Matching with Conflicts: An Application to the Advertising Industry*

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Abstract

In professional service markets, clients who are product market competitors are often reluctant to work with the same service agency. This can effectively restrict the choice set of clients seeking matches, and it may cause agency mergers to reduce efficiency even when static pricing inefficiencies are absent. To understand the importance of conflict, I construct a new data set on matches between pharmaceutical advertisers and advertising agencies from 2002 to 2010 in which competitors are defined by therapeutic classes, and estimate a two-sided matching model using a maximum score estimator. The results show that conflict does indeed reduce the match surplus, and the reduction is greater for a pair of agents who have matched with each other in the previous period. Also, preserving previously formed matches yields much higher surplus than forming new matches. Based on these estimates, I conduct a counterfactual exercise to illustrate the effect of conflict on allocation of matches. I find that 14% of all matches that would have formed in a non-conflict environment are unable to form when conflict is present. Another counterfactual exercise shows that mergers between advertising agencies that previously contracted with competing advertisers decrease surplus by bringing their clients into conflict. Mergers involving agencies that have not previously contracted reduce the number of matching opportunities for new clients and tend to lower the total number of matches made in equilibrium.

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1 Introduction

In many professional service markets, such as auditing, advertising, banking, and consulting, clients may prefer that the service agency they work with does not work for their product market competitors. This is mainly due to concerns about conflicts of interest. For example, strategically important information may be leaked to competitors, or the act of maintaining relationships with conflicting clients may lower the service agency's performance. In the advertising industry, an oft-cited example is that of Colgate-Palmolive, who terminated its long-standing relationship with Saatchi and Saatchi when the advertising agency started to work for Procter & Gamble following a merger.[1] To address potential conflict, the industry association American Association of Advertising Agencies (4A's) has advised advertising agencies to be vigilant in protecting clients' confidential information either by avoiding simultaneously serving clients who compete head-to-head or by setting up information firewalls (so called "Chinese walls") to actively prevent information leakage within the agency.[2]

Conflict lowers expected surplus of relationships between service agencies and clients and affects both sides' choices of who to contract with. This has the economic consequence of determining the allocation of contracts. The goal of this paper is to use a revealed preference approach to back out the effect of conflict on agents' preferences and examine how the existence of conflict impacts the overall allocation of contracts. Moreover, since conflict is determined by relationship structure in the market, I examine how a change to the market structure, such as a merger between service agencies, changes the market equilibrium.

In this paper, I investigate the importance of conflict in the context of advertising agencies working for prescription drug advertisers. Drug advertising is particularly suited to a study of agency-client relationships for several reasons. First, prescription drug advertisers are important clients for the advertising agencies, contributing roughly 10% of total agency revenue. Second, there is a clear definition of product market competition by therapeutic class. Third, although many pharmaceutical companies produce more than one drug, advertising agencies chosen for different drugs

[1] Advertising agencies Saatchi & Saatchi and Ted Bates merged in 1987. Before their merger, Colgate-Palmolive hired Saatchi & Saatchi, and Procter & Gamble hired Ted Bates. The merger between the two agencies brought Colgate- Palmolive and Procter & Gamble under the same roof and led to the immediate departure of Colgate-Palmolive (Siman 1989; Goldman 1997). In service industries, a merger of top service agencies with broad client bases almost inevitably leads to competition overlap among their clients. For example, the merger between Arthur Young and Ernst & Whinney in 1989 brought their clients PepsiCo and Coca-Cola together, resulting in Arthur Young's resignation from PepsiCo's contract. It is an aphorism within the service industry that secrets are harder to keep in advertising agencies (The Economist 1997).

[2] See American Association of Advertising Agencies (2009), "Confidentiality Of Marketing Services Information". Retrieved from http://goo.gl/hHGQ9i

within the same pharmaceutical company are often scattered. Conversations with the marketing directors of Pfizer and AstraZeneca suggest that advertising decisions are made independently by the marketing team of each drug, which allows me to assume that advertising agency choices are made at the drug level.

Based on a new dataset I construct of agency-drug relationships from 2002 to 2010 (combined from multiple industry sources), I build an empirical many-to-many matching model in which conflict acts as a cross-match externality when one advertising agency works for multiples drug advertisers in the same therapeutic category. More specifically, at the beginning of each year, advertising agencies and drug advertisers are assumed to observe drug/agency characteristics, match history of the previous year, and the draw of idiosyncratic shocks for each possible drug-agency pair. They then make matching choices to maximize their own surplus for the current year. The matching framework accounts for the fact that an advertising agency and a drug advertiser will only contract when both parties find it in their interests to do so, a feature often missed in a more standard one-sided choice model.

Compared to the classical matching literature, my setting is non-standard in two ways. First, conflict introduces an externality of one player's matching choice on other players' preferences.[3] Second, a many-to-many matching model is necessary as both drug advertisers and advertising agencies commonly match with multiple partners. In order to obtain a stable equilibrium solution when advertising agencies' preferences may not be substitutable, I made an assumption that drug advertisers do not face a binding capacity constraint in terms of how many matches they can form in a specific year. This assumption implies that a drug advertiser's decision to match with each agency is independent and leads to stable equilibrium. However, I am able to maintain the feature that the number of agencies a drug advertiser eventually hires is still limited since the match value of a drug-agency pair must overcome a fixed cost of signing up a contract and the cost of conflict if conflict exists. There is no explicit capacity constraint for advertising agencies in my model either, but since conflict increases the cost to match with another drug in the same therapeutic class, this negative externality is similar to a capacity constraint specific to the class.[4] The model yields the result that the equilibrium can be characterized by pairwise deviations that are independent of

[3]The negative externality in this model directly affects agents' preferences. This is different from the externality in the typical matching models in which capacity constraint places a negative externality on agents' choice set.

[4]More strictly speaking, since I assume that conflict cost does not depend on the number of drugs in a conflicting relationship, negative externality in my model arises when the number of drugs an agency serves in a therapeutic class rises from one to two. But when an agency already has two conflicting clients, adding the third client in the therapeutic class only creates the conflict cost to the extra match itself, and does not impose a negative externality to existing matches.

transfers made between contracting parties. This allows me to identify the surplus function using only information on matches.

To identify the relative contribution of conflict and characteristics of the drugs and agencies on matching surplus, I rely on the revealed preference approach that compares the observed matching with its counterfactual deviations. More specifically, I construct preference inequalities using the model prediction that the stable matching yields higher total surplus than the alternative matching from a pair-wise deviation. Following Fox (2008), I estimate the model using a maximum score estimator. Intuitively, parameters of the surplus function are identified by the relative frequency of characteristics observed in equilibrium and in its deviations. In particular, the effect of conflict on surplus is identified when a deviation from equilibrium changes the amount of conflict in the market relative to other characteristics of the match.

There are two main advantages to using the semi-parametric maximum score in this setting. First, maximum score does not require me to solve the matching model explicitly and write down the probability of equilibrium allocation. This reduces the computation burden, especially when the number of participants is large and equilibrium is slow to compute. Second, the maximum score estimator does not require specifying the error distribution, so it avoids error misspecification in choice models that may lead to inconsistent estimators (Hausman et al., 1998).[5]

Using the maximum score estimator, I find that conflict does indeed reduce the match surplus on the net and is especially costly for a pair of agents who have matched with each other in the previous period. Also, preserving a previously formed match yields a much higher joint surplus than forming matches with new partners. Moreover, conflict crowds out matches whose returns are positive but too low to offset the conflict cost. In a counterfactual, I find that 14% of all matches that would have formed in a non-conflict environment are unable to form when conflict is present. Among them, 95% are matches with new partners. In another counterfactual, I simulate the effect of a hypothetical merger between two large advertising holding companies, Omnicom and Publicis.[6]

[5] Also, normal error assumptions may be problematic in the vertical contract setting. Vertical relationships are observed to be persistent but can dissolve without sharp changes on observables. One possibility is that the relationship dissolves as a result of experiencing a rare but large negative shock. This suggests that the error distribution may be asymmetric with a long left tail. In such cases, maximum score estimation is preferred to parametric error assumptions. For the counterfactual exercise, I assume that the error follows a mixture of two normal distributions, and calibrate it by matching simulated moments given the error distribution and the data moments. I find that the distribution is bimodal with one normal component having a much more negative mean than the positive component, confirming the above big negative story.

[6] Mergers of service providers raise particular interest in previous studies of conflict since mergers directly change the relationship structure. Mergers increase the probability of conflict by reducing the number of service provider choices, and in some cases, by directly bringing conflicting clients to the same agency. The advertising agency industry is also of antitrust policy interest since the industry has been gradually consolidating since the merger waves in the

With a combined 32% market share in the US,[7] Omnicom and Publicis proposed to merge in August 2013 but canceled the deal ten months later for various reasons. With the hypothetical merger, I find that the number of matches with new partners is reduced by 7%; most previously formed matches survive conflict but lose 6.8% of the surplus due to the increased amount of client conflict in equilibrium.

This paper helps us to better understand the role of conflict in contractual relationships. Rogan (2013), Asker and Ljungqvist (2010), Aobdia (2012) model and identify conflict from clients' switching behavior when their service agencies are involved in exogenous mergers. Such an identification strategy ignores the fact that all clients' contracting decisions, whether or not they are currently in a contract, are affected by the market structure change. I am able to incorporate the market-wide interdependency through conflicts. In particular, I simulate the market equilibrium when conflict cost is reduced to zero and when mergers reduce the number of service agencies in the market. My findings are consistent with Asker and Ljungqvist (2010) in that conflict is costly for matches, and mergers reduce the number of matches formed in the market. My work also complements Asker and Ljungqvist (2010) by constructing a counterfactual that shows the magnitude of equilibrium effect of a change to the market structure on all agents in the market.

This paper is also closely related to the empirical matching literature that has recently advanced tools for estimating matching models (Fox (2008); Fox (2010); Agarwal (2012)). This line of work deals with the endogeneity that arises from capacity constraint that each agent's choice set is endogenous and unobserved. These models and empirical methods mainly use the sorting pattern of agents who are matched to identify matching preferences. However, the canonical matching models do not consider other types of externalities arising from client choices, such as conflict. One exception is Uetake and Watanabe (2012) that studies bank merger as a matching decision and allows post-match market competition as a sounce of negative externality. I provide an application of the matching model that incorporates conflicts.

Finally, my work has important implications for competitiveness of the professional service markets, especially when the number of viable service agencies is limited for each type of client due to clients' required experience and expertise. A typical antitrust analysis concerns whether a merger may generate price inefficiency because consumers have fewer suppliers from which to choose. I show

mid 1980s.

[7] The estimates of total U.S. agency revenue come from *Advertising Age*, which collects data from the 1,000 biggest agencies (http://adage.com/article/news/publicis-omnicom-group-facts/243346/). Until 2012, the four biggest agency holding companies in the US ranked by revenue captured 60% of the advertising service market share.

that a merger between professional service providers can exacerbate conflict of interest among clients and further limit a client's choice set. Whether this warrants additional antitrust concern depends on the pre-merger market structure and additional knowledge of the mechanism by which matches and payments are negotiated.

The rest of the paper is organized as follows: In the next section, I describe background of the advertising agency industry and explain the dataset I construct for this study. I then summarize the data and use descriptive regressions to show matching patterns in this market. In section 3, I explain the matching model and characterize the model equilibrium. In sections 4 and 5, I discuss identification and estimation of the model and explain the estimated structural parameters. In section 6, I conduct two sets of counterfactual exercises to analyze the effect of conflict and the effect of advertising agency mergers on the allocation of matches. Section 7 concludes.

2 Market Description and Data

2.1 The Advertising Agency Business and the Concern of Conflict

Advertising agencies provide a number of professional services to clients, including planning and creating advertising content, delivering finished creative content to consumers through media outlets, advising clients on overall marketing and branding strategies. In fact, with a total US revenue of $35.6 billion in 2012,[8] advertising agencies are in charge of almost all of the advertising activities of the majority of large advertisers, an arrangement that has existed since the 1920s (Mohammad et al., 2012). Among the 1,746 firms who spend more than $1 million annually on advertising and responded to the 2003 *Advertising Age* survey, 86% outsource all of their advertising services to advertising agencies (Horsky, 2006). This figure is lower among advertisers with smaller advertising budgets. And in the advertising industry, larger advertising agencies dominate: in 2003, advertisers spent $245 billion on advertising in the US, and 61% of the spending are billed through the largest 1000 advertising agencies (*Advertising Age* 2004).[9]

Client concerns about conflict have long been recognized in the advertising industry. One widely documented case was the merger between Saatchi & Saatchi and Ted Bates in the late 1980s. In this merger, the two agencies lost accounts worth more than $300 million, and at least one of the clients in a conflict relationship with his product market competitors dismissed the agency (Siman, 1989).

[8]See Advertising Age (2013). Retrieved from http://adage.com/article/agency-news/digital-media-drive-u-s-agency-revenue/241114/

[9]Billing is the total amount of marketing dollars given to the advertising agencies to spend for the advertisers.

Since then, modern advertising agencies have practiced conflict resolutions through organization structure and splitting accounts in the recent decades (Silk, 2012). The 4A's has also issued conflict policy guidelines to cope with "head-to-head conflict at the brand or category level".[10]

To date, conflict continues to attract attention in agency merger announcements, since mergers may directly bring conflicting clients into the same agency. The importance of client conflicts came to light again when Publicis and Omnicom, the second and third largest advertising holding companies ranked by 2012 revenue, announced plans to merge in July 2013. Given the size of these advertising agency holding companies, the potential competition overlap among clients was big. The proposed Publicis-Omnicom merger brought together high-profile competing advertisers, such as PepsiCo and Coca-Cola, Volkswagen and Mercedes, General Motors and Toyota, and AT&T and Verizon.[11] The merger was ultimately cancelled due to a variety of reasons, but the CEO of Publicis Maurice Levy mentioned part of the reason be the merger diverts agencies' attention to "best serve our clients". Inspired by this merger event, I will analyze the impact of a hypothetical Publicis-Omnicom merger on allocation of matches for pharmaceutical advertisers in the counterfactual exercise.

The advertising agency industry has been gradually consolidated since the merger waves in the mid 1980s.[12] By 2012, the biggest four advertising agency holding companies ranked by revenue in the US capture 60% of the advertising service market share.[13] Most strikingly, two of these big four agencies, Omnicom and Publicis who shared 32% of the market in the US just announced plans to merge in July 2013.[14] This ignites the industry's talk about conflicts created by merger that I will discuss in the following.

The costs of conflict arise from three main sources: clients concerns about information leakage, the cost to the agency of maintaining client relationships when conflict occurs (Asker and Ljungqvist (2010), Aobdia (2012)), and the disinclination of conflicting clients to forgo access to an agency's limited product-specific specialty resources (e.g., experts, marketing opportunities).

Advertising agencies access clients' confidential business information and marketing plans and act on their behalf to execute their advertising strategy. Advertising agencies' failure to protect clients' confidential marketing plans may hinder advertising effectiveness, so clients have the expectation

[10]See American Association of Advertising Agencies (2009), "Conflict Policy Guidelines". Retrieved from http://www.aaaa.org/agency/compensation/positionpapers/pages/070700_conflict.aspx

[11]See Adweek (2013), "Publicis-Omnicom Merger Set". Retrieved from http://www.adweek.com/news/advertising-branding/how-likely-actual-omnicom-publicis-merger-151468

[12]Silk and Berndt (1993) and Silk and Berndt (1994) find economies scale and scope in the advertising agency industry.

[13]The big four advertising agencies include WPP, Publicis, Omnicom, and Interpublic.

[14]The estimates of total U.S. agency revenue comes from the Advertising Age that collects data from the biggest 1,000 agencies. http://adage.com/article/news/publicis-omnicom-group-facts/243346/, retrieved February 22, 2014.

that agencies will carefully guard their confidential information. The promise to prevent client information from leaking becomes particularly fragile when a client shares the same advertising agency as his product market competitors. One reason is that the information barrier within an organization is much lower than across organizations. The other reason is strategic: when there is a large prospective gain for an advertising agency that uses one client's marketing strategy to benefit his competitor, the agency may have an incentive problem in committing to protect confidential client information.

The second conflict concern is the negative impact on an advertising agency's performance when it is trying to maintain relationships with conflicting clients. One direct cost is the "Chinese wall" advertising agencies build to serve conflicting clients. This includes creating separate office spaces, separate staffs, and separate communication channels to reduce communication between teams of employees who work on competing accounts. Another indirect cost is that the agency may sacrifice efficiency for fairness where the agency balance resources devoted to competing clients.[15] Sometimes, maintaining such conflicting relationships is so costly that the agency is willing to let the less valuable client go.[16]

Conflict can also occur when clients compete for advertising agency's market-specific resources. For example, if an agency has only one expert in the client's field and can assign that expert to only one client due to the "Chinese wall," clients in conflict matched with the agency should expect a lower chance that they will benefit from access to that expert.

2.2 Advertising Agency Market for Pharmaceutical Advertisers

Pharmaceutical companies spend heavily on marketing. Marketing expenditures on pharmaceuticals amount to $26-36 billion annually, representing 9-12% of the total drug sales between 2002 and 2010 (Kornfield et al., 2013). Among other promotional activities, advertising agencies participate in direct-to-consumer (DTC) advertising, which accounts for 12-15% of their marketing spending. Ad-

[15] Anecdotal evidence can be seen in discussions of industry magazines. Marc Brownstein, president of the Brownstein Group, whose clients includes IKEA, eBay, and Comcast mentioned in the article he writes for the *Advertising Age* magazine that serving competing clients at the same time is "utopian". He argues that maintaining relationships with competing clients and keeping every party happy is very hard. See Advertising Age (2012), "Can We, Should We, Serve Competing Clients at the Same Time". Retrieved from http://adage.com/article/small-agency-diary/serve-competing-clients-time/235777/

[16] In 2012, Omnicom resigned its contract with Farmers Insurance just weeks after winning the account when its other client State Farm, "a much bigger client by marketing spending", learned about Omnicom's new relationship with Farmers. See Advertising Age (2012), "Farmers Insurance, Omnicom's PHD Part Ways Due to Client Conflict". Retrieved from http://adage.com/article/agency-news/farmers-insurance-omnicom-s-phd-part-ways-due-conflict/237158/

vertising agencies also collaborate with pharmaceutical companies on promotional activities aimed at providers (e.g., journals, meetings and conference), which account for another 27-32% of the total marketing spending, which excludes face-to-face sales representative detailing. As a result, around $10-16 billion of pharmaceutical advertising spending is billed through advertising agencies annually.

Two features of the matching between drug advertisers and advertising agencies facilitate the study of conflict. First, product market competitors can be defined precisely. I define that clients are competitors if they seek advertising agencies to advertise for the same treatment indication (e.g. high cholesterol). The second feature is that drugs manufactured within the same company usually have independent marketing teams. This practice is also confirmed in the data. The advertising agencies hired by different drugs manufactured by the same pharmaceutical firm are not clustered. For example, in 2009, AstraZeneca has 22 drugs hiring advertising agencies, and the drugs hired 13 unique agencies; Sanofi-Aventis has 39 drugs hiring 17 unique agencies; and Pfizer has 70 drugs hiring 32 unique agencies. This practice allows me to model the each drug (advertiser) as the decision maker without worrying about the complementarity in the matching decision for different drugs within the same manufacturer.

In terms of commissions paid by drug advertisers to advertising agencies, I assume in the model that the commissions are determined endogenously by the bargaining rules between drugs and advertising agencies. In earlier years, the advertising industry's fee model compensated advertising agencies with 15% of the total billing, but since the late 1990s, the advertising agency fee model has gradually increased the proportion of incentive pay in the total amount of fee. Hence, it is reasonable to assume that the commission is not a fixed percentage of the billing.[17]

2.3 Data

2.3.1 Data Sources

I collect data on (1) matches between drug advertisers and advertising agencies, (2) drug advertisers and advertising agencies characteristics, and (3) the organizational structure of advertising agencies between 2002 and 2010.

I compile data on matches from advertising agency surveys conducted independently by two industry magazines, *Pharmalive* and *Medical Marketing and Media*, and one data vendor, Advertis-

[17] In 2003, advertising agencies' total revenue represented approximately 13% of the capitalized billings from clients (Horsky 2006).

ing Redbooks. To my knowledge, *Pharmalive* and *Medical Marketing and Media* are novel sources of data used for researching relationships between drug advertisers and advertising agencies. Each conducts annual surveys on US advertising agencies with a major client base in healthcare.[18] Advertising Redbooks (also known as the Standard Directory of Advertising Agencies) is a comprehensive data source on advertising agency characteristics and clients and has been used previously in research on advertising agencies (Horsky (2006); Rogan (2013)). The Redbooks data are used to complement the list of non-healthcare advertising agencies that form matches with drug advertisers.[19] Data on matches contain information on names of drugs and agencies that have a contract at a given year, the year the match was first established, and the specific treatment indication (e.g. High Cholesterol, Crohn's Disease) of the drug advertised.[20]

Conflict is defined as the situation in which advertisers for drugs of the same treatment class hire the same advertising agency in the same year. To define treatment class, I obtain class information from the Medical Expenditure Panel Survey (MEPS) and Drugs.com, both of which use the coding system provided by Cerner Multum.[21] For any drug advertised for multiple indications, I only keep the major indication.[22]

In addition to treatment class, I collect information on drug approval date from the FDA Orange Book and DTC advertising expenditures from the Kantar Media. I also construct a US blockbuster drug indictor with a dummy set equal to one if the drug was ranked in the top 200 in annual US sales, based on yearly information from IMS Health by way of Drugs.com.

An important component in the data construction is deciding at what agency organization level the clients' concerns about conflict are relevant (i.e., whether product competitors only avoid

[18] To ensure that the list of agencies working for pharmaceutical companies is comprehensive, I compare the agency data separately collected by the two industry magazines and find that their coverage overlaps and includes a similar list of 100 healthcare agencies.

[19] Although Advertising Redbooks is a standard data set for studying client-agency relationships, the documentation for matches between drug and advertising agencies is much less complete compared with data sourced from the industry magazine. Redbooks usually lacks information on product name (e.g., Lipitor) and only records the advertiser's name (e.g., Pfizer). It misses many healthcare specialized agencies, and it does not include information on when the account was first established.

[20] One caveat of the match data published by the above sources is that it lacks detailed documentation of the types of advertising services engaged for each drug-agency pair. Most of the services are marketing project assignments aimed at reaching consumers and healthcare professionals. In these instances, conflict is a concern. But there are also accounts for which conflict is not a major consideration when forming matches, such as media-buying agencies who pools clients' accounts together in order to negotiate better media prices. For this reason, I exclude media-buying agencies.

[21] I do not use drug indication provided by *Pharmalive*. Although they are available, they are usually narrow and the codings of disease names are not comparable across drugs.

[22] Drug characteristics are collected at the drug level rather than at the drug-treatment level: I collect the FDA drug approval date for the main treatment indications, but not for the minor treatment indications, so I drop matches indicating advertising for minor indications.

contracting with the same advertising agency, or if they also avoid contracting with agencies that are associated via a parent holding company). This consideration is especially relevant in the advertising industry since many advertising agencies exist in a tree-like organizational structure in which advertising agencies are affiliated with one giant parent holding company (e.g., Publicis and Omnicom), and the agencies themselves have branch offices in different locations (King III et al., 2003). The effect of conflict may be underestimated if conflict is defined at the holding company level when clients, in fact, only care about conflict within an agency. Conversely, the conflict effect may be overestimated if conflict is defined at the agency branch level. In principle, the conflict concern depends on how closely different units within the holding company are related in terms of communicating and decision-making.

I choose to define conflict at the level of the brand name agency, which is one level below the advertising holding company. The rationale is that brands within the same holding company run their own websites, on which they make account-winning and award-winning announcements under their own brand names. Industry news sources often quote agencies using their brand names, and agencies within the same holding company sometimes compete for the same client.[23]

As an example of the construction, I treat Area23, DraftFCB, McCann, and ICC Lowe as unique advertising agencies even though they are all directly affiliated with the holding company Interpublic. But I do not treat branch offices under the same brand name as independent agencies. So I treat ICC Lowe Pace, ICC Lowe Thermal, and ICC Lowe Trio as the same agency, ICC Lowe. I determine organizational structures and affiliations using the Corporate Affiliation data of Thomson Reuters, bundled with Redbooks.

Lastly, to identify organizational change, I collect merger information on all advertising agencies using the advertising agency SCI code 7311 and the data sources Bloomberg, CapitalIQ, and SDC Platinum from 2001 to 2011.

2.3.2 Sample Construction

I treat each treatment class in a given year as an independent matching market since advertising agency contracts are reviewed and renewed annually. I construct data on prescription drugs and agencies, their characteristics, and their matching statuses each year between 2002 and 2010.

More specifically, I first determine the set of drug advertisers that potentially seek matches in a given year and treatment class. In theory, any prescription drug advertiser may conduct marketing

[23] The data sources on drug-agency relationships are also most comprehensive at the brand level as defined above.

activities and consider hiring an advertising agency for assistance. But since a complete directory of all drugs currently marketed for each treatment class is not available, I compile the list of likely-to-match drugs using two criteria: a drug is included if it has ever appeared in the Medical Expenditure Panel Survey (MEPS)'s Prescribed Medicines File between 2002 and 2010, or if it has appeared in the DTC advertising data between 1996 and 2011.[24] This twofold inclusion criteria allows me to capture drugs that are either commonly prescribed by doctors or explicitly advertised to consumers. Drugs missing from my sample tend to be those that treat rare diseases. In that case, the entire treatment class is not included in my sample. There are also drugs with small and niche consumer bases that are captured by neither MEPS nor DTCA data. If such drugs also hire advertising agencies, I assume that they are not good substitutes for mass market drugs in their classes and hence do not impose conflict concerns.

To be conservative, I assume drugs may start looking for advertising agencies 5 years before surplus market approval. In the data, I observe that about 10% of the matches were formed by drugs before they get the FDA approval.[25] Majority of them have started hiring agencies up to 5 years before market approval.[26]

To determine the set of agencies that potentially serve a treatment class, I include all agencies that have ever done advertising work for any drug in the treatment class. Agencies that are newly formed during the sample period are assumed to have started serving the treatment class from the first year of their establishment. I assume that an agency has exited the market when it stops being observed in any data set that I use to compile matching and agency information in a given year.

2.4 Market Descriptive Statistics

There are an average of 627 unique prescription drugs in 152 treatment classes to be matched in each year between 2002 and 2010. The mean number of drugs in a treatment class market is 4, with a maximum of 28. Among the 1,214 class-years in the data, 46% of the treatment classes have only one drug in a given year and do not have any potential conflict concerns.[27] As I mention in the data construction, I treat each agency brand as a unique agency. There are 149 unique advertising

[24] MEPS is a nationally representative survey of the U.S. civilian non-institutionalized population conducted by the Agency for Healthcare Research and Quality (AHRQ) and covers drugs prescribed to the general US population.

[25] Many pharmaceutical companies start to inform medical professionals about the existence of a promising new drug when it is in the last phase of clinical trials, so we observes in the data that drugs starts to hire agencies before it gets the FDA approval.

[26] During the period between 2002 and 2010, there were only 20 matches formed more than 5 years before the drug was approved.

[27] Although these drugs do not help identify conflict, they help to identify preferences of drugs and agencies.

agency brands in the sample, and each agency can work in multiple markets, generating a total of 1,525 unique agency-class combinations in the sample. The mean number of agencies in a treatment class market is 8, with a maximum of 38.

Table 1 summarizes the size of each class-year, the number of matches formed, and the number of conflicts. On average, a class-year contains 4-5 drugs and 8 agencies. In a typical class-year, 68% of the drugs and 46% of the agencies find at least one match in the market, which results in around 4-5 matches per class per year. The median size of the market is small with 2 drugs and 5 agencies. But for the 300 classes that form the top quartile in terms of market size, each class has more than 6 drugs and 11 agencies. Drugs can match with more than one agency in a market. Restricting the sample to only those drugs that obtain at least one match, the mean number of advertising agencies a drug hires is 1.6. Of all the drugs seeking matches, 59% hire a single agency in a year, 25% hire two agencies, and 15% hire three or more agencies.

Agencies may also match with more than one drug in a market, which results in a client conflict. In a given market, 7% of agencies are involved in a conflict (roughly one agency in each class), and each conflict contains 2 drug advertisers, on average. An average of 2.5 matches, or 25% of all matches, are caught in conflict in a market. In the following descriptive regression, I will show which drugs and agencies are more likely to be matched and to be caught in conflict.

In addition to the static market statistics, Table 2 shows a high degree of state dependence among matches, which is commonly observed in vertical relationships. Among nearly 700 matches formed each year, around 73% of the drug-agency pairs will match with each other again in the next year. It should also be noted that the probability of match dissolution is similar regardless of how many years the relationship has been formed before. The probability of match dissolution appears independent of the relationship duration, remaining at a constant rate of 23 to 25 percent. This suggests that the value of preserving previous matches versus starting new matches is similar regardless of how many years the relationship has formed. Meanwhile, new drug-agency pairs form around 28% of all matches formed in a given year.

I use descriptive regressions to examine which drugs and agency characteristics are associated with a higher probability of forming matches. We expect that drugs have more incentives to hire agencies when they have a large marketing budget and when they conduct the types of promotional activities that they lack the specialty and resources to market on their own. For example, drugs often delegate DTC advertising, consumer and professional educational programs, and conference organization tasks to advertising agencies. And given that an advertising agency's capacity in dealing with each client is limited, we will also expect that a drug advertiser with a bigger marketing budget is also more likely to find it profitable to hire more than one agency. The lower panel of Table 3 presents simple comparisons by drug characteristics that do and do not hire any advertising agencies in a class-year and Table 4 shows the results of linear probability regressions of a drug's agency hiring decision. Both tables confirm the expectations. A drug that spends more on DTC advertising, in particular DTC advertising on TV, and a drug approved by the FDA and enjoying market exclusivity[28] is more likely to hire one or more advertising agencies. The result is similar if I compare across drugs in column (1), or within drugs in column (2) of Table 4.

I also examine whether drug advertisers with a larger marketing budget hire more agencies. (See columns (3) and (4) of Table 4.) Conditional on having any match in a given market, I regress the dummy variable of a drug having multiple matches on drug characteristics. Both regressions, with and without drug fixed effects, show that drugs with higher levels of DTC advertising and drugs that are between approval and patent expiration are more likely to hire multiple agencies.

The summary statistics in the upper panel of Table 3 and linear probability regressions of Table 5 compare the characteristics of advertising agencies that are hired or not hired in a market. The differences in characteristics are very small, and regression results are weak with a small R^2 of 0.01 if I do not control for agency fixed effects. The signs of the differences are still as expected: an advertising agency with a bigger size in terms of total billing and total number of employees is more likely to get matches, and more likely to have conflicting clients. In addition, an agency claiming consumer specialty is less likely to get a match, and an agency claiming specialty in handling health accounts is more likely to get a match. This is reasonable because advertising agencies with a consumer focus usually only deal with a few blockbuster drugs for which they create TV ads, but do not targets pharmaceutical clients in general.

In tracing the identity of the advertising agencies, I also identified nine merger cases that affect 20 advertising agencies in my sample period. Although the number of mergers is small, the agencies involved in the mergers worked in a wide range of treatment classes, and a single merger affects many classes at the same time. During the sample period, treatment classes that have ever had an advertisings agency affected by the mergers is 127, or 80% of all classes. Counting the number of class-years that are affected by an agency at the year of its merger, 389 are affected. And if counting all class-years with a merged agency post its merger event, there are 826 such class-years, or 54%

[28] Patent expiration data is approximated by 12 years as documented in the literature. The publicly accessible FDA Orange Book is incomplete in dating the exclusivity period for each individual drug in my sample.

of all class-years in sample. This gives us enough variation to identify the average merger effect of matching surplus.

3 Model Framework

To allow both drug advertisers and advertising agencies to choose whether to sign a contract, I analyze their choice problem using a two-sided matching model. Because advertising agency commissions are negotiated in the contracting process, I allow side payments to be endogenously determined in the matching game. In this section, I outline the model and necessary assumptions, I then establish that the socially optimal allocation belongs to the set of pairwise stable equilibrium of this model. Using pairwise stable equilibrium, I will derive conditions that characterize the equilibrium and use them to identify and estimate the model.

3.1 Model Setup

I define a matching market as a treatment class in a given year in which drugs and advertising agencies seek matches. I assume that each side of the market fully observes the characteristics and preference shocks of all drugs and agencies. Each drug and agency maximizes its own surplus for the current period. I also assume that agency decisions are independent across treatment classes. Because these two assumptions imply independence of agent decisions across markets, I will focus on a single market in the following analysis.

There are m drugs in the market, indexed by $i = 1, .., m \in I$ and n advertising agencies, indexed by $j = 1, .., n \in J$. Each drug can hire multiple agencies and each agency can serve multiple drugs. A *matching* μ is a mapping from the set $I \cup J$ into the set of all subsets of $I \cup J$, where $\mu(i) \in 2^J$ and $\mu(j) \in 2^I$, and $i \in \mu(j)$ if and only if $j \in \mu(i)$. Denote $\mathcal{M}$ as the set of all possible matchings.

Denote the transfer that a drug i pays to an agency j as t_{ij}. I can write the drug and agency surpluses illustratively as

$$
\begin{aligned}
S^i(i, j|\mu) &= y(X_i, Z_j) - \kappa_f - t_{ij} + \epsilon_{ij}^i \qquad (1) \\
S^j(i, j|\mu) &= -\mathbf{1}(|\mu_j| > 1)\kappa_c + t_{ij} + \epsilon_{ij}^j \qquad (2)
\end{aligned}
$$

where $y(X_i, Z_j)$ is the expected return that drug i yields from advertising agency j's service based on observed drug characteristics X_i and agency characteristics Z_j. κ_f is the fixed cost associated with establishing a match, which I assume to be common across all matches. For simplicity, I will refer to $y(X_i, Z_j)$ as the "return of a match", and to $y(X_i, Z_j) - \kappa_f$ as the "net return of a match". κ_c is the cost incurred when the pair (i, j) is involved in a client conflict. I assume κ_c is constant for any matched pair involved in a conflict. Conflict arises when an agency serves two or more drugs in the same market, that is, if $|\mu_j| > 1$. In the surplus function, I express that the conflict cost accrues to the agencies only for illustration; in the equilibrium I define, matching will depend only on the total net surplus, and not on which side pays the conflict cost. ϵ^i_{ij} and ϵ^j_{ij} are match specific preference shocks observable to all agents in the market, and shocks to drugs and to agencies are each distributed $i.i.d$ across all possible match pairs.

I make modeling assumptions as follows:

Assumption 1 Each drug and agency's total surplus is a simple summation of surplus from all matches the drug and agency obtain, i.e.

$$S_i = \sum_{j \in \mu(i)} S^i(i, j|\mu), \;\; S_j = \sum_{i \in \mu(j)} S^j(i, j|\mu). \tag{3}$$

More specifically, the model assumes that, for each drug, there are no complementarities among the set of agencies it hires. In particular, drug preference is responsive and satisfies substitutability given matching allocation of its competitors. However, preference of advertising agencies is not substitutable,[29] which may challenge the existence of a stable equilibrium in a usual matching setting.

Assumption 2 When agents make matching decisions, externalities arise only through client conflict.

It is common to expect that drug advertisers' surpluses may be influenced by externalities arising from product market competition. For example, one drug's advertising effort may affect his competitors' product revenue. This model does not preclude this type of externality, but it assumes that this type of externality does not interact with the characteristics and identity of the advertising agency, and hence does not affect matching choices. More specifically, think of the overall drug-agency matching and advertising production process as a two-stage game. In

[29] Consider the following example in which agent preference fails substitutability. For illustration, let advertising agencies have full bargaining power and let drugs obtain reservation value. Assume that an advertising agency obtains net return of 10, 4, 4 with drug D_1 , D_2 and D_3, and that the conflict cost for each matched pair is 2.5. If the agency is given the set $\{D_1, D_2\}$, it will choose to match with D_1 alone, which gives a surplus of 10, rather than matching with both drugs, which gives a total surplus of 9. When given the set $\{D_1, D_2, D_3\}$, the agency will choose the full set of drugs, which yields a surplus of 10.5. Hence the $\{D_1, D_2\}$ is chosen only when D_3 is chosen.

the first stage, drugs and agencies take preference draws, form expectations about the returns of possible matching opportunities, and decide what contracts to propose and to accept to maximize their expected surplus. In the second stage, the matches are formed and each drug's advertising strategy is determined based on his competitor's strategies. However, I assume that strategic interactions between drugs in the second stage are not affected by the first-stage hiring decisions. This assumption is made based on the literature that argues that relational characteristics, such as identity and impression, are important in determining relationships (Morgan and Hunt (1994), Alvesson (1994)). This is not surprising, given that the effectiveness of an advertising agency is hard to predict. So choices made at the matching stage can be perceived as drugs and agencies seeking matches that minimize the cost of doing business.

Assumption 3 The capacity constraints for both drugs and advertising agencies do not bind.

Given that the number of matching opportunities that yield positive returns is limited in a market, this assumption suggests that drugs and advertising agencies are willing to add a match as long as the additional match increases the total surplus of the agent. In fact, I can relax this assumption to allow the market-specific capacity constraint for advertising agencies to bind since conflict cost is a form of constraint on an advertising agency's ability to take on more drugs in given market. On the drug side, a capacity constraint can appear as an increasing cost for the drug to match with additional advertising agencies. I estimate a version of the model that allows a matching cost to increase as a drug takes on additional agencies. The result shows that, for a given drug, each additional match slightly reduces, rather than increases, the matching cost, but the magnitudes are very small, suggesting that capacity constraint for drugs is unlikely to bind.

3.2 Equilibrium Characterization

In the following section, I define the socially optimal allocation, and show that it can be implemented by pairwise stable contracts given the model setup.

For notation compactness, I follow contract notations in (Hatfield and Milgrom, 2005). Denote a bilateral contract between an drug-agency pair (i, j) as $a_{ij} = ((i, j), t_{ij})$. a_{ij} contains two elements. The first element describes the match between a pair of agents from each disjoint set that signs the contract, $a_I = i$ and $a_J = j$, where it corresponds to the prior notation of $i \in \mu(j)$ and $j \in \mu(i)$. The second element describes the transfer t_{ij} paid from drug i to agency j. Only one contract can be signed between i and j. An market allocation $\mathcal{A}$ is a collection of contracts that specify matching allocation over all agents and a set of transfers, $\mathcal{A} \equiv I \times J \times T$. Given a set of contracts $A \subset \mathcal{A}$, I denote $Ch_i(A)$ as the most preferred subset of contracts chosen by drug i among contracts that names i as a partner ($a_I = i$), and I denote $Ch_j(A)$ as the most preferred subset of contracts chosen by agency j among contracts with $a_J = j$.

Definition 1 A *socially optimal allocation* is a matching $\mu \in \mathcal{M}$ that maximizes the aggregate social surplus of all matches:

$$S(\mu) = \sum_i \sum_{j' \in \mu(i)} S^i(i, j') + \sum_j \sum_{i' \in \mu(j)} S^j(i', j).$$

This concept only considers the total surplus generated from each match, ignoring any transfers designated in the contact. Note also that, in the market I define, there is no capacity constraint on how many matches an agent can obtain. However, the socially optimal allocation does not imply that every possible pair of matches will be formed. Adding an additional match is costly for two reasons. The first cost is the cost of forming a match (κ_f) common to all matches. The second cost is the cost of conflict if an additional match increases the amount of conflict in the market. So at the socially optimal allocation, any additional match will only reduce the total surplus.

Definition 2 A set of contracts $A \subset \mathcal{A}$ constitutes *a pairwise stable equilibrium* if

(i) $Ch_I(A) = Ch_J(A) = A$, and

(ii) there does not exist a drug i and an agency j' and a new contract $a' = ((i, j'), t_{ij'})$, $a' \notin Ch_i(A)$, such that

$$a' \in Ch_i(A \cup a') \subset Ch_J(A \cup a')$$

(iii) there does not exist an advertising agency j and a set of contracts $a'' = ((i', j), t_{i'j})$, $a'' \neq Ch_j(A)$ such that

$$a'' \in Ch_j(A \cup a'') \subset Ch_I(A \cup a'').$$

Condition (i) for the pairwise stable equilibrium says that the equilibrium set of contract A is the best subset of contracts among those assigned to them in A, or that each agent is unwilling to drop the contract(s) it has at hand according to allocation A. Conditions (ii) and (iii) stipulate that, given allocation A, an agent cannot construct a new contract with an opponent it is not contracting with that makes the agent strictly better off and all other agents weakly better off.

Claim Given the above-defined surplus function S and all possible matchings $\mathcal{M}$, if a matching μ^* is socially optimal, there exists a set of contracts $A \subset \mathcal{A}$ that is pairwise stable and implements μ^*.

Proof Assume that advertising agencies have full bargaining power. The proof will proceed as follows: Given a matching μ, I will show that the set of transfers is endogenously determined by the bargaining rule, so each allocation A is reduced to a matching μ and the agent surplus can be written as a function of matching μ. I will then prove by contradiction that the social stable allocation μ^* is pairwise stable.

Since drugs are not capacity constrained and they evaluate contracts with different advertising agencies independently, when agencies have full bargaining power, each drug will accept a contract as far as its surplus is higher than that drug's reservation value for a contract, R. So for a given matching μ, $S^i = R$ and $S^j = \sum_{i \in \mu(j)} S(i,j) - |\mu_j| R$.

Let μ^* be a matching that is not pairwise stable. If μ^* violates assumption (i), or that

$$\sum_{i \in \mu(j)} S(i,j) < \sum_{i \in \mu(j) \setminus \{i'\}} S(i,j),$$

dropping i' from $\mu(j)$ improves surplus for j and does not affect other agents' payoffs, so μ^* is not socially optimal.

If μ^* violates assumption (ii), then there exists a pair (i',j), for which $i' \notin \mu(j)$ and

$$S(i',j) = R,$$
$$\sum_{i \in \mu(j) \cup i'} S(i,j) - (|\mu_j| + 1)R > \sum_{i \in \mu(j)} S(i,j) - |\mu_j| R.$$

By adding (i',j) to the current allocation μ^*, the social total surplus strictly increases, and therefore, μ^* is not socially optimal. Hence by contradiction, there exists a transfer schedule such that the socially optimal allocation is pairwise stable.

One of the key assumptions that leads me to this simple proof is that drug advertisers have no binding capacity constraint and make independent decisions on forming matches with each agency. Moreover, I use the assumption that advertising agencies have full bargaining power to make agencies internalize the externality of conflict.

To determine key characteristics of drug and advertising agency matching market, I allow features of the matching model to differ from canonical models of matching with transfers (Shapley and Shubik, 1971) and matching with contracts (Kelso Jr and Crawford (1982); Hatfield and Milgrom (2005)). In order to maintain model stability and obtain identification from the data I observe, I make the simplification assumptions discussed in the last section. Next, I will discuss further some of the model assumptions and their implications.

Firstly, in classical matching models, substitutability is the key concept that allows characterization of the one-to-one and many-to-one stable matchings by the fix-point set, and hence by a lattice(Adachi (2000); Hatfield and Milgrom (2005)), and it is also extended into the many-to-many settings (Echenique and Oviedo, 2004). In my model, substitutability fails because of the simple assumption that conflict cost does not change with the number of matches in the conflicting relationship. One could argue for defining the conflict cost such that it increases at some minimum rate when the number of conflicting drugs matching with an advertising agency increases. However, in an unreported version of the estimation, I allow the conflict cost for each drug in the conflicting relationship to rise when the number of conflicting drugs increases. The coefficient on the change of conflict cost is not significant, which rejects the above argument. Examples in the literature show that the situations in which stability fails in the absence of substitutability occur when agents on both sides of the market are capacity-constrained.[30] Lifting capacity constraint solves the problem since it makes an agent's decisions to match with each opponent independent. This does not get rid of all interesting externalities in the market, because advertising agency's decisions of which drugs to take are not independent because of the conflict.

Since transfers are not observed in the model, the concept of a socially optimal allocation allows me to identify preferences by focusing only on the matching allocation. Assuming away capacity

[30]The singular preference is the key where stability fails in the example given by Hatfield and Milgrom (2005). Assume that there are two hospitals h_1, h_2 and two drugs d_1, d_2. Preference of h_1 fails substitutability that $\{d_1, d_2\} \succ_{h_1} \{d_1\} \succ_{h_1} \emptyset \succ_{h_1} d_2$, assume also that h_2 has singular preference and $\{d_2\} \succ_{h_2} \{d_1\} \succ_{h_2} \emptyset$. Both doctors have singular preference: $\{h_2\} \succ_{d_1} \{h_1\} \succ_{d_1} \emptyset$ and $\{h_1\} \succ_{d_2} \{h_2\} \succ_{d_2} \emptyset$. Assume a matching A_1 in which both d_1 and d_2 are matched with h_1, and h_2 is unmatched. The pair (d_1, h_2) can block A_1, and forms the new matching A_2 in which d_1 is matched with h_2 and both d_2 and h_1 are unmatched. The pair (d_2, h_2) blocks A_2 and form a matching A_3 in which d_2 and h_2 are matched and d_1 and h_1 are matched. The pair (d_2, h_1) blocks A_3 and the matching is back to A_1. Hence stable matching does not exist.

constraints also plays a role in identifying the cost of conflict without needing transfer information. This will become clear when I discuss the model identification.

Secondly, note that the above proof shows that socially optimal matching can be characterized by pairwise stable equilibrium. However, socially optimal matching is not the only pairwise stable equilibrium. For example, in the non-substitutability example I gave in according to footnote 27, advertising agency j's preference, is $D_1 = Ch_j(D_1, D_2)$, $D_1 = Ch_j(D_1, D_3)$ and $(D_1, D_2, D_{3)} = Ch_j(D_1, D_2, D_3)$. Agency j's matching with D_1 is pairwise stable since neither pairwise deviation between (A_j, D_2) or (A_j, D_3) can block (A_j, D_1), but it is not socially optimal. However, socially optimal matching is setwise stable since D_2 and D_3 together can block (A_j, D_1). Although non-unique pairwise stable equilibrium can arise in this model, I assume that the socially optimal allocation is reached since it is robust to setwise deviations.

Thirdly, another feature of the model that arises from conflict externality is that a drug advertiser has preferences not only about the contracts that are assigned to it, but also about contracts that are assigned to its competitors. Sasaki and Toda (1996) and Hafalir (2007) point out that in a matching game with negative externalities, the outcome of a stable equilibrium depends on agents' expectation of blocking matching allocations. In the stability definition above, I have made the behavioral assumption that each agent expects that other matches will remain the same if it deviates.

Fourthly, the static model has two implications. One is that drug advertisers only try to maximize the current period's surplus, and the other is that drugs and agencies will not make negative transfer payments or demand payments that exceed the surplus of the match.

Lastly, although I assume that agencies have full bargaining power in the proof of results, there could exist other mechanisms that produce socially optimal matching.

4 Model Estimation and Identification

I use the maximum score estimator proposed by Fox (2010) to estimate the matching surplus function by assuming that the observed matches in the data represent the socially optimal equilibrium. Using pairwise deviation conditions that characterize the socially optimal allocation and a rank order property, I identify the model by comparing the total surplus of observed matches to counterfactual matches following pairwise deviation.

4.1 Maximum Score Estimator

Applying pairwise deviation conditions to the socially optimal allocation, I derive a system of inequalities that can be used to estimate the surplus function without requiring transfer information. The objective function of the maximum score estimator is

$$Q(\theta) = \frac{1}{K} \sum_{k \in K} \sum_{\tilde{\mu}_k \in \tilde{\mathcal{D}}_k} \sum_{(i,j) \in \mu_k^e} \mathbf{1}\{S(i,j|\mu_k^e, \theta) - S(i',j'|\tilde{\mu}_k, \theta) \geq 0\} \tag{4}$$

where k denotes each independent matching market, K is the total number of markets, $\tilde{\mathcal{D}}_k$ is the set of pairwise deviation matchings from allocation μ_k^e , and μ_k^e is the equilibrium matching in market k. The objective function of the estimator is to find a parameter vector $\hat{\theta}$ to maximize the number of times that the observed equilibrium yields greater surplus than the pairwise deviated allocations based on deterministic characteristics of the model.

Given that agents in the markets behave according to the set of random preference shocks they draw and that the shocks are unobserved by the econometrician, surplus inequalities constructed based on deterministic characteristics are not guaranteed to hold. In order to apply the maximum score estimator, Fox (2010) proves a rank-order property that is key to model identification. The rank-order property states that the match allocation that yields higher surplus based on observables is more likely to be observed in the data, under the condition that the errors are *i.i.d.* distributed for each match. Denote A as the realization of matching allocation, W as the observable, S as the surplus function, and G as the stochastic structure of the model. The probability of the allocation A given observables W is

$$Pr(A|W; S, G) = \int_{\epsilon} 1(A|W, \epsilon; S) dG(\epsilon).$$

The rank order property states that

$$Pr(A_1|W; S, G) > Pr(A_2|W; S, G)$$

if and only if

$$\sum_{(i,j) \in A_1} S(i,j) > \sum_{(i,j) \in A_2} S(i,j). \tag{5}$$

With the rank order property, the estimator is constructed to punish the wrong prediction of inequalities based on the deterministic part of the surplus. The crucial assumption for identification using maximum score is that $\epsilon_{ij} = \epsilon_{ij}^i + \epsilon_{ij}^j$ is *i.i.d.* across all matches. Specifically, heteroskedastic errors based on match characteristics are not allowed.

Table 7 listed the full set of pairwise deviation conditions used. In general, the deviations are of three types. The first involves replacing one partner in the current match with another opponent. This type of deviation does not change the total number of matches in a market. The second type involves adding a new match, and the third type involves dissolving a current match. This list exhausts all possible pairwise deviations. In estimation, I use all inequalities derived from these deviations.

My model setup, combined with the ability to observe all agents in the market, allows me to use a larger set of inequalities than that used in Fox (2010). These inequalities also help me to identify the impact of agent-specific characteristics. One major difference in my model setup from classic matching models is that I assume away capacity constraints for drugs, hence removing competition among advertising agencies contracted by drug advertisers. This assumption allows a drug marketing team's decision to add or drop a match to be independent of its decisions about other matches. Hence, inequalities based on unilateral deviation of a drug does not concern transfers. Such inequalities cannot be constructed by the model in Fox (2010) or in matching models with capacity constraints since a one-sided deviation involves an agent exceeding its quota of matches. To construct such a deviation, one needs to know the transfer paid to one agent in order to induce it to replace a partner.

There are two main advantages to using maximum score estimation in my setting. First, the maximum score estimator is free from error distribution assumptions, so it avoids the concern that misspecified error in choice models could lead to inconsistent estimators (Hausman et al., 1998). It is particularly useful in analyzing vertical relationships since the errors may be asymmetric. Given that vertical relationships are observed to be persistent, the adverse shock must be large to dissolve the relationship without sharp changes on observables. This suggests that an error may be associated with large downside risk disproportional to upside shocks in size. Without strong ex-ante information about the error distribution, maximum score estimation is preferred to making parametric error assumptions. I calibrate the error distribution assuming a mixture of two normal distributions, and I find that the distribution is bimodal, with one normal distribution having a much more negative mean than the positive mean of the other normal distribution. Second, maximum score estimation does not require solving the matching model fully. When the number of participants in the markets is large, the maximum score estimator reduces the computation burden relative to parametric models.

The estimation approach of using preference inequalities is known to lack point identification if there is not a match-specific densely distributed continuous variable. Although I include agency size as a continuous variable in the model, I do not have a comparable densely distributed variable for drugs, so I can only set-identify the parameters. In order to conduct inference, I estimate confidence regions for set-identified parameters following Shaikh (2006) and the estimation manual of Santiago and Fox (2008).

4.2 Model Specification

Descriptive regressions in section 2 show that some drug and agency characteristics are important for predicting matches, that past matching relationships matter, and that conflict may affect the match surplus. Assuming linearity in parameters, I specify the matching surplus function of an advertiser-agency pair as

$$S_{ij} = X_i\alpha + Z_j\beta + X_iZ_j\gamma + \lambda L_{ij} - 1(|\mu_j| \geq 2) \times \kappa_c - \kappa_f + \epsilon_{ij}$$

where X_i is a vector of drug characteristics, including drug life-cycle, an indicator for DTC advertising and DTC TV advertising, and an indicator if the drug was a top-200 selling prescription drug in the US in the previous year. I use an indicator of whether a drug does direct-to-consumer advertising for the current period because I assume that the drug advertiser has decided if it will do any DTC advertising before forming matches.[31] Z_j contains characteristics of the agency, including number of employees, total billing, age, and claimed specialty in the past year. I use agency information for the previous year since this is the information drug advertisers have when making matching decisions. Also, I include the interaction between drug and agency characteristics to determine whether synergy is created when drugs and agencies of specific characteristics match together.

Z_j also contains information on agency mergers. Since I do not explicitly model the endogenous merger decision, I add a dummy to control the unobserved differences of merging agencies in contributing to the match surplus. I add one dummy variable for an advertising agency that has ever had a merger during the sample period, and another dummy variable for an advertising agency during periods after its merger. Adding merger dummies to capture the unobserved synergy also prevents me from over-stating the adverse effects of mergers in the counterfactual analysis.

[31] One can argue that drug's observed current year advertising spending depends on if the drug is matched to an agency, and is endogenous. I also tried in the reduced form to include the previous year's advertising spending, assuming that past spendings predicts the amount the drug plans to spend in the current year. The results are similar.

Although mergers reduce matching opportunities, synergy makes each matching opportunity more attractive and hence could lead to more matches and matches with higher surplus. Endogeneity of merger decisions could lead to an over-estimation of merger synergy since only advertising agencies that stand to gain decide to merge. Since I argue that mergers reduce total surplus by reducing matching opportunities, if endogeneity of mergers is a concern, mergers' adverse effects on total surplus will only be understated in the counterfactual analysis.

From the persistence of contract, it is expected that preserving a match formed by partners matched in $t-1$ is much more valuable than a match formed by new partners in period t, so a dummy L_{ij} is added that is equal to 1 if $Match_{ij,t-1} = 1$. In some specifications, I inspect whether the value of past matches differs for matches with different advertising agency and drug characteristics by interacting L_{ij} with X_i and Z_j.

Matching cost is denoted as κ_f and is common across matches. Conflict cost is denoted as κ_c. Given that previously formed matches play an important role in predicting matches, I also interact L_{ij} with conflict to examine whether it is more or less costly for previously formed matches to be caught in conflict compared to newly formed matches.

4.3 Identification

To restate the key identifying assumption, I assume that errors are drawn independently from the same distribution. This assumes away heteroskedastic error, and the concern that there may be unobservables correlated with the controls.[32] In addition, assumptions made on the matching model are maintained in the estimation for identification.

The maximum score estimator applies the idea of revealed preference: the match allocation we observe in the market is more likely to yield higher aggregate surplus than alternative allocations. This suggests that the characteristics more often observed in the matches are likely have a positive impact on the match surplus. By checking each type of deviation from the observed equilibrium, the estimator compares the relative effects of the sets of characteristics affected by the deviation. In the following section, I explain the pairwise deviations derived from the surplus optimization conditions and show how different sets of deviations help identify different parameters of the model.

[32] One advantage of using inequalities that only involve the comparison between different matching opportunities is that this allows for the presence of market level unobservables that might be correlated with the controls. Depending on the set of inequalities used, we can even allow agent-specific unobservables when they are differenced away with the construction of inequalities. However, in order to recover all parameters for the counterfactual exercise, I need to use inequalities that compare opportunities of being matched with unmatched, and hence need to make a strong exogenous assumption.

Comparisons of surpluses between observed allocation and deviation should be written in expectation. For convenience of illustrating which coefficients are identified from different sets of deviations, I will only focus on the deterministic part of the surplus function.

The cost of conflict is identified when a deviation causes the number of matches formed by an advertising agency to change. For example, consider the deviation in which a drug i replaces one of its hired advertising agencies $j \in \mu(i)$ with another agency $j' \notin \mu(i)$, causing a change in the amount of conflict. The change in total surplus is illustrated in the following formula,

$$(Z_j - Z_{j'})\beta + X_i(Z_j - Z_{j'})\gamma + \lambda \Delta L_i + \Delta ConflictCost \geq 0$$

where $\Delta L_i = Match_{ij,t-1} - Match_{ij',t-1}$, and

$$\Delta ConflictCost = \begin{cases} 0 & if\ N_j = 1, N_{j'} = 0\ or\ N_j \geq 2, N_{j'} \geq 2 \\ \kappa_c & if\ N_j = 1, N_{j'} \geq 2 \\ 2\kappa_c & if\ N_j = 1, N_{j'} = 1 \\ -\kappa_c & if\ N_j > 2, N_{j'} = 0\ or\ N_j = 2, N_{j'} \geq 1 \\ -2\kappa_c & if\ N_j = 2, N_{j'} = 0. \end{cases} \tag{6}$$

In this type of deviation, the relative value (cost) of agency characteristics, agency and drug synergy, matches formed in the past, and conflict is identified. The above comparison between equilibrium and its deviation illustrates the properties associated with the identification from preference inequalities.

First, because of the sign of the conflict cost and the sign of the inequality, I must identify the upper and lower bounds of the conflict cost using different inequalities. For example, assume that the conflict is indeed costly and has a negative impact on surplus. I identify the lower bound of the magnitude of the conflict cost when the amount of conflict increases in the deviation, and I identify the upper bound of the absolute value of conflict cost when the amount of conflict decreases in the deviation. So it is necessary to include full sets of inequalities to identify both bounds.

Second, note that the one-sided deviation is necessary to identify conflict cost. If deviation involves two pairs of matches switching partners with each other (as in Fox (2008)), it causes no change in the number of drug advertisers an advertising agency works for and does not help identify conflict.

Third, it becomes clear in the inequality that the model can only be identified up to scale. Mathematically, scaling all coefficients up or down does not change the probability of the allocation being observed. Intuitively, I can only measure the relative effect of the impact of different characteristics on the match surplus. In the estimation, I choose to normalize coefficients by $||\theta|| = 1$.

The above deviation also hints at which coefficients are not identified if I focus only on a subset of the inequalities. Switching the advertising agencies a drug hires only involves changes in agency characteristics, and the drug's own characteristics are not identified since they are differenced away in the inequalities. Intuitively, the impact of drug characteristics on surplus can only be identified when deviation involves replacing a drug. I am also unable to identify the cost of matching since there is no change in the total number of matches formed. I can only identify the cost of matching by adding or dropping matches from the equilibrium.

The absolute "location" of the surplus function is not identified, but it is relative to the outside option of not forming a match. To be precise, when I discuss the benefits and costs of forming matches, these are actually the benefits and costs of forming matches relative to the outside option. For example, since the "cost" per match κ_f is the constant term for the surplus function, it represents the net cost (benefit) of forming a match relative to the outside option for the baseline match.[33] As for the coefficients on other characteristics involved in a match, I interpret them as the effect of each characteristic on the net surplus relative to the outside option of a match. In the case of a positive coefficient, for example, the model cannot separately identify whether the effect comes from increasing the relative value of a match or decreasing the relative cost of a match.

5 The impact of Conflict on Surplus

In this section, I first present suggestive evidence of the existence of conflict using reduced form regressions and then present the conflict parameters estimated in the structural model.

5.1 Descriptive Evidence on Conflict

I run descriptive regressions to look for evidence that matches are less likely to form when two or more drug advertisers in the same class contract with the same agency.

Ideally, I can condition on each drug's probability of forming a match and examine whether one drug's decision to match with an agency is affected by its competitor's probability of matching with

[33] In the estimation, continuous variables are centered at their sample mean.

the same agency. However, intention to match is not observed; only matches formed in equilibrium are observed. Replacing the intention to match with observed matches obviously causes endogeneity. In the same spirit but using a slightly revised regression, I define that a match with an agency causes "potential conflict" when the agency was observed to match with the drug's competitor in the previous period. When errors are not temporally correlated, matches in the past period are uncorrelated with error in the current period. Also, if an agency matched with a drug in the previous period, about 73% chance this match will form again, so the potential conflict defined in the past period is likely to be a good predictor of potential conflict in the present.

In the regression, I pool all possible matching opportunities between drugs and agencies in each class-year and use the linear probability model to describe which characteristics are associated with a higher probability of matches. Besides "potential conflict," I include the same set of controls as in the structural specification, including characteristics of drugs and agencies and past match relationships. The evidence in Table 8 is robust to adding heterogeneous effects of previously formed matches.

Table 8 also shows heterogeneous impacts of previously formed matches on current matching choices. Specifically, results show that matches with certain drug and agency characteristics are associated with a higher probability of matching again the next period, the implications of which fit both a story of sunk cost and one of value created in the previously formed relationship. On the one hand, matches with drug advertisers utilizing DTC and DTC TV spending are more likely to continue relationships with agencies, which can be explained by the high sunk cost association with TV ad production.[34] On the other hand, matches with agencies with more employees are more likely to continue into the next year, which is consistent with a value creation story in which advertising agencies with larger teams may be more likely to provide a diverse and more effective service in the long term than the more specialized smaller agencies.

5.2 Maximum Score Estimates of Conflict

The baseline specification of surplus function includes drug and agency characteristics, merger indicators for agencies, and an indicator for previously formed matches. It also allows conflict cost to vary between previously formed matches and new matches. Given that the estimators

[34] The regression also suggests that drugs that haven't yet received FDA approval are more likely to continue their contracts. This may be driven by the censoring of the number of years drugs start looking for agencies before approval. Drugs on average will contract with an agency for 4 years (with match dissolution rate at about 27%), but the majority (90%) of observed matches are formed at less than or equal to 3 years before approval.

are identified up to scale, I choose to normalize coefficients by restricting the sum of coefficients squared to be one, or $||\theta|| = 1$, and exclude the coefficient for the indicator for the previously formed matches given the normalization restriction. Maximum score estimates for the baseline specification are shown in specification (1) of Table 9.

The cost of conflict is relative to the value of the matches. The value of preserving a previously formed match relative to the cost of forming a match with a new partner is the most important contributor to the match surplus. Comparing the midpoint of the estimates, the cost of conflict to a previously formed match relationship is equal to roughly 25% the value of such a relationship. Conflict is also costly in matches with new partners, but the magnitude is much smaller, at only 2% of the cost associated with the new relationship. Although the cost of conflict is large only for previously formed matches, these matches represent 72% of all matches. Conflict affecting these matches also plays an important role in determining the overall matching allocation as I will show in the counterfactual exercise.

It is not surprising that conflict is much more costly for previously formed relationships. One reason is that an advertising agency's knowledge about a drug advertiser grows quickly in the first year of the relationship, so the agency puts a greater amount of confidential information at risk when it signs with the established client's competitor. Drugs will be more worried about information leakage after the initial year of a contract than when the match was first formed. The other reason is explained in Rogan (2013). She finds that conflicts result in higher probabilities of client switching when the relationships have existed for a longer time because the advertiser's trust is betrayed when the advertising agency he previously worked with takes on his product market competitor.

Given the important role of previously formed matches in affecting current matches, I discuss two main explanations - sunk cost and match-specific unobservables - in the matching market between drug advertisers and advertising agencies. The persistence of contracts may result from the fixed cost invested in the initiation of a relationship, for example, the cost of learning about the product, becoming familiar with advertising regulations specific to the drug, and conducting consumer research. In other words, these investments also become relationship-specific assets accumulated in the previous contractual period (Riordan and Williamson, 1985). Another interpretation is that this captures the unobserved time-invariant match-specific heterogeneity specific to the pair. If this is the case, we should expect that the pair that matched in any previous period but not in the past period would have a higher probability of forming a match again than a pair that has never contracted before. However, I do not find such evidence in the data. The probability of a pair that matched in the previous year matching again is 0.77. This probability is 0.028 for a pair who did not match in the previous year, but matched years before, and the probability is 0.20 for a pair who has never matched before. This evidence supports a sunk cost mechanism as the main driver of contract persistence. The sunk cost explanation may imply dynamic incentives that this paper does not directly address, but I will be careful in interpreting the effect of conflict on allocation of matches between previously formed matches and new matches.

Moreover, a merger produces a big synergy effect that is one-third the size of the cost of conflict for previously formed matches. In addition, agencies that have ever been involved in a merger produce a higher surplus in their matches. Merger synergy will make matching opportunities more desirable, counteracting the matching opportunities it takes away for drug advertisers, so counterfactual exercises are necessary to evaluate the merger effect. Other drug and agency characteristics appear to be much less important since the indicator for past relationship is included, and year-to-year variations of drug and agency characteristics are small.

I also run alternative specifications for robustness checks and find that the relative magnitudes of conflict costs and benefits of the previous matches and common matching costs are similar across specifications. One specification deserves special note: I investigate whether there is a capacity constraint for drug advertisers by allowing the matching cost to change when drugs form additional matches. The result is shown in column (2) of Table 9. There is no evidence that it is more costly for the drug to take on additional matches. In an unreported table, I also allow conflict cost to vary when the number of drugs in a conflicting relationship grows. The differential conflict cost is not significant, suggesting that it is reasonable to make the constant conflict cost assumption. Because the presence of previously formed matches has an important effect on surplus, I try allowing this effect to differ by drug and advertising agency characteristics and allowing the effect to differ by the duration of the established relationship. In the first model with heterogeneous effects of past matches, the coefficients are all insignificant, and the magnitudes of the main coefficients are unchanged. In the second model of heterogeneity with time, I add dummy variables to indicate the different durations of the established relationship.[35] There is no evidence that a longer relationship is more or less valuable, which is consistent with the data pattern: match dissolution rates are roughly the same conditional on number of years observing the relationship.

[35] I add dummies for matches that have lasted one, two, three, and four or more years.

6 Counterfactuals

I conduct counterfactual exercises to examine the effect of conflict on equilibrium matches given the current market structure, and I then examine the effect of a change in market structure when conflict is costly. I will explain how conflict affects the allocation of matches conceptually and then discuss details and results of the counterfactuals.

6.1 Conflict Crowds Out Matches

When there is no additional cost for an advertising agency to simultaneously serve directly competing advertisers, any pair of drug and advertising agencies with a positive net return should form a match, denoted as $r_{ij} = y_{ij} - \kappa_f + \epsilon_{ij} > 0$. However, when concern about conflict exists, it lowers the return of conflicting matches and makes some matches no longer profitable to form. This crowding out effect depends on the match return and number of matches caught in conflict.

A match with a net return lower than the conflict cost it incurs, $r_{ij} < \kappa_{c,ij}$, will not sustain conflict since it is never socially optimal to add a match whose net surplus is negative. When two or more matches in this range try to match with the same advertising agency, only the single match with highest return will form with the agency.

When the net return of the match is greater than its conflict cost $r_{ij} > \kappa_{c,ij}$, two situations may arise. In the first situation, the match is crowded out when there exists another match with the agency whose return is higher. Compared with having one match, adding an additional match not only incurs an extra conflict cost for the added match but also creates a conflict cost for the existing match. So in order to form, the additional match must be valuable enough to overcome both its own conflict cost and the externality it creates for the other match in order to form the match, $r_{ij} > \kappa_{c,ij} + \kappa_{c,i'j}$. In the second situation, the match will always form. This happens when the match's return is high enough to overcome the conflict cost externality, or that the match is of higher value for the advertising agency, so it crowds out other matches.

The above mechanisms through which matches are crowded out is interesting since they imply that even though conflict cost for new matches may be low, it is still difficulty for new matches to form because, when in conflict with a previously formed match, the new match must overcome the previously formed match's conflict cost in addition to its own conflict cost.

Since estimation does not support conflict cost as an increasing function of the number of matches in conflict, this negative externality only exists for the first marginal match added. Conditional on having two matches for an agency, the third match only adds a conflict cost for itself. This suggests that if the agency already has two matches in equilibrium with sufficiently high net returns to sustain conflict, a new match's return only needs to be higher than its own conflict cost for it to form.

6.2 Error Calibration

Simulating the market equilibrium requires knowledge of the error distribution. Since the maximum score estimation strategy does not impose assumptions on the error distribution, I calibrate the error distribution by matching simulated moments to the data moments using different distribution parameters. I explain the details of the calibration exercise in this section.

I choose a mixture of normal distributions because the error distribution is likely to be asymmetric based on the pattern of match formation and dissolution observed in the data. The previous data description indicates that most matches with partners matched in the previous year will form again in the current year. The parameter estimates reflect that preserving previously formed matches yields a much higher surplus than forming new matches. Without any preference shocks, the magnitude of the surplus gain for previously formed matches is so large that no observed characteristics, including conflict, can have enough impact to dissolve such matches. The data shows, however, that previously formed matches dissolve one fourth of the time in a given year. This suggests that there must exist some large unobserved downside shock that dissolves previously formed matches. Compared to previously formed matches, most matches not formed in the previous year will not form in a new year, as the cost of forming a match is larges. So there must be some large positive shocks to match the data pattern that one fourth of all matches formed in a given year are new matches. Since the mean value for an existing match is much higher in absolute value than the matching cost, I expect the shocks to have a longer left tail than right tail.

Besides the ratio of match formation and dissolution that helps to identify the error distribution, the amount of conflict in which previously formed matches and new matches are involved in also provides information on error distribution. Imagine the case in which the error distribution is a mixture of two normal distributions, each with mean fixed. The variances of the two normal components determine the distribution of surplus conditional on deterministic characteristics of the matches. The distribution of the match surplus, in turn, determines how many new matches with relatively low value will be crowded out because of conflict, and how many can sustain a relationship with conflict. At the same time, it determines how many previously formed matches crowd out new matches and remain matched without conflict and how many are matched while in conflict with new or previously formed matches. Hence I add two more moments in calibration, the percentage of previously formed matches, and the percentage of new matches involved in a conflicting relationship, to identify the variance of the two distribution components.

To summarize, I use four moments to identify four parameters governing the mixture of two normal distributions. The moments are, in each period, the percentage of previously formed matches that form again, the percentage of new matches among the currently formed matches, the percentage of previously formed matches caught in conflict, and the percentage of new matches caught in conflict. The lower panel of Table 11 shows the distribution of errors. The two normal components have one positive mean and one negative mean, and the negative mean much greater in absolute value than the positive mean. Since the error is centered at zero, the component with the negative mean has a much lower weight. It confirms the intuition that relationships can have very large downside shocks, but with some relatively small probability of occurring.

6.3 The Impact of Conflict on Market Equilibrium

In the first counterfactual, I compare the the match allocation with conflict cost as estimated with the match allocation that would arise if I assume the conflict cost is zero. Both are based on market observables and 500 paths of match-specific error draws. The results are shown in Table 12.

Taking the scenario without conflict cost as the baseline, the first result of note in Table 12 is that conflict crowds out 14% of matches that would have formed without conflict. Among 876 matches crowded out by conflict, 849 are new matches. This is consistent with my earlier analysis that even though the conflict cost for new matches is small, their chances of finding matches are the most affected. As the conceptual analysis illustrates, two types of matches are crowded out. The first type is a match that has a return lower than its conflict cost and cannot survive in a conflicting relationship. The second type is a match that has a high enough return to overcome its own conflict, but cannot compensate the negative externality it causes in conflict. The majority (75.5%) of crowded out matches belong to the second type. This illustrates the importance of taking into account the negative externality that conflict places on choices.

The crowding out effect also suggests a distributional effect on the market equilibrium. When conflict reduces the overall surplus for an agency, a socially optimal equilibrium dictates that only the match that yields the largest surplus can be kept. In the static framework, this suggests that new drugs or drugs not previously matched will find it harder to match with agencies. In a dynamic framework, however, matches may be formed based on the expected future return. That being said, we may still expect a similar result in a dynamic setting: the drug that is expected to remain a fringe product with lower market share and small marketing budget will find it harder to match with desirable advertising agencies.

The high-return matches are less affected by the conflict. Even in the event of conflict, they can either crowd out other lower return matches, or stay in the conflicting relationship if they are willing to accept a lower surplus due to affected agency performance or to spare enough resources to ensure that the agency firmly maintains information confidentiality. For the second type of matches, even though the drug advertiser knows that forming a conflicting match will lower the productivity of the relationship, it will still find it more profitable to form the match with conflict than to give up the matching opportunity. Comparing to the scenario without conflict, the mean surplus of matches in conflict is reduced by 11.5% due to conflict cost.

6.4 The Impact of Merger on Market Equilibrium

My second counterfactual simulates a market structure change resulting from a successful the merger between Publicis and Omnicom. The two advertising holding companies proposed to merge in July 2013, but the deal was called off in May 2014. The proposed merger would have affected pharmaceutical clients if Publicis and Omnicom had consolidated some of their health agencies. I consider a hypothetical integration of Publicis' Publicis Healthcare Communications Group(PHCG), and Omnicom's Cline, Davis and Mann (CDM). Because my data ends with 2010, I will use observed characteristics in 2010, and previous match relationship status at the end of 2009 to predict matches affected by the merger. At the end of 2009, both PHCG and CDM are sizable agencies that are available to match in a wide range of markets. PHCG and CDM overlap in 31 treatment classes overall. In 2009, they actively serve for drug advertisers in 15 of these treatment classes.

Conceptually, a merger has four kinds of effects, each of which affects the direction of surplus changes differently.

The first effect is that the synergy created by mergers helps to increase total surplus. Synergy raises the mean return of all matching opportunities with the merged agencies This creates a positive return for a greater share of matching opportunity and increase the surplus of matches that form.

The second effect runs counter to the first one. Mergers reduce the number of advertising agencies from which a drug marketer can choose and reduce the expected number of matches in the market. This is similar to the concept of welfare loss when product variety is reduces in a market with differentiated goods but differs in that drugs' demand for advertising agencies is not restricted to one unit. Because of the limited number of agencies working within a treatment class and the even fewer number of matching opportunities with a positive return, the model assumes that a drug marketing team always enjoys variety and would like to match with any agency with which it yields a positive return. With this assumption, when two agencies in a market consolidate into one, the expected number of matches is halved.

The third effect comes from the increasing probability of conflict. I will focus on the analysis in a single treatment market and explain two cases that raise potential conflicts. In the first case, a merger involves one agency that did not match with any drug in the previous period and another agency that matched with one drug in the market. When the agencies merge, not only does the matching opportunity decrease, but the match between the merged agency and the single previously matched drug also crowds out new matches with lower returns. In this case, merger exacerbates the crowding out effect.

In the second case, the merger involves two agencies that were both previously matched with one or more drugs in the market. Because of the value of the past relationship, both drugs brought into the merged agency are very likely to bear the conflict costs and continue the contracts. Because the negative externality only applies to the first marginal match that moves an agency from no conflict to some conflict. any other drug that wishes to match with the merged agency only needs to overcome its own conflict cost. Hence, in this case, the merger actually weakens the crowding out effect.

The last effect is on the previously formed high-return matches that would be brought to the same agency through merger. Whether the matches dissolve depends on the synergy and the variance of the downside shock. However, even when the conflicting matches remain in the same agency, the merged agency's performance is affected by having to deal with the rising number of conflicting clients.

The simulated hypothetical merger combines the above mechanisms, and Table 13 shows the results. Although the value of merger synergy is equal to 25% of the common matching cost (Table 11), suggesting that mergers significantly improve the matching opportunity for all matches, the number of matches and total surplus are reduced overall. The merger affects both the number and the surplus of equilibrium matches. First, the total number of matches decreases, and all of the decrease comes from a reduced number of new matches. Although only four matches are not formed because of the merger, this represents 10% of the new matches that would form in the absence of the merger. Second, previously formed matches are 68% more likely to be brought into actual conflict after the merger. Although none of these matches will dissolve due to the merger, their surplus is reduced by 6.8%.

PHCG and CDM both have contracts with at least one drug in each of the overlapping markets they serve. When the mergers bring these competing drugs into the same agency, the conflict cost is not large enough to dissolve these high-return matches and therefore increases the number of actual conflicts in the market. After these existing matches pay the big initial cost of conflict, additional conflicts only pay their own conflict cost and hence find it easier to match even when there is conflict. The second panel of Table 13 shows that the number of crowded out matches is actually reduced after the merger. Therefore, this merger reduces the number of matches mainly through disrupting matching opportunities of differentiated services rather than increasing the crowding out effect.

7 Conclusion

Using a matching model with conflict, I analyze contract decisions between drug advertisers and advertising agencies and examine the market equilibrium effect of client conflict. The model shows that it is important to take into account the negative externality generated from conflict for both the agents that were matched in the previous period and those that are seeking new partners. Focusing on the outcome of contract allocation, I show that conflict crowds out a significant amount of contracts with lower returns. The consolidation of advertising agencies reduces the number of equilibrium contracts by eliminating differentiated products (agencies). The crowding out effect through merger may increase or decrease depending on the contract allocation at the time of the merger.

Conflict raises new angles in merger analysis. Since I analyze a market equilibrium without pricing inefficiencies, I cannot analyze advertising agencies' market power beyond the above discussions. But the implication for merger analysis of the existence of conflict is clear and is easily extended to a wide range of professional service markets. Conflict reduces the alternatives for clients, and when service agencies merge, it further reduces substitution among service agencies. This limitation to the substitution pattern can be especially acute in professional service industries since the number of service agencies working for one type of client is usually limited due to the client's demand for expertise. And because experience is highly valued in service agencies, the entry barrier in these markets is also considerable. This suggests that a more thorough analysis is necessary to take into account conflict, market segmentation due to the expertise, and entry barriers when conducting merger analysis.

This paper bears several limitations due to data constraints. First, the assumption that the capacity constraint does not bind for drug advertisers is not directly testable but is necessary because I need a characterization of the equilibrium using only observed match allocations. Even with stability, conflict is not identified in canonical matching models that require knowledge of both transfer and matching allocation in characterizing the equilibrium. Second, due to the importance of sunk cost and the crowding out effect created by conflict, it would be interesting to investigate dynamic incentives and pricing powers in dynamic games Without transfer data, however, this work cannot be undertaken empirically, but theoretical analysis would be the first step toward drawing a complete picture in a dynamic framework. Third, the paper takes the market structure as given and examines the effect of conflict on equilibrium matches due to the limited time span of the observed data. With historical data, the exact entry date of advertising agencies into each therapeutic market may be observed. Endogenizing entry and merger decision in the model and analyzing the impact of conflict on market structure will be interesting directions for future research.

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Tables

Table 1: Statistics on Matching Markets

	Mean	StdDev	25th	Median	75th	N
Summary of # of Drug and Agency per Class-year[1]						
# of Drugs	4.4	11.1	1	2	6	1,214
# Drugs Matched	2.8	3.3	1	1	4	1,214
% of Drugs Matched	68%	36%	50%	76%	100%	1,214
# of Agencies	7.8	7.4	2	5	11	1,214
# of Agencies Matched	3.7	4.1	1	2	5	1,214
% of Agencies Matched	46%	29%	50%	28%	60%	1,214
Summary of # of Matches per Class-year						
# of Matches	4.5	5.6	1	2	6	1,214
# of Matches per Drug	1.1	1.1	0	1	2	5,012
# of Matches per Matched Drug	1.6	0.9	1	1	2	3,703
# of Matches per Agency	0.6	0.7	0	0	1	9,470
# of Matches per Matched Agency	1	0.6	1	1	1	4,995
Overview of Amount of Conflicts per Class-year[2]						
# of Class-year with Conflicts	322					
# of Matches in Conflicts	2.5	3.9	0	2	4	657
% Matches in Conflicts	23%	27%	0	13%	43%	657
# of Drugs in Conflicts	2.1	3.0	0	0	3	657
% of Drugs in Conflicts	23%	28%	0%	0%	40%	657
# of Agencies in Conflicts	1.1	1.5	0	0	2	657
% of Agencies in Conflicts	7%	11%	0%	0%	12.5%	657
# Drugs per Conflict Relationship[3]	2.3	0.5	2	2	2.5	657

[1] There are 158 unique treatment classes, and there are a total of 1,214 class-year (markets) in our analysis between 2002 and 2010. The number of classes is unbalanced across years due to new drugs and classes with all agencies exiting the market. [2] Among 1,214 class-year, there are 557 classes have only one drug in a given year, and there is no conflict in such classes. In producing statistics for conflict, I only focus on 657 class-year with two or more drugs in a given class-year. There are 322 class-year with actual conflicts. [3] A "conflict relationship" is one among multiple drugs in a class-year that hire the same agency, or one that an agency serves multiple drugs in a same class-year.

Table 2: Turnover of Matches

Year	# of Matches	# of New Matches	New%	# End Matches[1]	End%
2002	586	225	38.4%	150	25.6%
2003	651	187	28.7%	195	30.0%
2004	635	179	28.2%	154	24.3%
2005	715	227	31.7%	176	24.6%
2006	779	225	28.9%	248	31.8%
2007	731	202	27.6%	208	28.5%
2008	734	184	25.1%	204	27.8%
2009	673	148	22.0%	171	25.4%
2010	631	128	20.3%	.	.

[1] # of end matches is the number of matches that are in their the last year of the relationship.
Note: This table pools all matches together regardless of markets to examine the turnover rate of matches overall.

Table 3: Summary Statistics of Advertising Agency and Drug Characteristics

	Matched[1]		Unmatched[1]	
Variables	Mean	StdDev	Mean	StdDev
Advertising Agency Characteristics				
Billings(millions)	475	999.0	418	944.0
#Employees	342.2	667.4	338.7	739.1
Agency Age in # of Years	29.2	20.1	28.2	20.2
TV Specialty	0.2	0.3	0.2	0.3
DTC Specialty	0.2	0.3	0.2	0.3
Health Specialty	0.7	0.4	0.7	0.4
Drug Characteristics				
DTCA Expenditure (million)	9.4	29.4	0.23	3.3
DTCA TV Expenditure (million)	5.6	20	0.09	2.1
I(Top 200 Sales)	0.2	0.4	0.1	0.3
$I(DrugAge < 0)$	0.1	0.3	0.4	0.5
$I(0 \leq DrugAge \leq 5)$	0.4	0.5	0.2	0.4
$I(6 \leq DrugAge \leq 12)$	0.3	0.5	0.2	0.4
$I(DrugAge \geq 13)$	0.2	0.4	0.2	0.4

[1] The "matched" column summarizes characteristics of drugs and agencies that obtain any match in a class-year. And the "unmatched" column summarizes characteristics of drugs and agencies that does not obtain any match in a class-year. Among all agency-class-year, 46.6% are matched. Among all drug-(class)-year 66.3% are matched.
Note: 1 The table summarize characteristics of all drugs and agencies in the market between 2002 and 2010. The unit of observation is a drug-year, or an agency-class-year.

Table 4: Probability of Matching for A Drug

	$I(Match_{it} > 0)$		$I(Match_{it} \geq 2 \| I(Match_{it} > 0)$	
	(1)	(2)	(3)	(4)
$Ln(DTCA_t)$	0.0167***	0.0116***	0.00763***	0.00414***
	(0.00107)	(0.00119)	(0.00152)	(0.00158)
$I(DTCATV_t)$	0.0368**	0.0210	0.173***	0.0550
	(0.0162)	(0.0233)	(0.0294)	(0.0359)
$I(0 \leq DrugAge_t \leq 5)$	0.326***	0.336***	0.0951***	0.155***
	(0.0184)	(0.0205)	(0.0258)	(0.0281)
$I(6 \leq DrugAge_t \leq 12)$	0.250***	0.182***	0.113***	0.116***
	(0.0194)	(0.0265)	(0.0268)	(0.0377)
$I(DrugAge_t \geq 13)$	0.114***	-0.0419	0.0208	-0.0258
	(0.0218)	(0.0348)	(0.0295)	(0.0508)
$I(Top200Sales_{t-1})$	0.00731	0.0516**	0.0708***	-0.00926
	(0.0150)	(0.0255)	(0.0208)	(0.0362)
$Constant$	0.378***	0.439***	0.243***	0.280***
	(0.0146)	(0.0190)	(0.0211)	(0.0276)
FE	–	Drug	–	Drug
Observations	5,584	5,584	3,703	3,703
R^2	0.1745	0.4616	0.0687	0.3573

Note: 1 Specification in Column (1) and (2) regress the indicator of if a drug is matched with any agency at a given year on drug characteristics. Column (3) and (4) condition on the sample of drugs in years with any match and regress the indicator of if a drug has more than one match on drug characteristics. 2 Categorical dummy variable $I(DrugAge < 0)$ is excluded in the regression. 3 Standard errors are clustered at the drug level.

Table 5: Probability of Matching for An Agency

	$I(Match_{jt} > 0)$		$I(Match_{jt} \geq 2 \| I(Match_{jt} > 0)$	
	(1)	(2)	(3)	(4)
$AgencyAge_t$	0.000457	0.0189***	0.00119***	0.00833***
	(0.000416)	(0.00262)	(0.000318)	(0.00319)
$Ln(Billing_{t-1})$	0.0174***	0.0483***	0.0138***	-0.00430
	(0.00521)	(0.0112)	(0.00382)	(0.0121)
$Ln(Emp_{t-1})$	0.0328***	0.0117	0.00915*	0.0331**
	(0.00697)	(0.0164)	(0.00539)	(0.0164)
$DTC\ Specialty_{t-1}$	-0.0621***	-0.209***	0.0108	-0.0520
	(0.0204)	(0.0534)	(0.0149)	(0.0433)
$TV\ Specialty_{t-1}$	-0.0408*	-0.0723	-0.0195	-0.0770
	(0.0209)	(0.0513)	(0.0155)	(0.0525)
$Health\ Specialty_{t-1}$	0.0976***	0.175***	0.0327**	0.0116
	(0.0182)	(0.0460)	(0.0134)	(0.0438)
$Constant$	0.504***	-0.0390	0.0949***	-0.0722
	(0.0196)	(0.0803)	(0.0147)	(0.0968)
FE	–	Agency	–	Agency
Observations	10,716	10,716	4,993	4,993
R^2	0.0098	0.4722	0.0162	0.6152

Note: 1 Column (1) and (2) specifications regress the indicator of if an advertising agency is matched with any drug at a given year on agency characteristics. Column (3) and (4) condition on the sample of agencies in years with any match and regress the indicator of if an agency has more than one match on agency characteristics. 2 Standard errors are clustered at the agency level.

Table 6: Types of Pairwise Deviation

Parameter of Surplus function:

$$S_{ij} = X_i\alpha + Z_j\beta + X_iZ_j\gamma + \lambda L_{ij} - 1(|\mu_j| \geq 2) \times \kappa_c - \kappa_f + \epsilon_{ij}$$

Type	**Identified Parameters**	κ_c,κ_f
Replacing partners		
1 Swapping partners between two pair	γ, λ	/
2 Drug replacing an agency partner	β, γ, λ	κ_c
3 Agency replacing a drug partner	α, γ, λ	–
Adding new matches		
4 A new match added between a drug and an agency that already have matches with others	α, β, γ, λ	κ_c,κ_f
5 A new match added between a unmatched drug and an agency that already have matches with others	α, β, γ, λ	κ_c, κ_f
6 A new match added between an unmatched agency and a drug that already have matches with others	α, β, γ, λ	κ_f
7 A new match added between an unmatched agency and an unmatched drug	α, β, γ, λ	κ_f
Drop a current match		
8 A current match is dropped	α, β, γ, λ	κ_c, κ_f

Table 7: Descriptive Regression: Probability of a Forming Match

Dependent Variable:	$I(Match_{ijt} = 1)$	
	(1)	(2)
$PotentialConflict_{ij,t-1}$	-0.0295***	-0.0144***
	(0.00191)	(0.00144)
$I(Match_{ij,t-1} = 1)$		0.745***
		(0.00253)
$Ln(Emp_{t-1})$	0.00495***	0.00198***
	(0.000977)	(0.000700)
$Ln(Billing_{t-1})$	0.000486	-0.000503
	(0.000755)	(0.000561)
$AgencyAge_t$	-0.0000654	-0.000128***
	(0.0000590)	(0.0000412)
$DTC\ Specialty_{t-1}$	-0.00881***	-0.00412**
	(0.00279)	(0.00205)
$TV\ Specialty_{t-1}$	-0.0122***	-0.00314
	(0.00294)	(0.00220)
$Health\ Specialty_{t-1}$	0.0157***	0.00202
	(0.00250)	(0.00182)
$AnyMerge_j$	0.0331***	0.00122
	(0.00260)	(0.00170)
$PostMerger_{jt}$	0.0272***	0.00677***
	(0.00254)	(0.00228)
$I(0 \leq DrugAge_t \leq 5)$	0.00458*	-0.000508
	(0.00263)	(0.00201)
$I(6 \leq DrugAge_t \leq 12)$	-0.00244	-0.00467**
	(0.00260)	(0.00202)
$I(DrugAge_t \geq 13)$	0.0305***	-0.0132***
	(0.00242)	(0.00219)
$I(Top200Sales_{t-1})$	0.0292***	-0.00418**
	(0.00397)	(0.00168)
$I(DTCA_t > 0)$	0.0159***	0.0107***
	(0.00253)	(0.00156)
$I(DTCATV_t > 0)$	0.0240***	0.00639***
	(0.00369)	(0.00222)
$Constant$	0.0301	0.0269***
	(0.00323)	(0.00249)
Observations	76,887	76,887
R^2	0.0185	0.5389
$Mean(I(Match_{ijt} = 1))$	7.13%	

Note: 1 This regression pools observations of all possible combination of pairwise matches in each class-year and examine what characteristics predict current period match. 2 Potential conflict is defined by if a match between a drug and an agency involves an agency that also contracts with the drug's competitor. Since current period matches are interdependent, we use potential conflict in the past year instead. Potential conflict in the past year is defined as for a given drug-agency pair, if the agency contracted with any competitors of the drug in the past year. 3 The probability of any pair to form a match 7%, so the potential conflict and potential conflict reduces the chance of match 20-40% of the time.

Table 8: Descriptive Regression: Heterogeneous Effect of Previously Matching Relationships

Dependent Variable:	$I(Match_{ijt} > 0)$		
$PotentialConflict_{t-1}$	-0.0133***	$Match_{t-1}$	0.928***
	(0.00123)		(0.0279)
$Ln(Emp_{t-1})$	-0.000385	$Match_{t-1} \times Ln(Emp_{t-1})$	0.0344***
	(0.000547)		(0.00689)
$Ln(Billing_{t-1})$	-0.00000205	$Match_{t-1} \times Ln(Billing_{t-1})$	-0.0114**
	(0.000433)		(0.00551)
$AgencyAge_t$	-0.0000318	$Match_{t-1} \times AgencyAge_t$	-0.00148***
	(0.0000323)		(0.000386)
$DTC\ Specialty_{t-1}$	-0.00158	$Match_{t-1} \times DTC\ Specialty_{t-1}$	-0.0329
	(0.00155)		(0.0206)
$TV\ Specialty_{t-1}$	-0.00211	$Match_{t-1} \times TV\ Specialty_{t-1}$	-0.0351
	(0.00167)		(0.0232)
$Health\ Specialty_{t-1}$	0.00335**	$Match_{t-1} \times Health\ Specialty_{t-1}$	-0.0160
	(0.00145)		(0.0178)
$AnyMerge_j$	0.00522***	$Match_{t-1} \times AnyMerge_j$	-0.0482***
	(0.00148)		(0.0161)
$PostMerger_{jt}$	0.00600***	$Match_{t-1} \times PostMerger_{jt}$	0.0137
	(0.00213)		(0.0194)
$I(0 \leq DrugAge_t \leq 5)$	0.00350**	$Match_{t-1} \times I(0 \leq DrugAge_t \leq 5)$	-0.128***
	(0.00169)		(0.0235)
$I(6 \leq DrugAge_t \leq 12)$	-0.000873	$Match_{t-1} \times I(6 \leq DrugAge_t \leq 12)$	-0.128***
	(0.00160)		(0.0238)
$I(DrugAge_t \geq 13)$	-0.00708***	$Match_{t-1} \times I(DrugAge_t \geq 13)$	-0.166***
	(0.00162)		(0.0265)
$I(Top200Sales_{t-1})$	-0.00299**	$Match_{t-1} \times I(Top200_{t-1})$	-0.0129
	(0.00138)		(0.0141)
$I(DTCA_t > 0)$	0.00704***	$Match_{t-1} \times I(DTCA_t > 0)$	0.0519***
	(0.00137)		(0.0139)
$I(DTCATV_t > 0)$	0.00194	$Match_{t-1} \times I(DTCATV_t > 0)$	0.0340**
	(0.00212)		(0.0157)
$Constant$	0.0187***		
	(0.00197)		
Observations	76,887	$Mean(I(Match_{ijt} = 1))$	7.13%
R	0.5417		

Note: 1 This regression adds the interaction terms between indicator of matches previously formed and characteristics of advertising agencies and drugs. The regression is trying to produce suggestive evidences for what pervious formed matches are more likely to be continued. 2 This regression pools observations of all possible combination of pairwise matches in each class-year and examine what characteristics predict current period match. 3 Potential conflict is defined by if a match between a drug and an agency involves an agency that also contracts with drug's competitor. Since current period matches are interdependent, we use potential conflict in the past year instead. Potential conflict in the past year is defined as for a given drug-agency pair, if the agency contracted with any of the drug's competitors in the past year.

Table 9: Baseline Maximum Score Estimates

	(1)		(2)	
Parameters	L.B.	U.B.	L.B.	U.B.
$\kappa_c(Conflict)$	0.00235	0.00679	0.00026	0.03238
$\kappa_c(Conflict) \times Match_{t-1}$	0.17793	0.32090	0.07360	0.22472
$\kappa_f(FC)$	0.18334	0.24986	0.11156	0.54223
$\kappa_f \times \Delta DrugMatch^1$			-0.00034	0.00000
Drug Characteristics				
$I(0 \leq DrugAge_t \leq 5)$	0.00000	0.00001	0.00000	0.00001
$I(6 \leq DrugAge_t \leq 12)$	-0.00137	0.00197	-0.00101	-0.00000
$I(DrugAge_t \geq 13)$	-0.01381	-0.00656	-0.26384	-0.00022
$I(Top200Sales_{t-1})$	-0.00073	-0.00046	-0.00117	0.00070
$I(DTCA_t > 0)$	0.00386	0.00609	0.00057	0.30943
$I(DTCATV_t > 0)$	-0.00046	-0.00020	-0.00101	0.30892
Agency Characteristics				
$AgencyAge_t$	-0.00019	-0.00009	-0.00909	0.00031
$Ln(Billing_{t-1})$	-0.01206	-0.00389	-0.02084	-0.00002
$Ln(Emp_{t-1})$	-0.00423	-0.00120	-0.02943	0.01094
$DTC\ Specialty_{t-1}$	-0.00348	0.00010	-0.04255	0.00084
$TV\ Specialty_{t-1}$	0.00001	0.00005	-0.13799	0.00906
$Health\ Specialty_{t-1}$	-0.00340	0.00420	-0.00166	0.01297
$AnyMerge_j$	0.00987	0.01209	0.00456	0.13832
$PostMerger_{jt}$	0.00790	0.16711	0.00000	0.14076
$Match_{t-1}$ *bounds implied*	0.69894	0.94476	0.75005	0.86697
OptObj		201,312		201,695
Total Ineq		221,044		221,044
%Correct		91.07%		91.25%

[1] $\kappa_f \times \Delta DrugMatch$ measures value(cost) of an drug to add an additional match.

Note: 1 This table presents the main specifications of maximum score estimator. Specification (2) differs from (1) in allowing the matching cost to change with the number of agencies a drug hires. 2 L.B. and U.B. represents lower and upper bounds of the 95th percentile confidence region. It is derived using subsampling method. 3 Parameters are normalized by $||\theta|| = 1$, or that square of coefficients sum to one. $Match_{t-1}$ is excluded for normalizing the sum of squares. Inference for freely varying coefficients is directly derived from the subsampling method. For illustration, bounds for the excluded coefficient (impact of previously formed matches) shown above are $[(1-\tilde{\theta}_{lb})^{0.5}, (1-\tilde{\theta}_{ub})^{0.5}]$ where $\tilde{\theta}$ represents all coefficients other than the excluded one.

Table 10: Maximum Score Estimates: Controlling for Heterogeneous Effect of $Match_{t-1}$

Parameters	**Lower Bound**	**Upper Bound**
$Match_{t-1}$	0.8988	0.9910
$Conflict\ Cost$	0.0006	0.0099
$Conflict\ Cost \times Match_{t-1}$	0.0898	0.3903
$Match\ Cost$	0.0989	0.1418
$AnyMerger$	0.0086	0.0462
$PostMerger$	0.0019	0.0932
Other Controls		
Drug Characteristics	Yes	
Agency Characteristics	Yes	
Het. Past Match Effect	Yes	
OptObj	201,395	
Total Ineq	221,044	
% Correct Inequalities	91.20%	

Note: This table reports key parameters in the specification that includes interactions of indicator of matches previously formed and drug and agency characteristics. The coefficients for the interaction terms are all insignificant.

Table 11: Parameters in Counterfactual Simulations

Parameters	Value	Parameters, cont.	Value
$Match_{t-1}$	0.8793	$AgencyAge_t$	-0.0011
$\kappa_c(Conflict)$	0.0064	$Ln(Billing_{t-1})$	-0.0038
$\kappa_c(Conflict) \times Match_{t-1}$	0.2465	$Ln(Emp_{t-1})$	-0.0050
$\kappa_f(FC)$	0.3319	$DTC\ Specialty_{t-1}$	-0.0057
$I(0 \leq DrugAge_t \leq 5)$	0.0332	$TV\ Specialty_{t-1}$	-0.0119
$I(6 \leq DrugAge_t \leq 12)$	-0.0016	$Health\ Specialty_{t-1}$	0.0004
$I(DrugAge_t \geq 13)$	-0.2105	$AnyMerge_j$	0.0103
$I(Top200Sales_{t-1})$	-0.0013	$PostMerger_{jt}$	0.0877
$I(DTCA_t > 0)$	0.0364		
$I(DTCATV_t > 0)$	0.0328		
Calibrated Error Distribution Parameters			
$F(\epsilon) = \omega_1\Phi_1(x) + \omega_2\Phi_2(x)$			
$\Phi_1 \sim N(-0.7383, 0.0563)$			
$\Phi_2 \sim N(0.1819, 0.0024)$			
$(\omega_1, \omega_2) = (0.1977.0, 8023)$			

Note: 1 The parameter in the upper panel is the midpoint of each parameter range in its 95% confidence region according to results of the first column of Table 9. 2 The lower panel is the error distribution that I calibrate 4 parameters of the distribution using four data moments: in each period, the percentage of matches dissolving, the percentage of matches forming, the percentage of previously formed matches in conflict, and the percentage of new matches in conflict.

Table 12: Counterfactual: The Impact of Conflict on Equilibrium

	Costly-Conflict[1]	**Costless-Conflict**[1]	**Δ(Costly-Costless)%**
Total # of matches	5193.05	6068.99	-14.4%
Total surplus	2877.05	3205.59	-10.2%
Matches with conflict[2]			
Number	1765.91	3106.76	-43.1%
Mean surplus	0.33	0.37	-11.5%
Matches without conflict			
Number	3427.14	2962.23	15.6%
Mean surplus	0.67	0.69	-3.1%
Matches continued from $t-1$			
Number	4220.52	4247.90	-0.6%
Mean surplus	0.68	0.75	-9.2%
Matches new at t			
Number	972.53	1821.09	-46.6%
Mean surplus	0.01	0.02	-13.8%
Matches continued from $t-1$ & with conflict			
Number	1118.84	1481.06	-24.5%
Matches new at t & with conflict			
Number	647.07	1625.70	-60.2%
Crowded Out Matches[3] ($r_{ij} = y_{ij} - \kappa_f + \epsilon_{ij}$)			
$0 < r_{ij} < \kappa_{c,ij}$			
Number	214.27	0	-
Mean surplus	0.01	-	-
$r_{ij} > \kappa_{c,ij}$			
Number	661.67	0	-
Mean surplus	0.02	-	-

[1] I simulate two scenarios using characteristics of the agents and their matching history as observed in the data. The column "Costly-Conflict" assumes that there is an additional cost for an advertising agency to serve two competing drug clients simultaneously. And the column "Costless-Conflict" assumes that such additional cost is zero. [2] "with conflict" describes the situation when two or more drugs in the same class match with the same advertising agency in the same year. [3] r_{ij} denotes the net return of a match between drug i and advertiser j without taking into account the cost of conflict. In the r_{ij} expression, y_{ij} is the return of a pair of match, κ_f is the fixed cost of matching, common to all matches. $\kappa_{c,ij}$ is the cost of conflict incurred to the match itself, and ϵ_{ij} is the random shock of the match surplus.

Table 13: Counterfactual: The Impact of Mergers on Equilibrium

	With-Merger[1]	**Without-Merger**[1]	**Δ(With-Without)%**
Total # of matches	84.352	88.164	-4.3%
Total surplus	31.3877	33.7157	-6.9%
Matches with conflict[2]			
Number	71.39	54.428	31.2%
Mean surplus	0.3291	0.2415	36.3%
Matches without conflict[2]			
Number	12.962	33.736	-61.6%
Mean surplus	0.6105	0.6107	0.0%
Matches continued from $t-1$			
Number	50.92	50.918	0.0%
Mean surplus	0.6089	0.6533	-6.8%
Matches new at t			
Number	33.432	37.246	-10.2%
Mean surplus	0.0119	0.0125	-4.8%
Matches continued from $t-1$ & with conflict			
Number	40.982	24.33	68.4%
Matches new at t & with conflict			
Number	30.408	30.098	1.0%
Crowded Out Matches[3] ($r_{ij} = y_{ij} - \kappa_f + \epsilon_{ij}$)			
$0 < r_{ij} < \kappa_{c,ij}$			
Number	2.376	1.478	60.8%
Mean surplus	0.0275	0.0144	91.0%
$r_{ij} > \kappa_{c,ij}$			
Number	15.69	24.526	-36.0%
Mean surplus	0.0167	0.0156	7.1%

[1] I simulate two scenarios using characteristics of the agents and their matching history as observed in the data. The column "With-Merger" simulates matches that will form in 2010 if PHCG and CDM merge. And the column "Without-Merger" simulates matches that will form in 2010 if PHCG and CDM do not merge. [2] "with conflict" describes the situation when two or more drugs in the same class match with the same advertising agency in the same year. [3] r_{ij} denotes the net return of a match between drug i and advertiser j without taking into account the cost of conflict. In the r_{ij} expression, y_{ij} is the return of a pair of match, κ_f is the fixed cost of matching, common to all matches. $\kappa_{c,ij}$ is the cost of conflict incurred to the match itself, and ϵ_{ij} is the random shock of the match surplus.