enrollment (HMO)	3,480,377	3,717,962	4,028,858	5,077,263	4,905,955
# of plan-mkt (HMO)	839	906	997	1,083	1,181
Avg premium (HMO)	50.23	49.81	49.23	50.70	52.14

All welfare measures are in millions of dollars, calculated without $\Delta\xi_{jm}$.

program.

While endogenizing the entry-exit decision, I model product characteristics as exogenous components. This is a limitation of my model, especially when product choice is an important and readily adjustable strategic variable for firms and the choice affects social welfare significantly. The literature has never achieved combining welfare analysis with both entry and product choice decisions, but incorporating another discrete decision variable, such as the drug benefit availability, is a simple extension of my framework, at least conceptually, and seems a promising direction of the future study.

Appendix

A.1 Additional Tables

Table 17 shows the results of the first stage regression in the demand estimation. Overall, the instruments have reasonable coefficients and significances. Table 18 shows the results of

Table 16: Entry Simulation: 2004

HMO entry:	−174	−99	±0	+84	+179
Consumer surplus	2,074	2,260	2,476	2,657	2,830
HMO profits	7,836	7,850	7,777	7,643	7,410
Net government gain	−138	−209	−307	−394	−478
CMS payments	31,297	33,198	35,401	37,569	39,617
Expected FFS payment	31,158	32,990	35,094	37,175	39,139
Net social welfare gain	9,772	9,901	9,947	9,906	9,762
Enrollment (HMO)	3,695,149	3,979,549	4,309,146	4,603,436	4,890,993
# of plan-mkt (HMO)	920	995	1,094	1,178	1,273
Avg premium (HMO)	37.72	37.08	36.50	37.89	39.37

All welfare measures are in millions of dollars, calculated without $\Delta\xi_{jm}$.

the OLS regression for marginal costs. Since this estimation is reduced-form and simply for the extrapolation purpose, the estimated coefficients should be read as such.

A.2 Applying the GHK Simulator

In this appendix, I follow the customary notation and change the subscript for a market from m to $i = 1, ..., N$, as each market is the unit for which the individual likelihood is defined. For a vector of indices $(1, ..., J)$, the notation "$< j$" denotes the subvector $(1, ..., j-1)$, "$\leq j$" denotes the subvector $(1, ..., j)$, and "$-j$" denotes the subvector that excludes component j.

In the sequential move game, the order of subscripts for firms $(1, 2, ..., J_i)$ comprises the reverse of the decision order in market i — firm J_i makes a decision first, firm 1 makes a decision last, and so on. Firm j's strategy in market i is represented by $y_{j,i}$, a binary variable that takes "1" if the firm enters and "0" otherwise. To make the notation simple, I omit the difference between the independent variables in the demand and the fixed profits, x_{jm} and z_{jm}, and let X_{ji} denote the set of independent variables. The profits of entering firm j in

Table 17: The First Stage IV Regression

Dependent variable:	$\ln s_{j\|\text{private},m}$		premium	
avg # competitor	-0.063		-0.446	
	(.068)		(1.189)	
competitor: npo	-0.207	***	-5.404	***
	(.056)		(1.03)	
competitor: chain	0.022		-6.423	***
	(.057)		(1.18)	
competitor: IPA	-0.547	***	0.989	
	(.058)		(1.03)	
competitor: group	-0.269	***	0.110	
	(.033)		(.601)	
competitor: staff	-0.596	***	3.127	
	(.118)		(1.98)	
per capita # hospital	2.067	***	2.783	
	(.617)		(10.56)	
per capita # hospital bed	-0.003		-0.007	
	(.004)		(.072)	
county: no hospital	0.012		-0.305	
	(.042)		(.841)	
per capita # medical doctor	-0.156	*	0.825	
	(.094)		(1.50)	
R^2	0.770		0.921	
F-test (distributed $F(10; 2, 987)$)	43.98	***	7.68	***

The number of observations: 3,289. *, **, and *** denote p<.1, p<.05, and p<.01, respectively. Heteroskedasticity consistent standard errors are used. Other independent variables and fixed effects are used but not reported.

market i are:

$$\pi_{ji}(X_{\cdot i}, \varepsilon_{ji}, y_{-j,i}; \gamma) \equiv VP(y_i, X_{\cdot i}) + X_{ji}\gamma + \varepsilon_{ji}. \tag{12}$$

A subgame perfect Nash equilibrium (SPNE) is obtained when (1) all entering firms are profitable with their optimal prices and (2) all firms that do not enter expect non-positive

Table 18: Marginal Cost Regression

Dependent variable:	MC_{jm}	
(out-of-pocket cost − premium)	−0.108	(.023)
entire enrollees	−0.082	(.011)
no experience	18.30	(3.71)
experience year	−0.343	(.226)
nonprofit	18.06	(2.41)
national chain	18.51	(2.29)
group model	−39.57	(4.19)
staff model	−29.92	(5.69)
IPA model	−31.52	(4.65)
DEMO plan	31.62	(6.72)
cost plan	35.39	(4.36)
cost missing	−147.8	(8.82)
PPO plan	−11.69	(7.43)
PFFS plan	−24.29	(4.61)
PSO plan	−33.40	(12.6)
POS	31.35	(4.36)
demo factor HMO	346.0	(21.3)
risk factor HMO	149.0	(9.97)
Std FFS per capita cost	0.332	(.014)
medigap premium	0.396	(.046)
ln per capita # hospital	−2.228	(1.84)
ln per capita # hospital bed	−4.588	(2.16)
ln hospital expenditure	6.928	(2.24)
impatient days	0.033	(.012)
per capita # medical doctor	−19.60	(6.25)
county: no hospital	−22.21	(5.47)
HMO penetration rate 98	68.82	(8.67)
eligibles	−0.090	(.031)
year: 2004	33.05	(2.12)
constant	−165.3	(27.4)
R^2	0.830	

The number of observations: 3,289. Standard errors are in the parentheses. Heteroskedasticity consistent standard errors are used. Plan and MSA fixed effects are included in the estimation.

profits from entry. Formally, an SPNE strategy in market i, (y_i^e), is any strategy that satisfies:

$$\pi_{ji}\left[X_{\cdot i}, \varepsilon_{ji}, y^e_{-j,i}\right] \geq 0, \text{if firm } j \text{ enters} \tag{13}$$

$$\pi_{ji}\left[X_{\cdot i}, \varepsilon_{ji}, \left(y^e_{>j,i}, y^*_{<j,i}(y^e_{>j,i}, y_{j,i}=1)\right)\right] \leq 0, \quad \text{if firm } j \text{ does not enter,} \tag{14}$$

for all $j = 1, ..., J_i$, where $y^*_{<j}(y_{\geq j})$ is the solution to the downstream subgame, i.e. the best responses of the downstream players given $X, \varepsilon_{<k}$, and the upstream players' strategies. The unique equilibrium solution always exists. Denote this solution, after dropping index i, as

$$y^*(X, \varepsilon; \gamma) \equiv \{y \text{ is the unique solution in the sequential move game with } X, \varepsilon, \gamma\}.$$

The component unobserved to the econometrician is specified as

$$\varepsilon_{ji} = \omega\eta_{ji} + \rho\eta_i. \tag{15}$$

η_{ji} and η_i are assumed to be independent of $X_{\cdot i}$, and distributed i.i.d. standard normal across firms and markets.[25] The heteroskedasticity adjustment in (7) is dropped for simplicity of explanation. This simplification does not affect the argument in this appendix.

The log likelihood function can be written as

$$\widehat{\theta}_{ML} = \arg\max_{\theta} \left\{ \frac{1}{N} \sum_{i}^{N} \ln \Pr\left[y_i^o = y_i^*(X_{\cdot i}; \theta)\right] \right\}, \tag{16}$$

where y_i^o is the observed market configuration and θ is the vector of parameters, (γ, ω, ρ). The probability in the likelihood does not have an analytical form solution due to the multidimen-

[25] Unlike the previous studies, no normalization such as $\omega^2 + \rho^2 = 1$ is necessary because the level of profits is identified. Moreover, this specification of the error components is not crucial for the argument below.

sional integrals, and, unless the dimension of the unobservables is very small, the numerical approximation is infeasible. Hence, I use the maximum simulated likelihood (MSL).

The Modified GHK Simulator The most straightforward simulator for MSL is the crude frequency simulator. However, such simple discontinuous simulators, which require many random draws, are practically infeasible, because my data set has at most sixteen players in some markets and the use of the backward induction technique makes each likelihood evaluation quite expensive. Here I propose the use of the GHK simulator.

The GHK simulator is a smooth recursive conditioning simulator and is often useful when the log-likelihood function involves high dimensional integrals with the multivariate normal distribution. The GHK algorithm draws recursively from truncated univariate normals. It relies on the decomposition,

$$f(v_1, ..., v_J) = f(v_1)f(v_2|v_1)...f(v_{J-1}|v_{J-2}, ..., v_1)f(v_J|v_{J-1}, ..., v_1),$$

along with the fact that the conditional normal density can be written as a univariate normal. The GHK simulator produces probability estimates that are bounded away from 0 and 1. The estimates are continuous and differentiable with respect to parameters, because each contribution is continuous and differentiable. It is also an unbiased estimator of individual likelihood, $l(\gamma, \omega, \rho; y_i^o, X_{\cdot i})$. It has a smaller variance than the crude frequency simulator, because each element is bounded away from 0 and 1.

The use of the GHK simulator in a game-theoretic situation, however, is not straightforward, because the original GHK simulator can deal with interactions across j through the disturbance structure, but not strategic interactions across j. The use of the GHK simulator in this study relies on the sequential game assumption. In a sequential move game, the prior players' decisions are given for a player. This fact harmonizes the estimation of a sequential move game with recursive conditioning simulators, as shown below.

The GHK simulator exploits the Cholesky triangularization to decompose the multivariate normal into a set of univariate normal distributions. The multivariate normal disturbance vector, ε_i, can be rewritten as: $\varepsilon_i = \Gamma_i \eta_i$, where η_i is a $(J_i + 1) \times 1$ vector of independent standard normal variates, $\eta_i \sim N(0, I_{J_i+1})$, and Γ_i is a $J_i \times (J_i + 1)$ parametric array,[26]

$$\Gamma_i = \begin{bmatrix} \omega & & & 0 & \rho \\ & \ddots & & & \rho \\ & & \ddots & & \vdots \\ 0 & & & \omega & \rho \end{bmatrix}.$$

Thus, ε_i can be rewritten as: $\varepsilon_i \sim N(0, \Omega_i)$, where Ω_i is a positive definite matrix, $\Omega_i = \Gamma_i \Gamma_i'$. It follows that ε_i can be written by using the Cholesky decomposition as:

$$\varepsilon_i = L(\Omega_i) \cdot v_i, \tag{17}$$

where $L(\Omega)$ is the lower-triangular Cholesky factor of Ω, or $LL' = \Omega$, and v_i is another multivariate standard normal vector, $v_i \sim N(0, I_{J_i})$.

The individual likelihood can be written, after dropping index i, as

$$\begin{aligned} l(\theta; y^o, X) &= \Pr\left[y^o = y^*(X; \gamma, \omega, \rho)\right] \\ &= \int_{y^o = y^*(X, \varepsilon; \gamma)} n(\varepsilon, \Omega) d\varepsilon. \end{aligned}$$

This expression involves multiple integrals, which are hard to compute in a straightforward way. The general objective here is to obtain random draws from the distribution ε_i subject to $y^o = y^*(X; \gamma, \omega, \rho)$. To do so, first rewrite the probability expression that explicitly expresses

[26] More flexible models can be dealt with by changing Γ_i and the size of η_i.

the rectangle in which the event, $y^o = y^*(X;\gamma,\omega,\rho)$, occurs:

$$\Pr\left[y^o = y^*(X;\gamma,\omega,\rho)\right] = \Pr\left[\text{for } \forall j,\ \pi_j(X_j,\varepsilon_j,(y^{o'}_{>j},y^*_{<j}(y^{o'}_{>j},1)');\gamma)\begin{cases} > 0 \text{ if } y^o_j = 1 \\ \leq 0 \text{ if } y^o_j = 0 \end{cases}\right].$$

By defining

$$\left\{\begin{array}{c} a^*_j = 0, b^*_j = \infty \text{ if } y^o_j = 1 \\ a^*_j = -\infty, b^*_j = 0 \text{ if } y^o_j = 0 \end{array}\right\},$$

the probability can be written as:

(18)

$$\Pr\left[y^o = y^*(X;\gamma,\omega,\rho)\right] = \Pr[\text{for } \forall j,\ a^*_j(y^o_j) \leq \pi_j(X_j,\varepsilon_j,(y^{o'}_{>j},y^*_{<j}(y^{o'}_{>j},1)');\gamma) \leq b^*_j(y^o_j)].$$

Remember the form of the profit function, (12). By defining

$$\begin{aligned} a_j &\equiv a^*_j - X_j\gamma - VP((y^o_{>j},y^*_{<j}(y^o_{>j},1)),X) \\ b_j &\equiv b^*_j - X_j\gamma - VP((y^o_{>j},y^*_{<j}(y^o_{>j},1)),X), \end{aligned}$$

(18) can be rewritten as

$$\Pr\left[y^o = y^*(X;\gamma,\omega,\rho)\right] = \Pr[\text{for } \forall j,\ a_j(y^o,X,\varepsilon_{<j};\gamma) \leq \varepsilon_j \leq b_j(y^o,X,\varepsilon_{<j};\gamma)].$$

This expression shows us the rectangle in which the event, $y^o = y^*(X;\gamma,\omega,\rho)$, occurs. To obtain the interval of ε_j, we only need $\varepsilon_{<j}$. This is because the upstream firms' decisions are given for firm j. The Cholesky decomposition, (17), makes this expression as:

(19)

$$\Pr\left[y^o = y^*(X;\gamma,\omega,\rho)\right] = \Pr[\text{for } \forall j,\ a_j(y^o,X,v_{<j};\gamma,\Omega) \leq L(\Omega)\cdot v \leq b_j(y^o,X,v_{<j};\gamma,\Omega)]$$

or,

$$\Pr\left[y^o = y^*(X;\gamma,\omega,\rho)\right] = \int_{\text{for } \forall j,\ a_j(y^o,X,v_{<j};\gamma,\Omega)\leq L(\Omega)\cdot v\leq b_j(y^o,X,v_{<j};\gamma,\Omega)]} \left[\prod_{j=1}^{J}\phi(v_j)\right] dv,$$

where $\phi()$ is the probability density function of standard normal.

Now we are ready to apply the GHK simulator. For each time of simulation draws, prepare a vector of independent uniform $(0,1)$ random variates, $(u_1, ..., u_{J_i})$. Define the following function:

(20) $q(u,a,b) \equiv \Phi^{-1}\left(\Phi(a)\cdot(1-u)+\Phi(b)\cdot u\right)$, where $0<u<1$ and $-\infty \leq a < b \leq \infty$.

This function, $q(\cdot)$, is a mapping that takes a uniform $(0,1)$ random variate into a truncated standard normal random variate on the interval $[a,b]$.

For given y^o, X, u, γ, L, define recursively for $j = 1, ..., J$:

$$\begin{aligned}
\widetilde{v}_1 &\equiv q\left(u_1, \frac{a_1}{L_{11}}, \frac{b_1}{L_{11}}\right) \\
\widetilde{v}_2 &\equiv q\left(u_2, \frac{a_2(\widetilde{v}_1) - L_{2,1}\widetilde{v}_1}{L_{22}}, \frac{b_2(\widetilde{v}_1) - L_{2,1}\widetilde{v}_1}{L_{22}}\right) \\
&\quad ... \\
\widetilde{v}_J &\equiv q\left(u_J, \frac{a_J(\widetilde{v}_{<J-1}) - L_{J,1}\widetilde{v}_1 ... - L_{J,J-1}\widetilde{v}_{J-1}}{L_{JJ}}, \frac{b_J(\widetilde{v}_{<J-1}) - L_{J,1}\widetilde{v}_1 ... - L_{J,J-1}\widetilde{v}_{J-1}}{L_{JJ}}\right)
\end{aligned}$$

and

$$
\begin{aligned}
Q_1 &\equiv \Pr\left(\frac{a_1}{L_{11}} \leq v_1 \leq \frac{b_1}{L_{11}}\right) \\
Q_2 &\equiv \Pr\left(\frac{a_2(\widetilde{v}_1) - L_{2,1}\widetilde{v}_1}{L_{22}} \leq v_2 \leq \frac{b_2(\widetilde{v}_1) - L_{2,1}\widetilde{v}_1}{L_{22}}\right) \\
&\quad \ldots \\
Q_J &\equiv \Pr\left(\frac{a_J(\widetilde{v}_{<J-1}) - L_{J,1}\widetilde{v}_1 \ldots - L_{J,J-1}\widetilde{v}_{J-1}}{L_{JJ}} \leq v_J \leq \frac{b_J(\widetilde{v}_{<J-1}) - L_{J,1}\widetilde{v}_1 \ldots - L_{J,J-1}\widetilde{v}_{J-1}}{L_{JJ}}\right).
\end{aligned}
$$

Given all the a, b, L, and $\widetilde{v}$, every Q_j is truncated univariate standard normal, so can be calculated by, for example,

$$Q_1 = \Phi\left(\frac{b_1}{L_{11}}\right) - \Phi\left(\frac{a_1}{L_{11}}\right).$$

Repeat this simulation R times and define the likelihood contribution simulator as

$$\widetilde{l}(\gamma, \Omega; y^o, X; R, u) \equiv \frac{1}{R}\sum_{r=1}^{R}\prod_{j=1}^{J} Q_j(\widetilde{v}_{1r}, \ldots, \widetilde{v}_{J-1,r}). \tag{21}$$

The model is estimated by solving the following maximum simulated likelihood problem:

$$
\begin{aligned}
\widehat{\theta}_{MSL} &= \arg\max_{\theta}\left\{\frac{1}{N}\sum_{i}^{N} \ln \widetilde{l}(\gamma, \Omega; y_i^o, X_{\cdot i}; R, u_i)\right\} \\
&= \arg\max_{\theta}\left\{\frac{1}{N}\sum_{i}^{N} \ln \frac{1}{R}\sum_{r=1}^{R}\prod_{j=1}^{J} Q_j(\widetilde{v}_{1r}, \ldots, \widetilde{v}_{J-1,r})\right\}.
\end{aligned} \tag{22}
$$

In the computation, I use the Quasi-Newton method with BFGS updating algorithm for the maximization routine. When I make the random draws for the simulator, I use antithetics to reduce simulation variance and bias. For more details, see Maruyama (2007).

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