Essays in Empirical Industrial Organization

by

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ABSTRACT

This dissertation studies competition in the pharmaceutical and airline industries, focusing on two types of firm conduct: advertising and pricing. In the following chapters, I apply econometric models to novel datasets to study important policy questions in these industries.

The first chapter studies the effects of direct-to-consumer advertising (DTC) on the market shares of new branded prescription drugs. This chapter contributes to the debate in the literature over whether advertising is more advantageous to entrants, who might use it to gain traction in the market, or to incumbents, who might use it to persuade consumers away from the entrants. Moreover, the permissibility of DTC for prescription drugs is a contentious policy issue. I focus on Type 2 diabetes drugs because this category has seen a wave of brand entry in the last decade. To account for the endoegeneity of advertising, I use political advertising as an instrument. I find that DTC has a business-stealing effect on the margin. In order to assess the effects of a counterfactual policy which bans DTC, I estimate a discrete-choice model of drug demand by diabetes patients. I find that new brands would have lost significant market share under a DTC ban, and that patients would have substituted to cheaper drugs. These results suggest that the desirability of DTC hinges on whether the therapeutic benefits of new drugs outweigh their higher prices.

The second chapter extends the study of DTC to an additional element of firm strategy: pricing. High drug prices are a cause for great concern in the United States, particularly for diabetes drugs such as insulin. The effect of advertising on prices is theoretically ambiguous, however. This chapter studies the question empirically in the market for diabetes drugs. I find that the marginal effect of DTC is to lower prescription drug prices. This is explained by business-stealing – DTC makes consumers more willing to substitute between drugs, which limits drug manufacturers' ability to set high prices. To study the effects of a ban on DTC, I augment the demand model of the first chapter with a model of drug price negotiations between insurers and drug manufacturers. I find that both higher and lower average prices are possible

after a ban. I also find that the results of the first chapter are robust to allowing for price changes – market shares of new brands fall in both cases. These results show that price adjustments should be taken into account in the policy debate around DTC.

The third chapter, with Paul Brehm and Andrew Usher, examines the relationship between airfares and oil prices in the Australian airline industry. We find that pass-through exceeds 100% on average and increases with competition. We also find evidence of heterogeneity in pass-through across different products – business class pass-through is lower than economy, while non-stop flights have higher pass-through rates than flights with stops. These results reflect a tension between second-degree price discrimination and pricing higher to high-value consumers. Heterogeneity in consumers' willingness to pay and the existence of products targeted at different consumers are key to explaining these results. Our findings have important implications for environmental policy in industries with imperfect competition and differentiated products. In particular, they suggest that a carbon tax on the airline industry would be shifted onto consumers to a great extent.

CHAPTER I

Direct-to-Consumer Advertising and New Drug Diffusion

1.1 Introduction

Direct-to-consumer advertising (DTC) is an important feature of many industries, but is nowhere more controversial than in the market for prescription drugs. DTC can affect drug choices if patients ask for a specific drug by name, which doctors report causes them to feel pressure to prescribe that drug (FDA, 2015). Supporters of DTC say that this empowers patients to be more involved in their health care and have more informed discussions with their physicians. Detractors argue that such advertising biases patient decisions and contributes to the high cost of health care in the US (FDA, 2015). Indeed, the US is an outlier among the world as one of only two countries (along with New Zealand) to permit DTC for prescription drugs.

The role of DTC is particularly interesting in the context of new products. On this question, the economics literature is split between entry-deterring and pro-competitive views of advertising.[1] The former view suggests that advertising is used by incumbents to create barriers to entry (Braithwaite, 1928). The latter view argues instead that entrants can advertise to gain traction in the market and become stronger competitors to the incumbents (Telser, 1964).[2] As theory delivers ambiguous predictions, this paper empirically studies how DTC affects the market shares of new prescription drug brands. This question has not been addressed by the literature, yet it is highly relevant as several drug categories are seeing entry by multiple brands, many of which

[1]See Bagwell (2007) for a nice summary of this literature.

[2]These arguments apply to advertising in general. Drugs are advertised through multiple channels, of which DTC is but one (albeit an important and controversial one). Since this paper focuses exclusively on DTC, I will use the terms “DTC” and “advertising” interchangeably.

advertise. The context I study is the market for drugs used to treat Type 2 diabetes, which has seen a wave of brand entry and intense advertising over the past decade. I use claims data from the employer-sponsored health insurance market provided by Truven and advertising data from Kantar Media. I focus exclusively on television advertising in this paper, as that is the most important DTC channel for anti-diabetic drugs. Beyond answering questions about the nature of advertising, this setting is important from a public health standpoint as diabetes becomes more prevalent.[3]

To better understand how advertising operates in this market, I start with a regression analysis of the marginal effects of advertising on drug sales. I allow for spillover effects of a given drug's rivals' ads onto sales of that drug. Since firms choose advertising strategically, it is likely to be correlated with demand shocks unobservable to researchers. I follow Sinkinson and Starc (2018) in using political advertising to instrument for drug advertising. During election years, certain "battleground" states receive high levels of political advertising, which exogenously displace drug advertising. This identifies the effects of own advertising. To identify spillover effects, I take advantage of the fact that some drugs do not advertise. These drugs should only receive the spillover effect and so can be used for identification. I find that advertising has strong business-stealing effects – a drug's own advertising increases its sales, while advertising by its rivals decreases its sales.

However, the policy of interest that would put the US in line with most other countries is a ban on DTC. To study this, I estimate a discrete-choice model of patient drug demand that accounts for endogeneity of both drug price and advertising. Political ads are again used to identify the effects of drug advertising. The model delivers three main results. First, consistent with the previous literature (e.g. Shapiro, 2018), DTC has positive spillover effects. Second, when DTC is banned, consumers substitute to less expensive drugs on average (holding drug prices fixed). Finally, when DTC is banned, new drugs lose significant market share. This final result lends support to the argument of Telser (1964) that entrants can use advertising to gain traction in the market.

This paper makes several contributions. First, I add to the literature on new drug entry by focusing on new brands. The previous literature (e.g. Scott Morton, 1999; Scott Morton, 2000) largely studies entry of generics, which do not advertise and so do not create the issues discussed above. Ellison and Ellison (2011) study how

[3] About 1.5 million new cases of diabetes occur every year in the US (ADA, 2018).

brands use advertising strategically when faced with generic entry. It is important to study competition between brands due to the length of drug patents, which prevent generics from entering for a long time; and because branded entrants, unlike generics, might use advertising to gain traction in the market. A large literature in marketing studies learning about new brands (e.g. Chintagunta et al., 2012) but generally in the context of detailing (i.e. marketing to physicians) rather than DTC. Previous work has shown that firms' detailing and DTC strategies can be quite different (Shapiro, 2018). Moreover, the marketing literature is more concerned with strategies of individual firms rather than the market-wide effects of policies like a ban on DTC.

This paper also adds to the recent literature that uses natural experiments to identify the effects of DTC. Shapiro (2018) finds spillover effects of DTC and Sinkinson and Starc (2018) find business-stealing between brands. Shapiro (2018) uses boundary discontinuities between DMAs to identify spillovers while Sinkinson and Starc (2018) use a combination of two natural experiments. The approach taken here is to use drugs that do not advertise to identify spillovers. This is arguably more general than both approaches above – unlike Shapiro (2018), the results apply away from the boundaries; unlike Sinkinson and Starc (2018), researchers can use this approach without needing multiple natural experiments.

Finally, the focus on anti-diabetic drugs is important from a policy and public health standpoint. This market has been understudied in the health economics and marketing literatures – the only other paper I am aware of is Guo et al. (2017).

The paper proceeds as follows: Section 1.2 discusses institutional details of the anti-diabetics market, Section 1.3 explains the data and descriptive analysis, Section 1.4 introduces the structural model, Section 1.5 discusses estimation of the model, Section 1.6 shows results, Section 1.7 discusses counterfactuals, and Section 1.8 concludes.

1.2 Empirical Setting

1.2.1 Type 2 Diabetes

Type 2 diabetes mellitus is a chronic, progressive disease characterized by insulin resistance. Insulin is the hormone produced and used by the body that allows cells to absorb glucose from the bloodstream (e.g. after a meal). In Type 2 diabetes, the body's cells develop resistance to insulin, and/or the pancreas does not produce insulin in sufficient amounts. This makes blood glucose levels too high, which leads to dangerous consequences such as kidney failure, blindness, and amputations. In 2015, 30.3 million Americans (9.4% of the population) had diabetes of some kind. Type 2 diabetes accounts for 90–95% of cases (CDC, 2017). Both genetic and lifestyle factors contribute to developing Type 2 diabetes. Historically, it mainly affected adults, but it increasingly affects children as rates of childhood obesity continue to grow. Because of the disease's link to unhealthy lifestyles, public health experts fear that its prevalence will rise. In 2012, costs of diabetes were estimated to be $245 billion in the US (CDC, 2017).

1.2.2 The Market for Treatments

Treatment of Type 2 diabetes proceeds in stages. Depending on the pathophysiology of the disease for a given individual, the first step might be diet and exercise. The first medicine used is generally Metformin, which is available as a low-cost generic. There is a consensus among medical professionals that Metformin should be the first line of defense against Type 2 diabetes. While the patient is being treated, blood glucose levels are monitored regularly. If Metformin fails to control blood glucose levels, another medicine is added. The American Diabetes Association (ADA) recommends that this second medicine come from one of six classes: sulfonylurea (SU), TZD, DPP-4 inhibitor, SGLT-2 inhibitor, GLP-1 receptor agonist, and basal insulin (Bailey, 2013). This is the stage of treatment I focus on, as this is where branded drugs become important. Unlike with Metformin, there is no clear consensus on which of these classes is most effective (Inzucchi et al., 2015). If dual therapy with Metformin fails to control blood glucose levels after a period of time, the doctor can move to triple therapy. Eventually, insulin therapy will be initiated.[4]

Of the above drug classes, SUs and TZDs are the oldest with several generic options. The latter four classes have seen substantial new brand entry over the past decade (see Table 1.1). SGLT2 in particular is an all-new class that started with the introduction of Invokana in 2013. Because the relative efficacies of the various drugs are not yet well-established, doctors are encouraged to tailor treatments to individual cases, taking into account patient preferences even over factors like costs. Doctors can in principle switch patients between any of the six classes. Given the lack of

[4]Frequently, patients in insulin therapy also take one or even two non-insulin drugs from the aforementioned classes. As I discuss below, when constructing my sample I select those patients that take only one non-Metformin drug in a month, making it unlikely that they are in this advanced stage of therapy.

scientific consensus, DTC might play an important role in shaping preferences.

Pharmaceuticals are some of the most heavily advertised products in the United States, and within pharmaceuticals, diabetes drugs are a heavily advertised category. Drug manufacturers spent approximately $1.8 billion on national DTC television ads for diabetes drugs between 2009 and 2017 (author's calculations). In a dynamic category like this, advertising could be a valuable tool for new entrants to raise awareness of their products and more effectively compete. On the other hand, incumbents could use advertising combatively to prevent entrants from gaining traction.

1.2.3 Employer-Sponsored Health Plans

The context for my analysis is the employer-sponsored population. As of 2017, about half of all Americans accessed health care through an employer-sponsored plan, either directly or by virtue of being a spouse or dependent of someone on such a plan (KFF, 2017). Large, self-insured employers offer their employees a selection of plans (increasingly limited in recent years), possibly contracting with an insurance company to administer the plans. Employers, or more likely the insurers they contract with, also negotiate with health providers over terms of service (henceforth I will use "insurers" to refer to this side of the market). Chapter II focuses more on this aspect of the market.

1.3 Data

I utilize multiple data sources to answer the questions of interest. The period of analysis is 2010-2017.

1.3.1 Pharmaceutical Claims

For information on prescription drugs, I use the Truven MarketScan Commercial Claims and Encounters database. Truven contains data on medical claims for employees at a sample of large US firms. For prescription drugs, the data show the national drug code number of the drug purchased, the purchase date, the patient's CBSA of residence, the patient's out-of-pocket price, and the amount paid by the insurer to the health provider net of patient cost-sharing and third-party payments.

I first select pharmaceutical claims from the individuals in the Truven data age 18-64 who have been diagnosed with Type 2 diabetes.[5] Unlike Type 2 diabetics, Type 1 diabetics can only use insulin, so the other classes of drugs described above are not true substitutes for them. Thus, it is important to distinguish between the two groups. Diabetics use a variety of medical services to manage not only their diabetes, but the various complications associated with the disease, such as blood pressure. I select only the claims corresponding to diabetes medication.

As discussed above, diabetes treatment proceeds in stages. I focus on the "dual therapy" stage, where patients take one drug in addition to Metformin after Metformin alone stops working. Restricting attention to this stage of treatment allows me to assume that patients choose only one drug from the six classes discussed above, greatly simplifying the subsequent analysis. This stage of treatment also appears to be the most important segment of the data. The majority of patients in the data purchase one non-Metformin drug in a given month.[6] Of these, the majority of prescriptions are for a 30-day supply, which is what I focus on. To get the number of products down to a reasonable size, I aggregate over generics of the same active ingredients made by different companies, different delivery forms of the same drug, and different dosages of the same drug. What is important for the analysis is how advertising influences the choice of drug, while things like dosage and delivery form are more idiosyncratic and depend on the specific pathophysiology of each individual patient's disease.

The data contain information on the portion of the drug price paid by the patient and the portion paid by the insurer. I construct the patient's out-of-pocket price as the sum of the copay, coinsurance, and deductible. The deductible potentially introduces complications because it creates a dynamic problem for the patient – using medical services early in the year puts the patient closer to his or her cap and decreases the expected cost of medical services later in the year. The literature has found mixed results about whether patients actually consider this dynamic problem.[7] In my context, I find that the vast majority of claims have no deductibles at all, perhaps reflecting the generosity of these insurance plans or that these patients use so many other medical services that they exceed the cap early. In any case, this makes concerns about dynamic behavior less relevant.

[5]I thank Tanima Basu at IHPI for preparing this data for me.

[6]This is after dropping all claims for Metformin, which make up the vast majority of Type 2 diabetes-related claims.

[7]For example, see Aron-Dine et al. (2015) and Dalton et al. (2015).

On the insurer side, the Truven data record how much the insurer reimbursed the health provider (likely a pharmacy in this context) for the drug. I drop observations where both the patient out-of-pocket price (as defined above) and the insurer reimbursement are zero as likely being miscoded. I also drop outliers, defined as prices below the 1st percentile or above the 99th percentile of the overall distributions of the constructed out-of-pocket price and insurer reimbursement. For the subsequent analysis, all that is important is the out-of-pocket price, as this paper focuses entirely on patients' drug choices. Chapter II discusses the reimbursement data in more detail.

1.3.2 Pharmaceutical Advertising

Advertising data come from Kantar Media. I observe the number of local and national product-specific television ads monthly at the Designated Market Area (DMA) level. Drug manufacturers use both local and national ads (Figure 1.1). For this category, national ads are much more common, but certain DMAs see heavy local advertising at certain times. Figure 1.2 plots total national advertising over time and shows a clear upward trend.

Different firms appear to have different advertising strategies. Some brands are advertised heavily, others sporadically, and others not at all.[8] Furthermore, at least some brands appear to advertise heavily not when they themselves are first introduced but when *other* brands are introduced. The clearest cases of this are Victoza and Januvia, whose advertising paths are shown in Figure 1.3. Both incumbent drugs have sharp spikes in advertising around 2014, when several new brands are introduced (Table 1.1). These facts all show that drug manufacturers use advertising strategically. In particular, the cases of Victoza and Januvia suggest that advertising may be used combatively by incumbents against entrants.

Previous work has shown that advertising can have "goodwill" effects that persist and build over time. Firms do not necessarily advertise to boost demand at any given time but to build up goodwill among consumers (Narayanan et al., 2005; Shapiro, 2018). That is, advertising should be treated as a stock variable. Let a_{jmt} represent the number of ads for product j in market m and month t. The ad stock

[8] Generics are generally not advertised, but they are not an important factor in this market beyond Metformin and the sulfonylureas.

measure I use is defined as:

$$Ad_{jmt} = \sum_{\tau=0}^{t} \gamma^{t-\tau} a_{jm\tau} \tag{1.1}$$

where τ is the first month product j advertised in market m and γ is a persistence parameter. Following Narayanan et al. (2005), I calibrate γ to 0.7.[9]

The geographic market definition differs between the Kantar (DMA) and Truven (CBSA) data. I use a crosswalk from the NBER to match the two. There are 210 DMAs in the US, of which Kantar covers 101 (plus national advertising). Furthermore, CBSAs are not an exhaustive geographic breakdown of the US. For these two reasons, there will not be perfect overlap between the two data sources, but there is a great deal of overlap. I am able to match 268 CBSAs to 100 DMAs.[10] National ads are assigned to every DMA and are included in the ad stock measure above.

1.3.3 Political Advertising

I follow Sinkinson and Starc (2018) in using political advertising as an instrument for pharmaceutical advertising. The intuition is that political ads get preferential treatment and so displace other kinds of ads exogenously in battleground states during election years. Political ad data come from the Wesleyan Media Project which, in partnership with Kantar, tracks all political ads in different kinds of elections (e.g. presidential, federal Congressional, state, etc.).[11] The data also contain the length of the ad, which allows me to normalize to 30-second ads. Except for presidential ads, these ads should largely shift local drug advertising.

1.3.4 Reduced-Form Evidence

The first column of Table 1.2 shows the results of a first-stage regression of log anti-diabetic ad stock (as defined above) on log political ads (both in 100s). The unit of observation is a product-DMA-month using the sample of DMAs that were matched to the Truven data. The regression includes product, DMA, and year fixed effects. I

[9] I have advertising data starting in 2009, which I use in the construction of the ad stock variable but not in the subsequent analysis. This mitigates concerns about an initial conditions problem. I test a range of values for γ which all produce similar results.

[10] A small number of CBSAs cross different DMAs, which prevents me from assigning advertising to them. I drop these CBSAs.

[11] Data from the 2016 presidential election were not available at the time of purchase.

specifically test the intensive margin effect of political ads, i.e. the effect given that a product has already chosen to advertise. The coefficient is highly significant. The magnitude implies that a 10% increase in political ads lead to a 0.22% decrease in drug advertising. This magnitude is smaller than what is found in Sinkinson and Starc (2018), possibly reflecting the relative importance of national advertising in this category, which the instrument does not shift as much. In the second column of Table 1.2, I find that political ads displace pharmaceutical ads at a point in time (i.e. ad flow) as well, reducing concerns that drug manufacturers are simply re-timing their ads to avoid the political ads.

In order to evaluate the marginal effects of advertising in this market, I run a two-stage least squares regression of the quantity of drug j sold in market m and time t on own and rival advertising (both using the stock measure defined above) using the political ad instrument to account for the endogeneity of drug advertising:

$$\ln(Q_{jmt}) = \beta_a \ln(1 + Ad_{jmt}) + \beta_s \ln(1 + Ad_{-jmt}) + \alpha X_{jmt} + \epsilon_{jmt} \tag{1.2}$$

Here, the unit of observation is a product-CBSA-month.[12] Rival advertising might be important because of spillover effects. These are identified due to the presence of drugs that do not advertise, meaning they only receive spillovers. I interact political advertising with an indicator for no pharmaceutical advertising to form an instrument for spillovers. Though the decision not to advertise is an endogenous choice, recall that the measure of advertising used here is the ad stock. In order for a particular drug's ad stock to be zero in a particular DMA-month, that drug cannot have advertised in that DMA and cannot have advertised nationally at any point up to and including that month. Such a decision is less likely to be influenced by local demand shocks and is more likely to be part of a larger strategy by the drug manufacturer. Product, CBSA, and year fixed effects (X) are also included.

The two-stage least squares regression in Table 1.3 shows that advertising has strong business-stealing effects. A 10% increase in product j's advertising leads to 2.9% higher sales in a given CBSA-month, while a 10% increase in advertising by product j's rivals leads to a loss in sales of 1.7%. The signs are consistent with what is found in Sinkinson and Starc (2018).

[12] Recall that a DMA is a geographic measure for media markets. Advertising does not vary within DMA, which is why the first stage was done at the DMA level, but the 2SLS is done at the CBSA level.

While this regression provides useful information, there are a few limitations. The coefficients of the quantity regressions are a composite of business-stealing and market expansion, though it seems the former outweighs the latter. A structural model is required to disentangle these effects. Moreover, the regressions do not capture the policy of interest – a marginal increase in advertising could have different effects from a total ban on advertising. A ban is not observed in the data, so again a model is required.

1.4 Model

I estimate a structural model of demand for anti-diabetic drugs in order to perform the main counterfactual of interest: a ban on direct-to-consumer advertising. Consumers choose the prescription drug that maximizes utility. Physicians are assumed to be perfect agents for consumers; this is supported by the ADA heavily emphasizing that physicians should take patient preferences into account when making prescribing decisions.[13] Consumer i receives utility from drug j in market (CBSA) m, month t, and year y given by:

$$u_{ijmt} = \beta_a \ln(1 + Ad_{jmt}) + \beta_s \ln(1 + Ad_{-jmt}) - \alpha\kappa_{jmy}p_{jmy} + \alpha_j + \alpha_m + \alpha_y + \xi_{jmt} + \varepsilon_{ijmt} \tag{1.3}$$

where Ad_{jmt} is drug j's advertising stock (as defined above), and Ad_{-jmt} represents rival drugs' total advertising stock in market m and month t. The term κ_{jmy} represents the coinsurance rate for drug j in market m for year y. Similarly, p_{jmy} is the negotiated drug price between the insurer and drug manufacturer. The product of these two terms thus corresponds to the out-of-pocket price for drug j faced by consumers in market m and year y. The notation reflects the assumption that prices are negotiated and coinsurance rates are set yearly (see Chapter II for further explanation). α_j, α_m, and α_y are product, market, and year fixed effects, respectively. ξ_{jmt} is a product-market-month unobservable, and $\varepsilon_{ijmt} = \epsilon_{igmt} + (1 - \lambda_g)\epsilon_{ijmt}$ is a "nested logit" error. The nest parameter λ_g controls substitution within group g vs. across groups. If λ_g is zero, the model collapses to a simple logit. As λ_g approaches one, there is less within-group variance in utility across products, i.e. only the groups matter. As is standard, I assume that ϵ_{ijmt} is distributed iid type 1 extreme value.

[13]However, physician agency could enter the model in a reduced-form way through the spillover term. Suppose, for example, that a patient asks his or her doctor for a particular advertised drug, but the doctor ultimately prescribes a different drug. This type of behavior would be interpreted by the model as a spillover effect of advertising by the drug that the patient initially requested.

The utility of the outside option $j = 0$ is normalized to zero: $u_{i0mt} = \epsilon_{i0mt}$. I define the outside option as choosing a sulfonylurea. In the medical literature, this class is recommended if cost is a concern to the patient (Raz, 2013).[14]

It is convenient to define the mean utility of product j in market m at time t as:

$$\delta_{jmt} = \beta_a \ln(1 + Ad_{jmt}) + \beta_s \ln(1 + Ad_{-jmt}) - \alpha\kappa_{jmy}p_{jmy} + \alpha_j + \alpha_m + \alpha_y + \xi_{jmt} \quad (1.4)$$

The distributional assumptions yield the following market share equation:

$$s_{jmt} = \frac{\exp(\delta_{jmt}/\lambda_g)}{\sum_{j\in\mathcal{J}_{gmt}} \exp(\delta_{jmt}/\lambda_g)} \cdot \frac{\left[\sum_{j\in\mathcal{J}_{gmt}} \exp(\delta_{jmt}/\lambda_g)\right]^{1-\lambda_g}}{1 + \sum_g \left[\sum_{j\in\mathcal{J}_{gmt}} \exp(\delta_{jmt}/\lambda_g)\right]^{1-\lambda_g}} \quad (1.5)$$

where $\mathcal{J}_{gmt}$ is the set of products belonging to group g in market m and time t. The first term on the right-hand side is the probability of choosing product j given a choice of group g. The second term is the probability of choosing group g.

The elasticities derived from this model are:

$$\frac{\partial s_{jmt}}{\partial p_{kmt}} \cdot \frac{p_{kmt}}{s_{jmt}} = \begin{cases} -\alpha\kappa_{jmt}p_{jmt}\left(\frac{1}{1-\lambda_g} - \frac{\lambda_g}{1-\lambda_g}s_{j|gmt} - s_{jmt}\right), & \text{if } j = k \\ \alpha\kappa_{kmt}p_{kmt}s_{kmt}\left(\frac{\lambda_g}{(1-\lambda_g)s_{gmt}} + 1\right), & \text{if } j \text{ and } k \text{ are in the same nest} \\ \alpha\kappa_{kmt}p_{kmt}s_{kmt}, & \text{otherwise} \end{cases} \quad (1.6)$$

where $s_{j|gmt}$ is the within-group share of j and s_{gmt} is the share of group g. These expressions make clear that insurance dampens consumer price sensitivities by exactly the coinsurance rate κ.

1.5 Estimation

Following Berry (1994), demand can be transformed as follows:

$$\begin{aligned} \ln\left(\frac{s_{jmt}}{s_{0mt}}\right) = & \sum_g 1\{j \in g\}\lambda_g \ln(s_{j|gmt}) + \beta_a \ln(1 + Ad_{jmt}) + \beta_s \ln(1 + Ad_{-jmt}) \\ & - \alpha\kappa_{jmy}p_{jmy} + \alpha_j + \alpha_m + \alpha_y + \xi_{jmt} \end{aligned} \quad (1.7)$$

[14]Sulfonylureas are largely consumed as generics. The cost to both patients and insurers is fairly low, therefore for simplicity I assume that the price of the outside option is zero.

where s_{0mt} is the share of the outside option. I use separate nests for insulins and non-insulins. Conveniently, this demand system can be estimated with a linear IV. I use only the CBSA-months that have at least 150 sales (including the outside option) to reduce noise in the market shares. Because prices are assumed to be negotiated yearly, I take average prices in the Truven data for both patients and insurers at the CBSA-product-year level. See Chapter II for more detail on the price variables.

The endogenous variables in this equation are the within-group share ($s_{j|gmt}$), out-of-pocket price ($\kappa_{jmy} p_{jmy}$), and advertising (Ad_{jmt}, Ad_{-jmt}), all of which might be correlated with unobserved demand shocks ξ_{jmt}. I instrument for the price of product j in market m using the Hausman instrument, i.e. the average out-of-pocket price of product j in all other markets besides m. This instrument is valid if product j's price in other markets is related to product j's marginal cost, and thus price in market m, but unrelated to demand shocks in market m. The well-known threat to the validity of this instrument is if there are factors that affect demand in all markets simultaneously, such as a national advertising campaign. I explicitly control for this particular factor. As is standard in the literature, I instrument for the within-group share with the number of products in each group; when new products enter, this mechanically shifts within-group shares.

As discussed in Section 1.3, I instrument for drug advertising with political ads, following Sinkinson and Starc (2018). Certain battleground states become flooded with political ads during election years, exogenously displacing drug ads and permitting identification of β_a. Identification of β_s comes from the fact that there are drugs in the data that do not advertise. These drugs only receive the spillover effect and so can be used for identification – i.e. when $Ad_{jmt} = 0$, the only way advertising can have an effect on drug j is through Ad_{-jmt}. As in Section 1.3, I instrument for spillovers by interacting political ads with an indicator for zero ad stock by drug j. As before, the decision not to advertise can reasonably be assumed independent of ξ_{jmt} because the instrument requires the ad *stock* to be zero, meaning the drug cannot have advertised in market m at or before month t and cannot have advertised nationally at or before month t. This decision is less likely to be correlated with a local demand shock.

1.6 Results

Demand estimates are shown in Table 1.4. All estimates are significant. Price and own ads have the expected sign. Consistent with Shapiro (2018), spillovers are estimated to be positive. The reduced form regression in Table 1.3 masked this fact, as it appears business-stealing is stronger on net. Both nest parameters are around 0.5, showing that within-group substitution is important. Average own-price elasticities are around –2 and similar for insulins and non-insulins. Consumers are not overly price sensitive, as might be expected since they are insured, but the availability of many substitutes and relatively high prices appear to make them more elastic than in some other contexts, e.g. Grennan et al. (2018).[15]

1.7 Counterfactuals

Given the structural parameters, we can now simulate how consumer choices would adjust in response to a ban on DTC. In all counterfactual scenarios, I hold drug prices fixed; Chapter II considers the more general case when prices are also allowed to adjust. I drop all firms' advertising to zero and compute new equilibrium quantities using the demand system. Figure 1.4 plots quantity-weighted average yearly prices.[16] This counterfactual provides insight into the "partial equilibrium" effect of advertising. It shows that advertising creates a preference for more expensive products – consumers substitute to cheaper products on average when there is no advertising and prices are held constant, conditional on choosing the inside option. The decrease in average price in each year ranges from 0-6%, with the larger reductions coming in the later years of the sample. This is consistent with the fact that more products are introduced – and more advertising is used – in this part of the sample.

Figure 1.5 shows that two entrants in the SGLT2 class would have had lower market shares on average without the ability to advertise. These results show that the entrants were able to use advertising to gain traction in the market, despite the seemingly combative advertising of incumbents (see Figure 1.3).

Figure 1.6 shows evidence of spillover effects; Humalog, a major insulin that does not advertise at all in this period, loses market share relative to baseline when advertising is banned. Figure 1.7 shows that without advertising, more consumers would switch to the outside option. This is consistent with DTC having spillover effects that expand the market. Without DTC, consumers would utilize low-cost generic sulfonylureas to a greater extent.

[15] Chapter II, which uses the demand model of this paper along with a model of insurer-drug manufacturer bargaining, shows that the model fits the data well.

[16] The "baseline" series and the baseline prices used to construct the "CF" series come from the more general model in Chapter II.

1.8 Conclusion

The effects of DTC on the market for anti-diabetic drugs are nuanced. Using political advertising as an instrument for drug advertising, two-stage least squares estimates show that the marginal effect of DTC is business-stealing. To study the effects of a ban on DTC, this paper estimates a structural model of anti-diabetic drug demand. A partial equilibrium counterfactual shows that DTC creates a preference for more expensive products. A ban on DTC lowers the market shares of entrants in the new SGLT2 class. Despite incumbents using DTC in the face of new brand entry, entrants were able to use DTC to gain traction in the market. However, a ban on DTC would also increase the use of low-cost generics. Taken together, these results suggest that DTC creates a tradeoff between encouraging consumption of new drugs vs. substituting to cheaper drugs, including generics.

There are several avenues for future research. All of the results of this paper assume that prices are held fixed. Chapter II extends these results to the case where prices are allowed to adjust after a ban on advertising. Future work could also attempt to quantify the therapeutic benefits of new anti-diabetic drugs for patients to shed more light on the tradeoff discussed above. Given that the anti-diabetic category is fast-growing with unclear relative efficacies of different drugs, modeling patients' learning process could yield valuable insights. Expanding the analysis to other drug categories would also be interesting.

Figure 1.1: Total National and Local Advertising, Anti-Diabetic Drugs

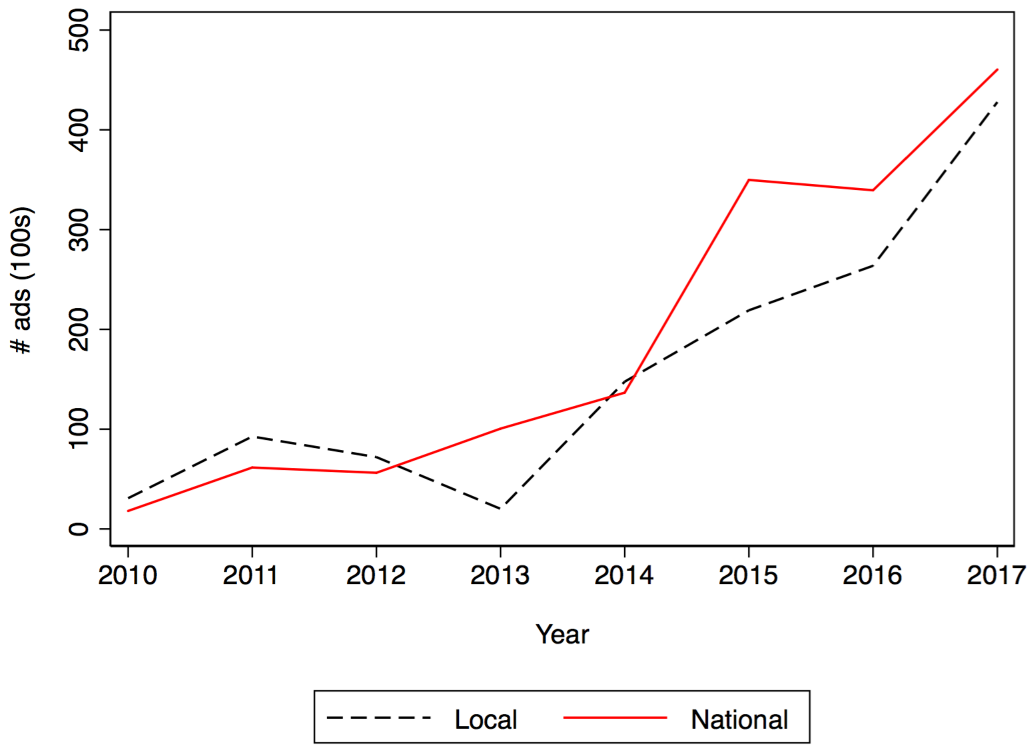


Figure 1.2: Monthly National Advertising, Anti-Diabetic Drugs

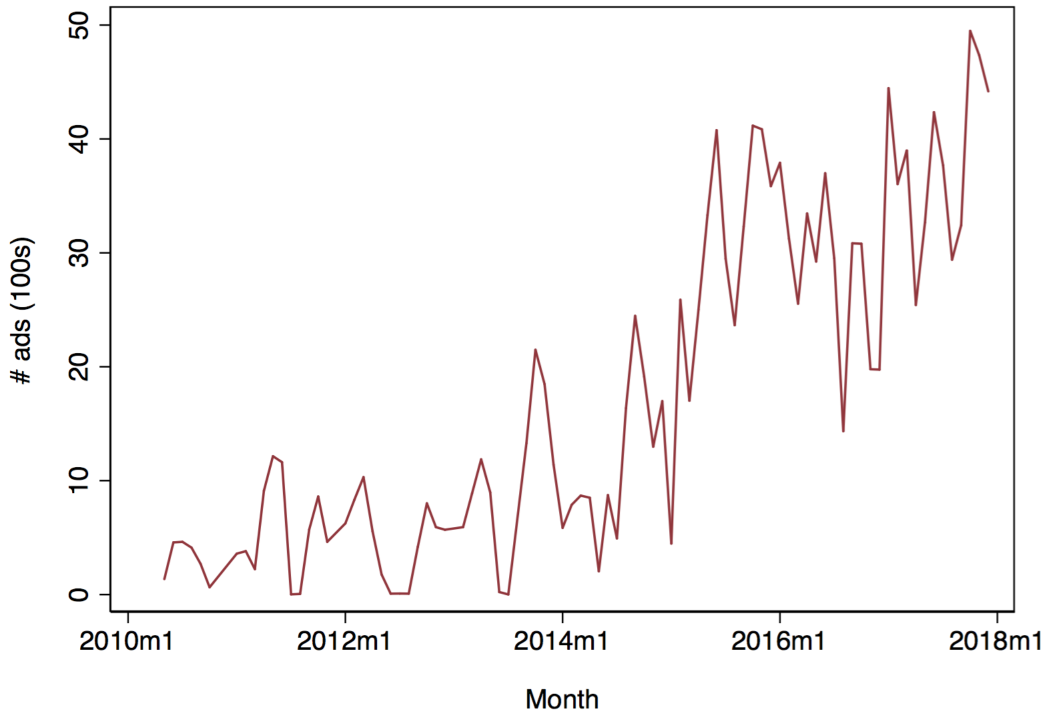
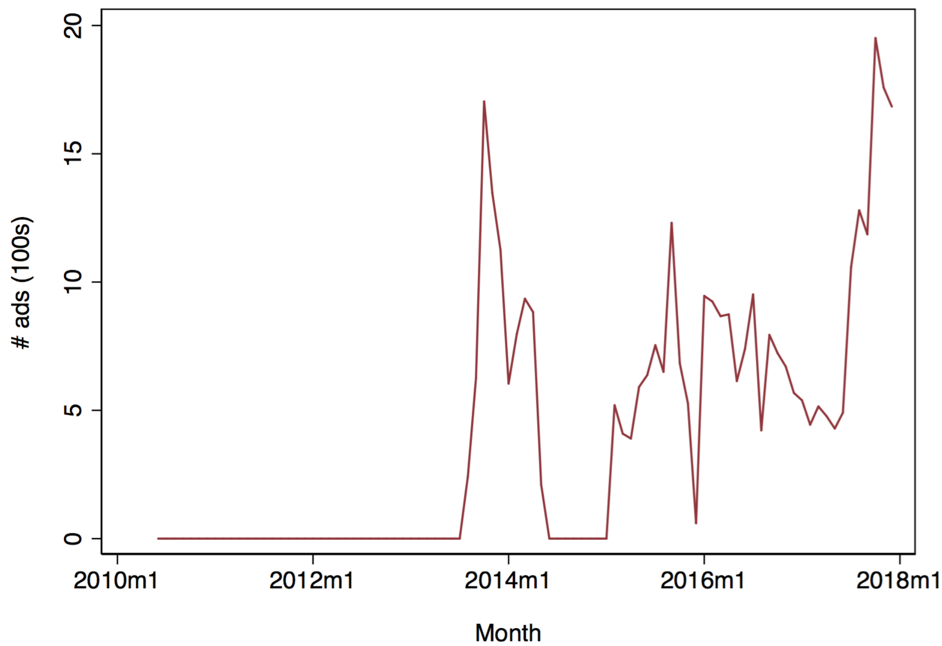
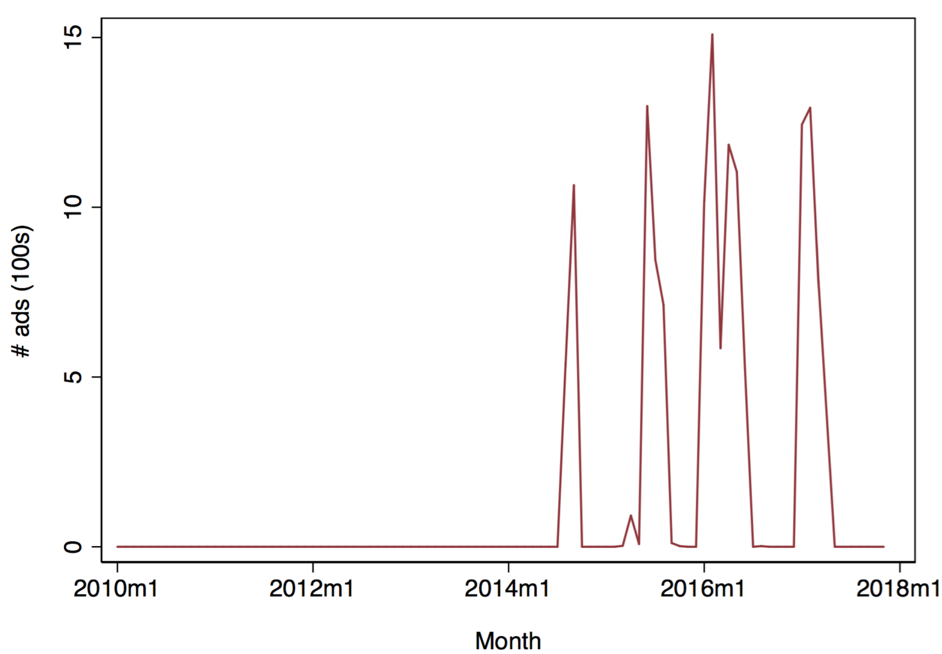


Figure 1.3: Strategic Advertising by Incumbents



(a) Victoza



(b) Januvia

Figure 1.4: Average Drug Prices after a Ban on DTC

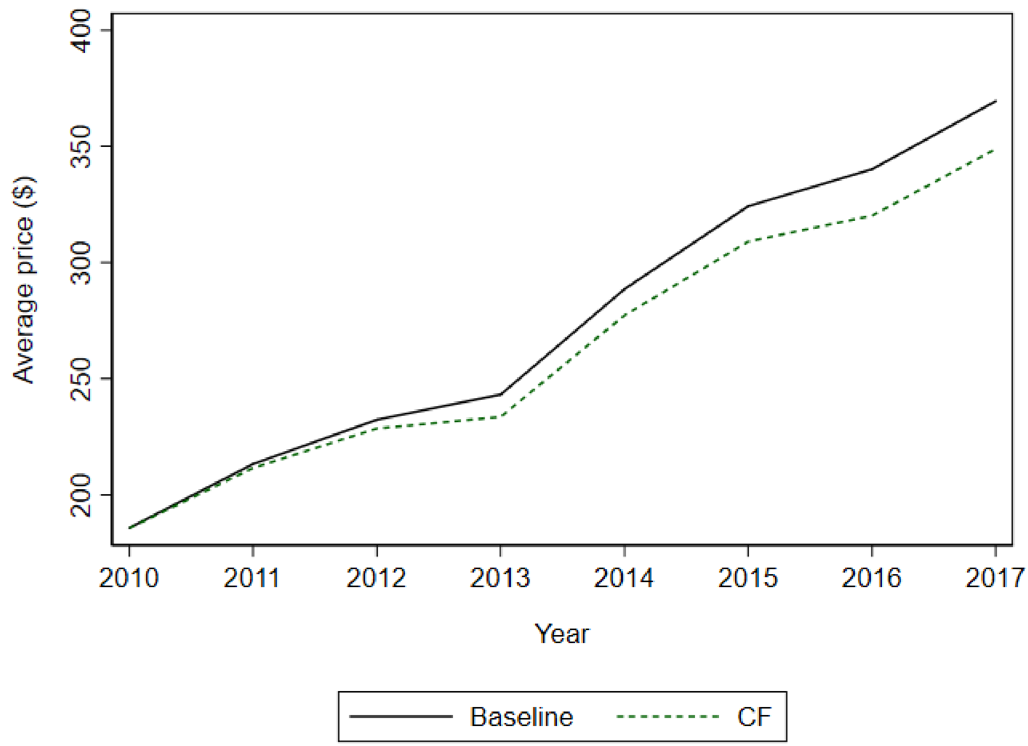
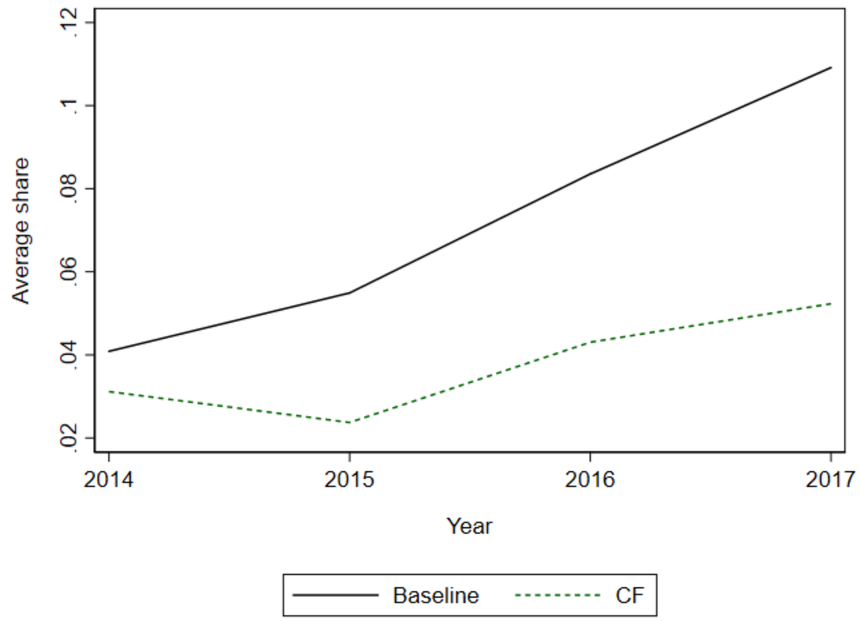
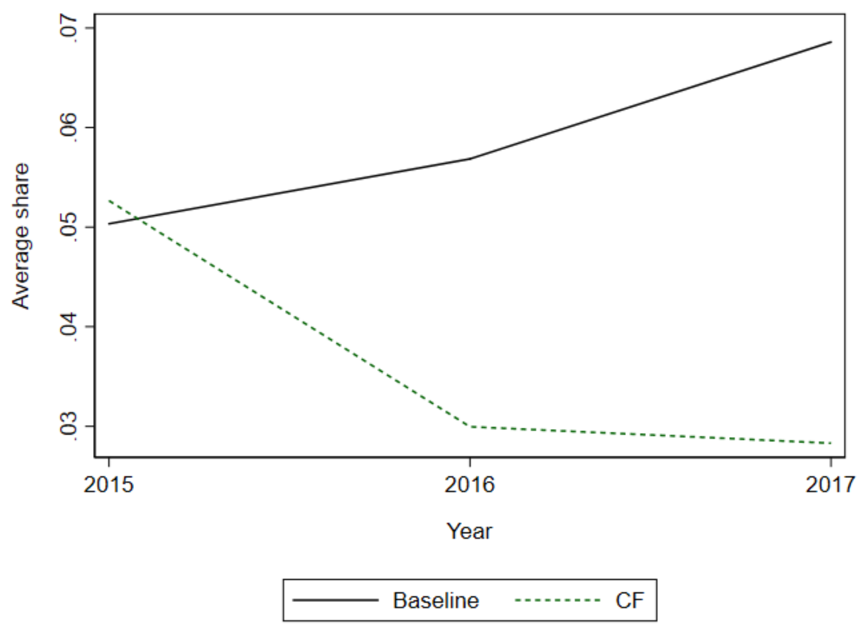


Figure 1.5: Effect of DTC on Entrant Market Shares

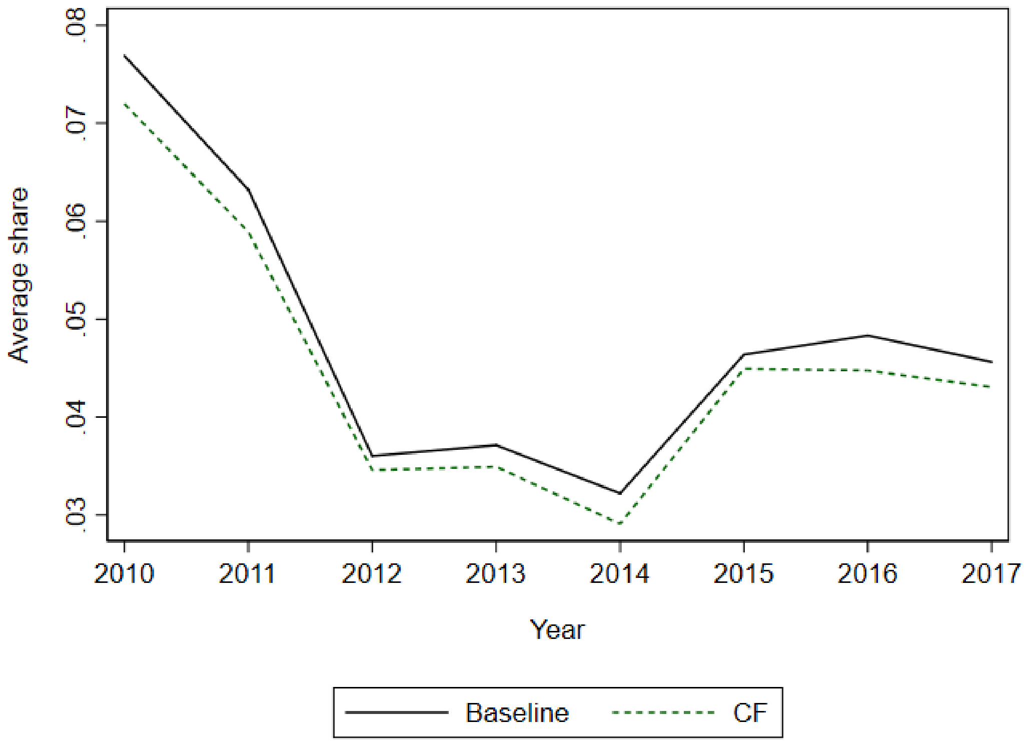


(a) Farxiga



(b) Jardiance

Figure 1.6: Effect of DTC on Non-Advertised Incumbent



Notes: The graph shows average market shares of Humalog, a popular insulin that did not engage in DTC television advertising during the sample period.

Figure 1.7: Effect of DTC on Outside Option Shares

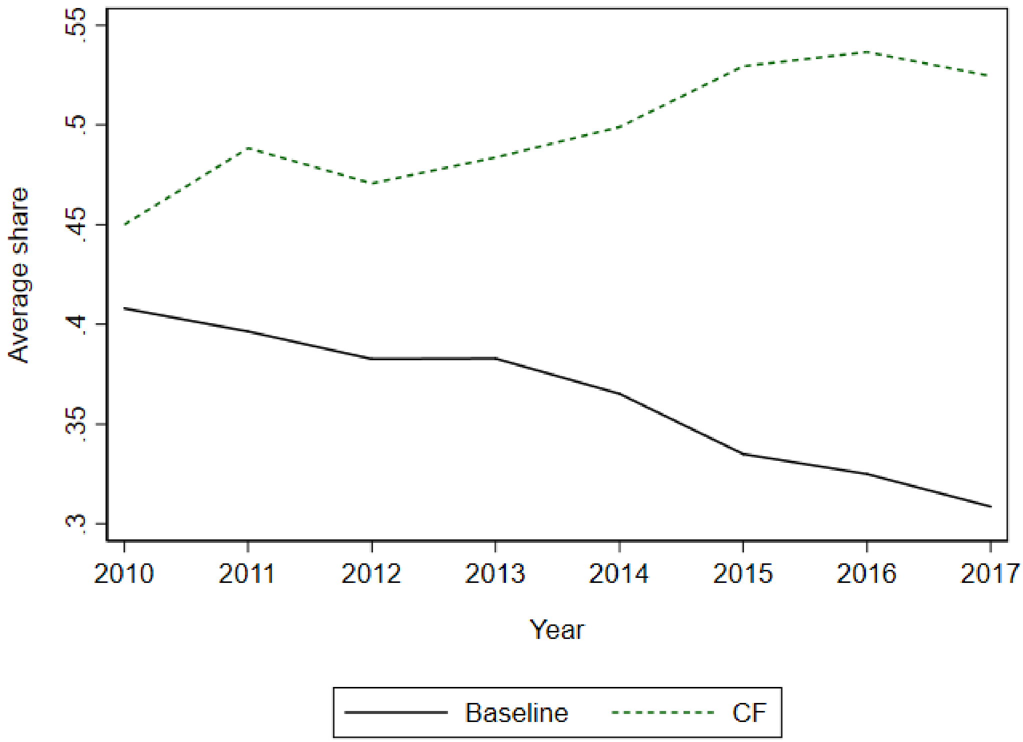


Table 1.1: Anti-Diabetic Drug Approval Dates, Advertised Brands

Brand Name	Manufacturer	Approval Date	Drug Class
Avandia	GlaxoSmithKline	5/25/1999	TZD
Novolog	Novo Nordisk	6/7/2000	Insulin
Levemir	Novo Nordisk	6/16/2005	Insulin
Januvia	Merck	10/17/2006	DPP4
Onglyza	AstraZeneca	6/31/2009	DPP4
Victoza	Novo Nordisk	1/26/2010	GLP1
Invokana	Johnson & Johnson	3/29/2013	SGLT2
Farxiga	AstraZeneca	1/8/2014	SGLT2
Tanzeum	GlaxoSmithKline	4/15/2014	GLP1
Afrezza	Sanofi	6/27/2014	Insulin
Jardiance	Boehringer Ingelheim	8/1/2014	SGLT2
Trulicity	Eli Lilly	9/18/2014	GLP1
Toujeo	Sanofi	2/25/2015	Insulin
Tresiba	Novo Nordisk	9/25/2015	Insulin

Table 1.2: Political Ads Displace Anti-Diabetic Drug Ads

	ln(1+Ad_{jmt})	ln(1+a_{jmt})
ln(1+Political ads$_{mt}$)	-0.0224	-0.0337
	(0.0019)	(0.0036)
Observations	36,152	36,152
R^2	0.4212	0.6321

Notes: Dependent variable is log ad stock in first column, log ad flow in second column. All ad units are measured in 100s. Includes product, DMA, and year fixed effects. Standard errors are clustered at the DMA level.

Table 1.3: Effect of Advertising on Anti-Diabetic Drug Sales

	$\ln(Q_{jmt})$
$\ln(1+Ad_{jmt})$	0.2920
	(0.0746)
$\ln(1+Ad_{-jmt})$	-0.1658
	(0.0607)
Observations	273,046
R^2	0.7278

Notes: Includes product, CBSA, and year fixed effects. Standard errors are clustered at the CBSA level.

Table 1.4: Demand Estimates and Elasticities

Estimates:	κp	Ad_j	Ad_{-j}	λ(non-insulin)	λ(insulin)
	-0.0284	0.2269	0.1246	0.5063	0.5748
	(0.0018)	(0.0309)	(0.0246)	(0.0089)	(0.0162)

Elasticities:	$\bar{\eta}_j$	$\bar{\eta}_j$(non-insulin)	$\bar{\eta}_j$(insulin)
	-2.135	-2.052	-2.218
	(1.115)	(1.214)	(0.997)

Notes: $N = 273,046$. Includes product, CBSA, year fixed effects. $R^2 = 0.8747$.

CHAPTER II

The Role of Direct-to-Consumer Advertising in Negotiated Drug Prices

2.1 Introduction

High prescription drug prices have been a source of public concern in the United States, particularly for essential drugs like insulin. The US is also one of the only countries in the world that permits direct-to-consumer advertising (DTC) for prescription drugs. What role might DTC play in the level of drug prices? This question is theoretically ambiguous. Advertising that creates product differentiation could increase drug manufacturers' market power and raise prices. On the other hand, advertising that is business-stealing could encourage consumers to substitute between products and thus create greater competition.[1] A key aspect of the prescription drug market in particular that the previous literature has largely ignored is that prices are negotiated between providers and insurers. Depending on how advertising affects demand, drug manufacturers could gain bargaining power through product differentiation, or insurers could gain bargaining power by playing different products off of each other. Empirically, the effects of DTC on the supply side of the prescription drug market are under-studied.

This paper studies empirically how DTC affects the prices of branded prescription drugs and how the effect varies depending on the level of brand entry. I consider the market for drugs used to treat Type 2 diabetes. This is a good setting to study these questions due to the high levels of DTC, high prices, and recent brand entry. I use Truven MarketScan's medical claims data from the employer-sponsored health

[1] I will use the terms "DTC" and "advertising" interchangeably throughout the paper. See Bagwell (2007) for a summary of the literature on advertising.

insurance market and DTC data from Kantar Media. I focus exclusively on television advertising in this paper, as that is the most important DTC channel for anti-diabetic drugs. Beyond answering questions about advertising and drug prices, this market is important in its own right due to the public health costs of diabetes (ADA, 2018).

To answer these questions, I start with a descriptive analysis of the marginal effects of advertising on drug sales and prices. I run a series of two-stage least squares regressions of drug prices on DTC using political advertising to account for the endogeneity of drug advertising (Sinkinson and Starc, 2018). I allow both own and rival ads to affect outcomes (i.e. I allow for spillover effects; Shapiro, 2018). I find that advertising leads to lower prices on the margin. This can be explained by business-stealing advertising making consumers more willing to substitute between products – i.e. more elastic – which prevents drug manufacturers from charging high markups. Thus, advertising is pro-competitive on the margin. I further find that this effect is stronger when more brands enter.

However, the marginal effects of DTC are likely to be different from a ban on DTC. To study this policy, I estimate a structural model of patient drug choices and insurer-drug manufacturer bargaining over drug prices. I use the demand model of Chapter I as an input into the bargaining model. The solution concept is Nash-in-Nash bargaining. The model delivers four main results. First, I find that drug manufacturers have a higher bargaining weight than insurers. Second, I show that allowing for price adjustment in the counterfactual is important – average prices can look very different when parties renegotiate. Third, I show that both of the mechanisms discussed above are possible. There are equilibria where prices increase after a ban on DTC and there are others where prices decrease. Finally, I show that a ban on DTC causes new brands to lose significant market share, even after allowing for price adjustment. This final result is robust to different kinds of equilibria.

This paper makes several contributions. First, I add to the growing literature that studies interactions between firms in vertical chains, such as cable companies and content providers (Crawford and Yurukoglu, 2012; Crawford et al., 2018) and hospitals and health insurers (Gowrisankaran et al., 2015; Ho and Lee, 2017). These papers employ the Nash-in-Nash framework which has now become the workhorse model to study price negotiations under a variety of counterfactual policies (e.g. mergers). This paper is the first to study how DTC affects prescription drug price negotiations.

This paper also contributes to the literature on new drug entry, which has largely focused on generics rather than brands. Frank and Salkever (1997) and Ching (2010) show that branded drug prices can rise after generic entry. Grennan et al. (2018) study the effects of a ban on detailing (i.e. marketing directly to physicians) using the Nash-in-Nash model to endogenize price negotiations. However, that paper does not study new brand entry as it examines a context (statins from 2011-2012) when major patents expired and prompted generic entry. Moreover, drug manufactures' detailing and DTC strategies can be quite different (Shapiro, 2018), so it is important to understand both.

The paper proceeds as follows: Section 2.2 discusses institutional details of the anti-diabetics market, Section 2.3 explains the data and descriptive analysis, Section 2.4 introduces the structural model, Section 2.5 discusses the estimation strategy, Section 2.6 shows results, Section 2.7 discusses counterfactuals, and Section 2.8 concludes.

2.2 Empirical Setting

This paper focuses on the market for anti-diabetic drugs. These drugs are largely used to treat Type 2 diabetes.[2] There are three features of this market that make it a natural setting to study the effects of advertising on prices and new products: prices are high, several new brands have been introduced, and there is a high level of advertising. For a detailed explanation of Type 2 diabetes, the market for treatments, and employer-sponsored health insurance plans, see Chapter I. This section makes two additional points that are relevant for the discussion in this paper.

First, in the market for DTC television advertising, firms buy advertising time in an up-front market usually in the calendar year preceding when the ad will run. The timing assumption for the structural model will reflect this fact.

Second, in the employer-sponsored health insurance context, employers generally contract with insurance companies to administer health plans and negotiate with health providers over terms of service (henceforth I will use "insurers" to refer to this side of the market). In the pharmaceutical context specifically, insurers may work with a pharmacy benefit manager (PBM) to handle these negotiations. Rebates

[2]Type 1 diabetics can only use insulin. All of the other (non-insulin) drugs studied in this paper can only be used by Type 2 diabetics. 90% to 95% of diabetes cases are Type 2 (CDC, 2017).

from drug manufacturers to PBMs/insurers are an important feature of this industry. Unfortunately, they are highly confidential. Like all other research in this area, I do not observe rebates and assume they are held fixed in counterfactuals. In Section 2.7, I discuss how I try to account for the bias rebates may introduce into the results.

2.3 Data

I utilize multiple data sources to answer the questions of interest. The period of analysis is 2010-2017. Three main sources are used: prescription drug data from the Truven MarketScan Commercial Claims and Encounters database, DTC television advertising data from Kantar Media, and political advertising data from the Wesleyan Media Project. See Chapter I for a detailed explanation of dataset construction.

Truven contains data on medical claims for employees at a sample of large US firms. For prescription drugs, the data show the national drug code number of the drug purchased, the purchase date, the patient's CBSA of residence, the patient's out-of-pocket price, and the amount paid by the insurer to the health provider net of patient cost-sharing and third-party payments.

It is crucial that the observed price paid by the insurer is the actual reimbursed amount rather than the list price set by the drug manufacturer (which almost no payer actually pays) or a retail price that can be negotiated down. Having this information is important for getting accurate estimates from the bargaining model and performing counterfactuals (again, subject to rebates, which I discuss below). Unfortunately, the data do not allow me to distinguish between different employers, insurers/PBMs, or pharmacies. I therefore make two assumptions. First, I define a market as a CBSA and assume each CBSA contains one insurer bargaining on behalf of all patients who live there.[3] Second, following Grennan et al. (2018), I abstract from upstream supply interactions between drug manufacturers, wholesalers, and pharmacies and treat each drug manufacturer as a bargaining unit in each market. However, the prices charged by the manufacturer and those charged by the pharmacy should move in concert and be highly related.

I link the claims data to advertising data from Kantar Media. Kantar provides the number of local and national product-specific ads monthly at the Designated Market Area (DMA) level. Figure 2.1 plots the total number of anti-diabetic television

[3]This could be the case if all employers in an area use a common PBM.

ads and average negotiated anti-diabetic drug prices over time. Both series trend upward and follow each other quite closely; while this fact is not proof of a causal relationship, it certainly suggests that the link between drug prices and DTC is worth investigating further.

As in Chapter I, I use the ad stock as my measure of advertising in all empirical analyses (Narayanan et al., 2005; Shapiro, 2018). Let a_{jmt} represent the number of ads for product j in market m and month t. The ad stock measure I use is defined as:

$$Ad_{jmt} = \sum_{\tau=0}^{t} \gamma^{t-\tau} a_{jm\tau} \tag{2.1}$$

where τ is the first month product j advertised in market m and γ is a persistence parameter rate. Following Narayanan et al. (2005), I calibrate γ to 0.7.

2.3.1 Reduced-Form Evidence

To account for the endoegeneity of advertising, I follow Sinkinson and Starc (2018) in using political advertising as an instrument for pharmaceutical advertising. The intuition is that political ads get preferential treatment and so displace other kinds of ads exogenously in battleground states during election years. See Chapter I for more details on the instruments.

In order to evaluate the marginal effects of advertising on prices in this market, I run regressions of the negotiated drug price on DTC advertising by that drug and by rival drugs:

$$\ln(P_{jmt}) = \beta_a \ln(1 + Ad_{jmt}) + \beta_s \ln(1 + Ad_{-jmt}) + \alpha X_{jmt} + \epsilon_{jmt} \tag{2.2}$$

Including advertising by rival drugs allows for spillover effects. I use as my price measure the sum of the average patient out-of-pocket price and insurer net reimbursement for each product-CBSA-year (the reasoning behind this measure is explained further in Section 2.4).[4]

The first column of Table 2.1 shows results from an OLS regression of price on own and rival ads. The positive coefficients are consistent with Figure 2.1. However,

[4] While it is possible that insurers negotiate a national drug price with drug manufacturers, in the data I do see variation in prices across CBSAs.

the two-stage least squares results in the second column show that a 10% increase in own advertising decreases prices by 1.2%, while the same increase in rival advertising increases prices by 0.61%. This shows that endogeneity is a real concern. The difference between the OLS and 2SLS results suggest that drug manufacturers target ads to high-demand markets, which would bias OLS coefficients upward. Prices in these markets would be high anyway, but those prices would have been even higher with less advertising.

The 2SLS results can be explained by advertising having a business-stealing effect, as was found in Chapter I. Holding rival ads fixed, an increase in product j's advertising steals business from its rivals by making consumers more willing to switch. The higher elasticity for consumers limits drug manufacturers' ability to charge high markups, which ultimately lowers j's price. Conversely, holding own advertising fixed, when rivals advertise, it steals business from product j. The positive price coefficient could be explained by rival drugs using advertising to differentiate themselves, and thus charging higher prices. Since prices are strategic complements, j's price rises as well. The reason that these effects are asymmetric has to do with the interpretation of the coefficients – it is likely that an increase in advertising by one firm, holding all rivals' advertising constant, has a different effect than an increase in all rivals' advertising.

To study whether these price effects vary with the number of entering brands, I run the price regression separately on two subsamples of the data: periods of "light" vs. "heavy" entry. Several drugs in my sample enter in and after 2014 (Table 1.1), which is the year I use to delineate the heavy entry period. The 2SLS results are shown in Table 2.2. The effects described above are concentrated in the period of heavy entry (2014-2017) when there is more advertising, illustrating the interplay between entry and advertising.

These price regressions, while illuminating, mask complicated competitive effects of advertising. Moreover, a marginal increase in advertising could have different effects from a total ban on advertising. To determine the effects of a ban, a structural model is required.

2.4 Model

I estimate a structural model of demand and pricing for anti-diabetic drugs in order to study the effects of a ban on direct-to-consumer advertising on drug prices.

The components of the model include discrete-choice demand for prescription drugs and bargaining over drug prices between drug manufacturers and employers/insurers (see Grennan et al. (2018) for a similar approach).

The timing of the model is as follows:

0a. Insurers choose formularies and coinsurance rates.

0b. Demand and marginal cost shocks are realized.

0c. Drug manufacturers choose advertising schedules for the year.

1. Insurers and drug manufacturers negotiate over drug prices for the year.

2. Consumers choose drugs each month.

In the data, it is most common to see patients filling prescriptions for a 30-day drug supply. However, it is highly unlikely that price negotiations happen at this frequency. Therefore, an assumption needs to be made about how frequently prices are negotiated. I assume that prices are negotiated at the beginning of each year. The timing assumption for advertising reflects the fact that most advertising is purchased well in advance of when it airs.

2.4.1 Demand

The demand model of Chapter I is used as an input into the bargaining model. For the sake of coherence, some details from that paper are repeated here. Consumers choose the prescription drug that maximizes utility. Consumer i receives utility from drug j in market (CBSA) m, month t, and year y given by:

$$u_{ijmt} = \beta_a \ln(1 + Ad_{jmt}) + \beta_s \ln(1 + Ad_{-jmt}) - \alpha\kappa_{jmy}p_{jmy} + \alpha_j + \alpha_m + \alpha_y + \xi_{jmt} + \varepsilon_{ijmt} \tag{2.3}$$

All terms are defined exactly as in Chapter I: Ad_{jmt} is drug j's advertising stock (as defined above), Ad_{-jmt} represents rival drugs' combined advertising stock in market m and month t, κ_{jmy} represents the coinsurance rate for drug j in market m for year

y, and p_{jmy} is the negotiated drug price. By assumption, prices are negotiated and coinsurance rates are set yearly. α_j, α_m, and α_y are product, market, and year fixed effects, respectively. ξ_{jmt} is a product-market-month unobservable, and $\varepsilon_{ijmt} = \epsilon_{igmt} + (1-\lambda_g)\epsilon_{ijmt}$ is a "nested logit" error. As is standard, I assume that ϵ_{ijmt} is distributed iid type 1 extreme value. The utility of the outside option $j = 0$ is normalized to zero: $u_{i0mt} = \epsilon_{i0mt}$. I define the outside option as choosing a sulfonylurea.

It is convenient to define the mean utility of product j in market m at time t as:

$$\delta_{jmt} = \beta_a \ln(1 + Ad_{jmt}) + \beta_s \ln(1 + Ad_{-jmt}) - \alpha\kappa_{jmy}p_{jmy} + \alpha_j + \alpha_m + \alpha_y + \xi_{jmt} \quad (2.4)$$

The distributional assumptions yield the following market share equation:

$$s_{jmt} = \frac{\exp(\delta_{jmt}/\lambda_g)}{\sum_{j\in\mathcal{J}_{gmt}}\exp(\delta_{jmt}/\lambda_g)} \cdot \frac{\left[\sum_{j\in\mathcal{J}_{gmt}}\exp(\delta_{jmt}/\lambda_g)\right]^{1-\lambda_g}}{1 + \sum_g \left[\sum_{j\in\mathcal{J}_{gmt}}\exp(\delta_{jmt}/\lambda_g)\right]^{1-\lambda_g}} \quad (2.5)$$

where $\mathcal{J}_{gmt}$ is the set of products belonging to group g in market m and time t.

The elasticities derived from this model are:

$$\frac{\partial s_{jmt}}{\partial p_{kmt}} \cdot \frac{p_{kmt}}{s_{jmt}} = \begin{cases} -\alpha\kappa_{jmt}p_{jmt}\left(\frac{1}{1-\lambda_g} - \frac{\lambda_g}{1-\lambda_g}s_{j|gmt} - s_{jmt}\right), & \text{if } j = k \\ \alpha\kappa_{kmt}p_{kmt}s_{kmt}\left(\frac{\lambda_g}{(1-\lambda_g)s_{gmt}} + 1\right), & \text{if } j \text{ and } k \text{ are in the same nest} \\ \alpha\kappa_{kmt}p_{kmt}s_{kmt}, & \text{otherwise} \end{cases} \quad (2.6)$$

where $s_{j|gmt}$ is the within-group share of j and s_{gmt} is the share of group g. These expressions show how advertising can have both product differentiation and pro-competitive effects in this model. Looking at the own-price elasticity, advertising by j should increase s_{jmt} and $s_{j|gmt}$, which makes consumers more inelastic and allows j to charge a higher price. This is the product differentiation effect. Looking at the cross-price elasticities, advertising by k should increase s_{kmt}, which makes consumers more likely to substitute to k, leading j to charge lower prices. This is the pro-competitive effect. The relative magnitudes of these effects are an empirical question and are not imposed by the model.[5]

[5] The nested logit model does impose IIA within nests, which is perhaps not unreasonable because of the lack of scientific consensus on the relative efficacies of these drugs (see Chapter I).

2.4.2 Bargaining

Drug manufacturers $f \in 1...F$ maximize profit from the set of drugs $j \in \mathcal{J}_{fmy}$ sold in market m and year y:

$$\pi_{fmy} = \sum_{j \in \mathcal{J}_{fmy}} (p_{jmy} - mc_{jmy}) q_{jmy} \tag{2.7}$$

where q_{jmy} is the quantity of j sold, and mc_{jmy} represents marginal costs. This formulation accounts for multiproduct firms. The quantity sold comes out of the demand model through the relation $q_{jmy} = \sum_t s_{jmt} M_{mt}$. Market size M_{mt} varies exogenously and is defined as the number of prescriptions filled each month in a given market. This is a reasonable definition because in the stage of treatment my model focuses on, patients are beyond the point where diet and exercise alone (i.e. no drugs) are effective.

Drug manufacturers negotiate with insurers over the "point-of-sale" price p_{jmy}. I assume that they do so through "Nash-in-Nash" bargaining. The two parties maximize their joint surplus, which is split according to their bargaining weights. The weights are normalized to sum to one. Consider a single manufacturer-insurer pair in a given market-year (recall that the "insurer" is implicitly defined by the market). The Nash bargaining problem is:

$$\max_{\{p_{jmy}\}_{j \in \mathcal{J}_{fmy}}} \left((\pi_{fmy}(\mathbf{p}_{my}, \mathbf{mc}_{fmy}) \right)^b \left(\mathcal{W}_{my}(\mathcal{J}_{my}) - \mathcal{W}_{my}(\mathcal{J}_{my} \setminus \mathcal{J}_{fmy}) \right)^{1-b} \tag{2.8}$$

where $\mathcal{W}_{my}(\mathcal{J}_{my}) \equiv CS_{my}(\mathcal{J}_{my}) - \sum_{k \in \mathcal{J}_{my}} (1 - \kappa_{kmy}) p_{kmy} q_{kmy}$, and b is a bargaining parameter. Collard-Wexler et al. (2019) offer a microfounded interpretation of this parameter as a discount rate in a repeated game. The party with the higher bargaining weight is more patient and can therefore capture a larger portion of the joint surplus. Note that these negotiations are over all products $\mathcal{J}_{fmy}$ drug manufacturer f offers in market m and year y. The drug manufacturer takes into account how a particular negotiated price for one of its drugs affects market shares and profits from its other drugs.

The insurer balances patients' consumer surplus from all offered drugs $\mathcal{J}_{my}$ against the cost of providing those drugs. I follow Ho and Lee (2017) in assuming that employers fully internalize their employees' welfare (which the insurers implicitly take into account through their contracts with the employers). Consumer surplus derived from the nested logit demand model is:

$$CS_{my}(\mathcal{J}_{my}) = \sum_t M_{mt} \frac{1}{\alpha} \ln \left(1 + \sum_g \left(\sum_{j \in \mathcal{J}_{gmt}} \exp\left(\delta_{jmt}/(1-\lambda_g)\right) \right)^{1-\lambda_g} \right) \tag{2.9}$$

This formulation, along with the timing assumption given above, assumes that both insurers and drug manufacturers can forecast demand accurately when negotiating prices at the start of the year. Insurers include "utility" from advertising in patients' consumer surplus.

The Nash-in-Nash framework does not allow the set of agreements to change when prices change. Like the previous literature, I assume that all agreements are held fixed in the counterfactuals. This is consistent with the assumption that rebates are held fixed. Industry analysts suggest that drug manufacturers use rebates to get their drugs onto an insurer's formulary.[6] Since the analysis is "partial equilibrium" in the sense that formularies will not change in the counterfactual, this restriction of the Nash-in-Nash model is consistent with holding rebates fixed.

2.5 Estimation

Estimation of demand follows Chapter I. Berry (1994) shows that demand can be transformed as follows:

$$\begin{aligned} \ln\left(\frac{s_{jmt}}{s_{0mt}}\right) = & \sum_g 1\{j \in g\}\lambda_g \ln(s_{j|gmt}) + \beta_a \ln(1 + Ad_{jmt}) + \beta_s \ln(1 + Ad_{-jmt}) \\ & - \alpha\kappa_{jmy}p_{jmy} + \alpha_j + \alpha_m + \alpha_y + \xi_{jmt} \end{aligned} \tag{2.10}$$

where s_{0mt} is the share of the outside option. I use separate nests for insulins and non-insulins. Conveniently, this can be estimated with a linear IV. I use only the CBSA-months that have at least 150 sales (including the outside option) to reduce noise in the market shares. Because prices are assumed to be negotiated yearly, I take average prices in the Truven data for both patients and employers at the CBSA-product-year level. I impute coinsurance rates by dividing the patients' out-of-pocket price by the total price for each CBSA-product-year. The out-of-pocket price does not come entirely from coinsurance (e.g. there are copays as well), but this

[6] E.g. "...[PBMs] wrangle rebates and discounts from the manufacturers in exchange for getting their drugs placed on the insurance companies formularies..." (Entis, 2019).

formulation is able to capture any cost-sharing changes the insurer might make in the counterfactual in a reduced-form way. If the price for a drug were to increase or decrease significantly, the insurer might pass on a portion of that change to patients.

Chapter I explains in detail the instruments used for the endogenous variables in the above equation: within-group share, out-of-pocket price, and advertising. To summarize, I use the number of goods in each nest to instrument for within-group share, the Hausman instrument for out-of-pocket price, and instruments based on political advertising described in Section 2.3 for own drug advertising and spillovers. It is worth saying more here about the political advertising instrument given the timing assumption introduced in Section 2.4. For political advertising to be a valid instrument in the context of this model, the identifying assumptions must be consistent with the timing assumption. This implies that drug manufacturers (or the advertising agencies they hire) must know the political advertising schedule when setting their own ad schedules for the year. This is likely a good approximation of reality. Sinkinson and Starc (2018) argue that the intensity of political advertising was a "surprise" in 2008, but in my sample period, drug manufacturers would have observed what happened in 2008 and adjusted to it. The Citizens United decision was made at the beginning of my sample period, which should have further led drug manufacturers to expect high levels of political advertising.

Though the model requires manufacturers to have predicted political advertising, this does not threaten identification. What is important for identification is that the timing and geographic variation of the political advertising exogenously shifted pharmaceutical advertising from what it would have been had there been no election. A drug manufacturer in 2011 that sets its advertising schedule for 2012 knows that Ohio is likely to see a lot of political advertising, and so would adjust its advertising in Ohio accordingly. The key is that 2012 being an election year and Ohio being a battleground state are exogenous factors, so the drug manufacturer's adjustment has nothing to do with drug demand shocks in Ohio in 2012. Hence, the predictability of political advertising is not an issue for identification.

After estimating the demand model, I make a few restrictions before turning to bargaining. First, I consider only the CBSA-years for which the CBSA appears in the data for all 12 months of that year (i.e. it meets the market size threshold in all 12 months). This is done to accurately model negotiations (which cover the entire year) and to account for products that enter in the middle of the year. Second, I restrict the sample to the top 50 CBSAs by number of drug sales throughout the sample period to ease computational burden. Third, I drop uncommon or unpopular products for which it would be difficult to accurately estimate marginal costs.[7] Dropping these products also implicitly assumes that drug manufacturers only consider major rivals in the bargaining game, which is plausible.

To estimate the parameters of the bargaining model, I take the first-order condition of the log of the Nash bargaining problem presented above. The exposition closely follows that in Gowrisankaran et al. (2015). There is a departure from that model here in that demand decisions are being made monthly while price bargaining is happening yearly, but it is straightforward to show that the FOC is of the same form. Taking the FOC and rearranging we get:

$$\begin{aligned} q_{mjy} + \sum_{k \in \mathcal{J}_{fmy}} \frac{\partial q_{kmy}}{\partial p_{jmy}} (p_{jmy} - mc_{jmy}) &= \\ -\frac{(1-b)}{b} \cdot \underbrace{\frac{\frac{\partial \mathcal{W}_{my}}{\partial p_{jmy}}}{\mathcal{W}_{my}(\mathcal{J}_{my}) - \mathcal{W}_{my}(\mathcal{J}_{my} \setminus \mathcal{J}_{fmy})}}_{\frac{A}{B}} & \sum_{k \in \mathcal{J}_{fmy}} q_{kmy}(p_{kmy} - mc_{kmy}) \end{aligned} \tag{2.11}$$

Collect the FOCs for a single manufacturer-insurer pair in a market-year:

$$\mathbf{q} + \mathbf{\Omega}(\mathbf{p} - \mathbf{mc}) = -\mathbf{\Lambda}(\mathbf{p} - \mathbf{mc}) \tag{2.12}$$

where Ω and Λ are $\#\mathcal{J}_{fmy} \times \#\mathcal{J}_{fmy}$ matrices. $\Omega(j,k) = \frac{\partial q_{kmy}}{\partial p_{jmy}}$ and $\Lambda(j,k) = \frac{1-b}{b}\frac{A}{B} q_{kmy}$ for all $j, k \in \mathcal{J}_{fmy}$. Rearranging, we get:

$$\mathbf{mc} = \mathbf{p} + (\mathbf{\Omega} + \mathbf{\Lambda})^{-\mathbf{1}}\mathbf{q} \tag{2.13}$$

Everything on the right-hand side of this equation can be constructed using data and parameters. With the demand parameters in hand, marginal costs can be backed out given any candidate value of the bargaining parameter b.

I now turn to the estimation of the bargaining parameter b. First, I parametrize marginal costs:

$$\mathbf{mc} = \boldsymbol{\eta}\mathbf{v} + \boldsymbol{\omega} \tag{2.14}$$

[7] Specifically, I drop products that have less than 1% market share in a CBSA-month or less than 0.1% of the total sales in a CBSA-year. The goal in choosing these thresholds is to balance dropping products that may be one-off or unusual prescriptions with not dropping too many observations. These restrictions drop about 10% of sales in the average CBSA-month.

where $\mathbf{v}$ are product, CBSA, and year fixed effects. The shock ω will be used to form a moment condition that identifies b. Inverting (2.14) and re-writing marginal costs in terms of observables and parameters using (2.13) gives us:

$$\boldsymbol{\omega} = -\boldsymbol{\eta}\mathbf{v} + \mathbf{mc} = -\boldsymbol{\eta}\mathbf{v} + \mathbf{p} + (\boldsymbol{\Omega} + \boldsymbol{\Lambda})^{-1}\mathbf{q} \tag{2.15}$$

Note that price is endogenous here because manufacturers observe the marginal cost shock before choosing prices. But with an appropriate instrument $\mathbf{z}$, the moment condition $\mathbb{E}[\boldsymbol{\omega} \otimes \mathbf{z}] = 0$ identifies b. The instrument I choose is consumer surplus from the manufacturer's products at the average out-of-pocket price of these products in other markets (i.e. an analog of the Hausman instrument). This surplus is related to the surplus that appears in the insurer's agreement value because it is calculated using the same demand parameters, but it should not be related to the marginal cost shock in that particular market.

Because b enters (2.15) nonlinearly, it must be searched for. The Nash bargaining problem is highly nonlinear, however; very small changes in the bargaining parameter can drastically change the value of the objective function, which makes it very important to try a lot of starting values. I use 901 starting values spaced evenly from 0.1 to 1. I use a simplex routine with a tight tolerance on both the step size and changes in the objective function to estimate b.[8]

2.6 Results

See Chapter I for demand estimates. Table 2.3 shows the estimates of marginal costs and the bargaining parameter. Manufacturers have a larger bargaining weight than insurers, consistent with the high prices observed in the data and noted by the popular press. Mean marginal costs for a 30-day supply are estimated to be \$191. While production costs for drugs are generally thought to be low, distribution and administrative costs could be playing a role here. Figure 2.2 shows that the model fits the data reasonably well.

2.7 Counterfactuals

Given the demand, cost, and bargaining parameters, we can now simulate the policy of interest: a ban on DTC. I allow both consumer choices and prices to adjust

[8] Results are robust to allowing b to vary by year.

after the ban. I drop all firms' advertising to zero and compute new equilibrium prices and quantities using the FOCs. Upon doing this, I find that there is not a unique equilibrium – prices can increase or decrease after a ban.[9] Figure 2.3 plots quantity-weighted average yearly prices for two representative equilibria, which I call EQ 1 and EQ 2. In EQ 1, the price increase is concentrated in 2014-2017, which coincides with the wave of new entry shown in Table 1.1. This result suggests that entrants can use advertising to steal business and become better substitutes with incumbents, creating stronger price competition. On the other hand, EQ 2 shows that advertising can have a strong market power effect through product differentiation.

Figure 2.3 also replicates the "partial equilibrium" counterfactual (i.e. with no price adjustment) from Chapter I for comparison. I again drop all firms' advertising to zero and use the demand model to find consumers' new choices. This series in Figure 2.3 shows that advertising creates a preference for more expensive products. This effect is quite different, however, from both counterfactuals with price adjustment, suggesting that upstream price adjustment should be considered when thinking about a ban on advertising.

Figure 2.4 extends the results on new brands from Chapter I. The figure shows that two entrants in the SGLT2 class would have had lower market shares on average without the ability to advertise in both representative equilibria, showing that the results from Chapter I are robust to allowing for price adjustment. Similarly, Figures 2.5 and 2.6 extend results from Chapter I on spillover effects and outside option shares; the main conclusion from both of these figures is that the results are again robust to allowing for price adjustment.

To address the concern about rebates, I impose a uniform 12% discount on the prices insurers pay for all products in all years and re-estimate the bargaining model.[10] Figure 2.7 shows average drug prices after a ban on DTC; the results are qualitatively the same as above.

To get an idea of how the bargaining parameter affects these results, I re-run the main counterfactual with b calibrated to 0.5, representing a symmetric position for insurers and manufacturers.[11] Figure 2.8 shows the results; again, both higher

[9] Second-order conditions hold in both cases.

[10] This was the average rebate in the employer-sponsored market in 2016 (Antos and Capretta, 2019). Rebates are not thought to affect patients' out-of-pocket prices, so demand is unchanged.

[11] Given the non-linear nature of the problem and the difficulty of finding a global minimum described above, this also serves as a robustness check for the main results.

and lower prices are possible. Notice, however, that the price levels are lower than in Figure 2.3 due to the higher bargaining weight of the insurer.

2.8 Conclusion

This paper is the first to provide evidence on the effects of DTC on negotiated drug prices in the presence of new brand entry. I find that DTC can have both pro-competitive and market power effects. Using political advertising as an instrument for drug advertising, two-stage least squares estimates show that the marginal effect of DTC is to lower drug prices through business-stealing. To study the effects of a ban on DTC, this paper estimates a structural model of drug demand and insurer-drug manufacturer bargaining. A partial equilibrium counterfactual shows that DTC creates a preference for more expensive products. When prices are allowed to adjust, both higher and lower average prices are possible, showing that accounting for upstream price adjustment is important. In both cases, however, a ban on DTC lowers the market shares of entrants in the new SGLT2 class. Taken together, these results show that the supply side of the prescription drug market is important when judging the effects of DTC.

There are several avenues for future research that could build on the results of this paper. The issue of multiple equilibria should be studied further. This paper made the assumption that formularies were held fixed in counterfactuals; allowing insurers to choose formularies strategically would be a very important step forward. This would not only permit a richer exploration of the effects of advertising, but it would more fully capture the ways in which insurers can exert bargaining power.

Figure 2.1: DTC and Prices, Anti-Diabetic Drugs

Figure 2.2: Model Fit

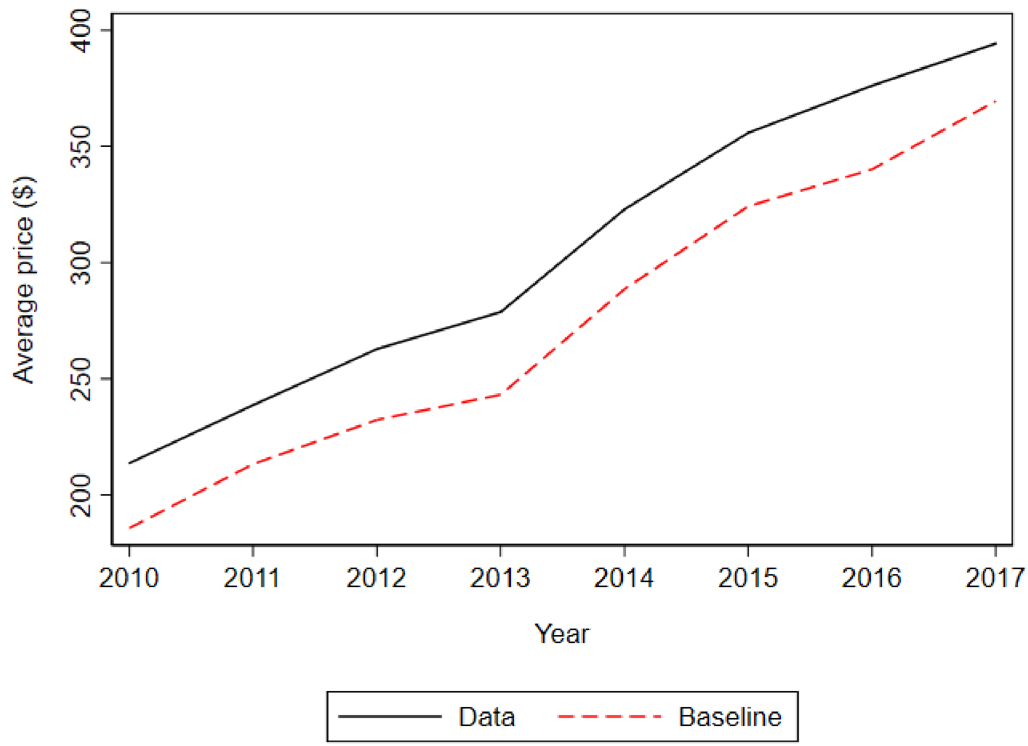
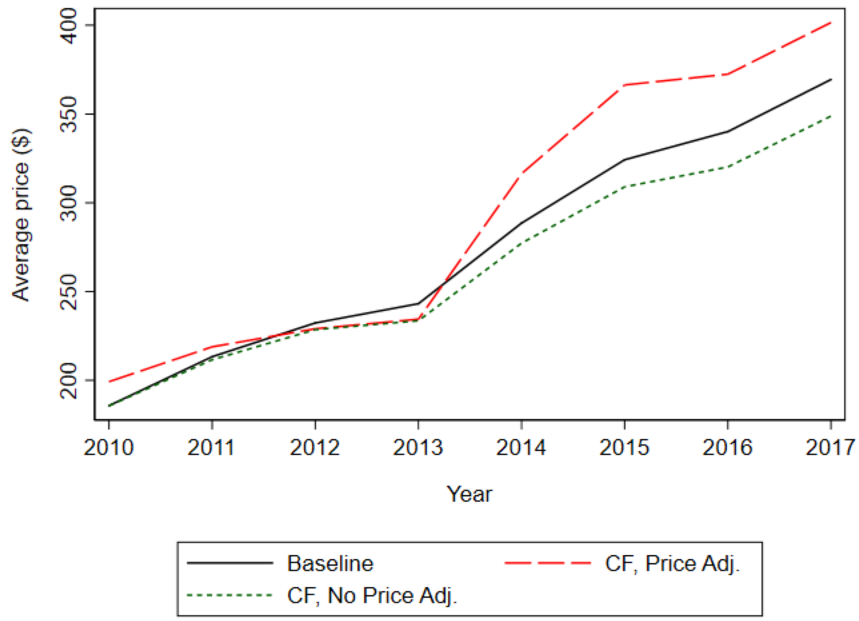
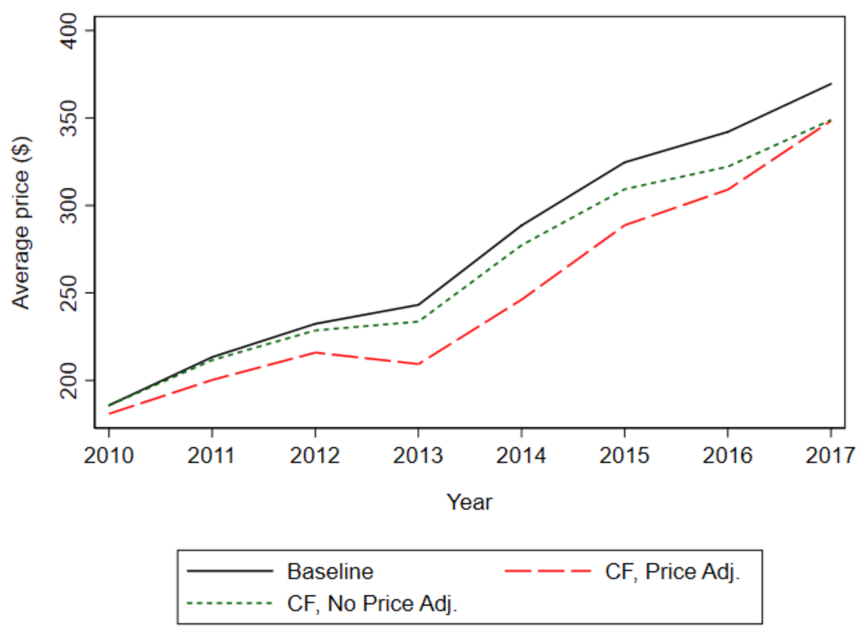


Figure 2.3: Average Drug Prices after a Ban on DTC

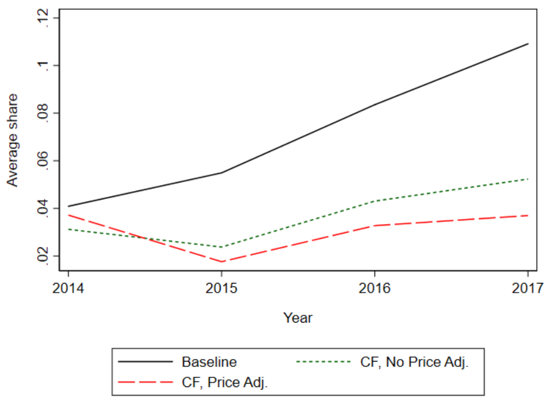


(a) EQ 1, prices rise

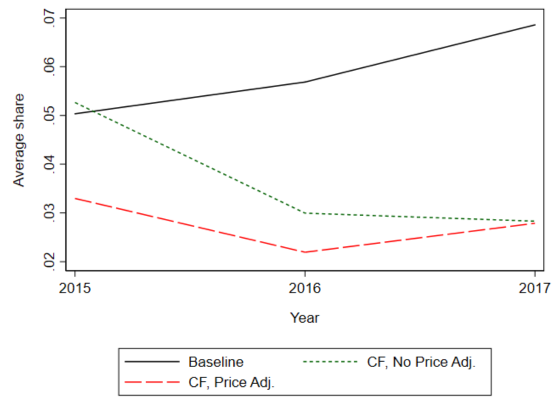


(b) EQ 2, prices fall

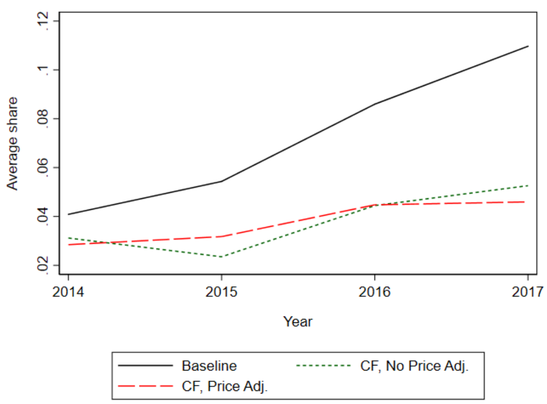
Figure 2.4: Effect of DTC on Entrant Market Shares



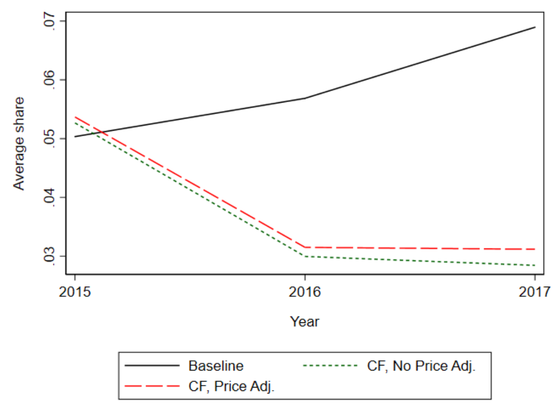
(a) Farxiga, EQ 1



(b) Jardiance, EQ 1

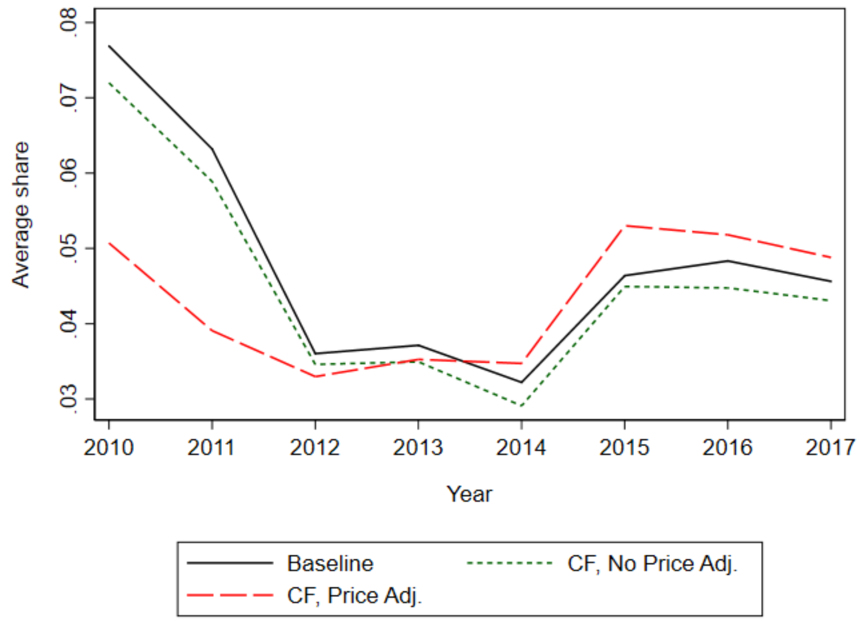


(c) Farxiga, EQ 2

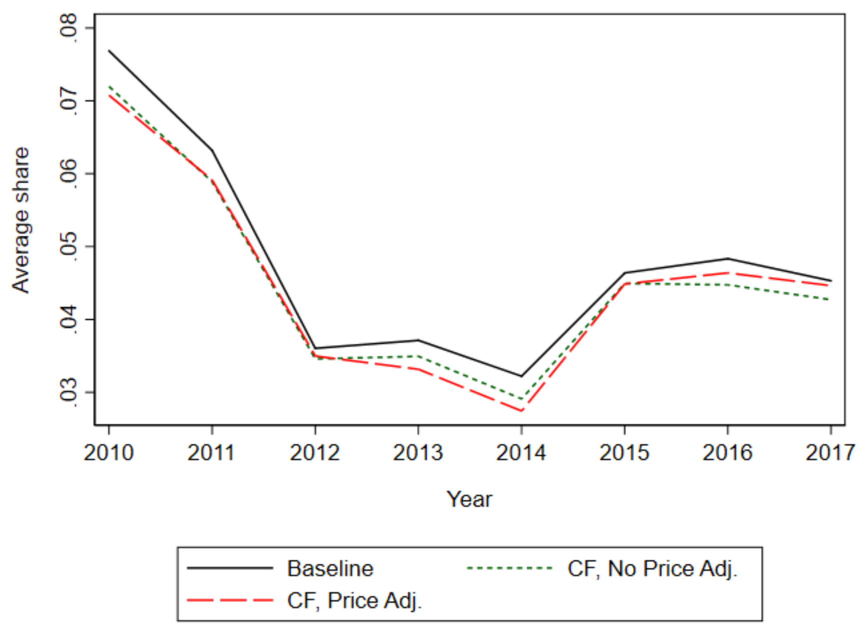


(d) Jardiance, EQ 2

Figure 2.5: Effect of DTC on Non-Advertised Incumbent

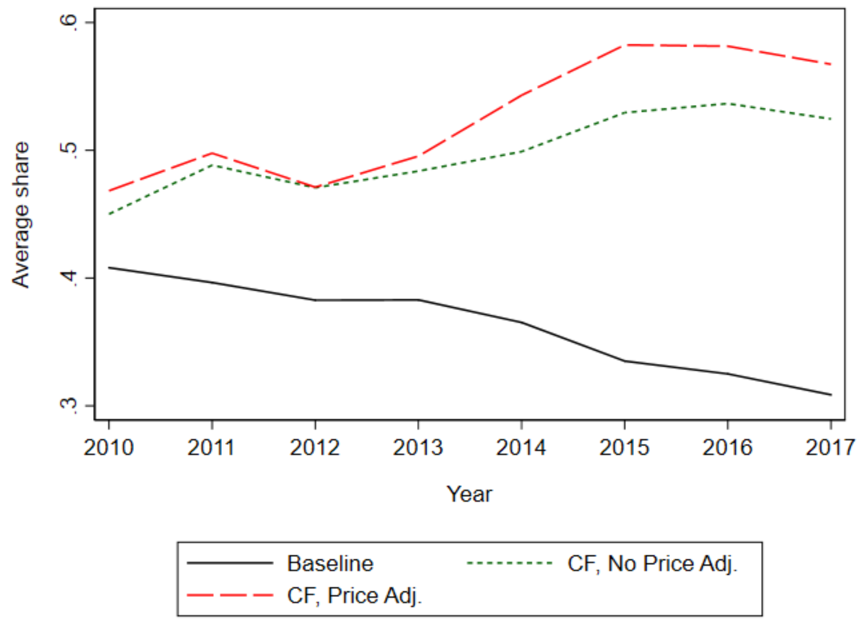


(a) Humalog, EQ 1

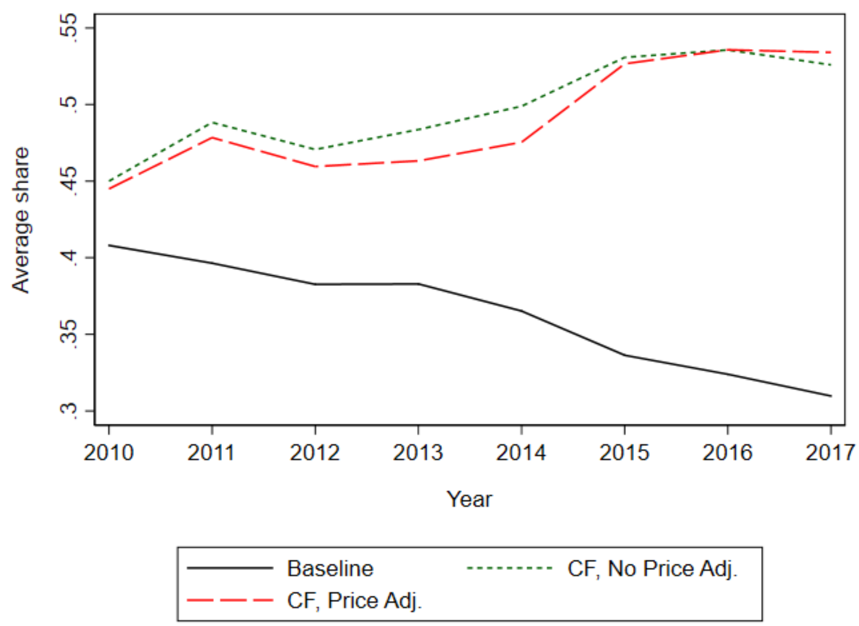


(b) Humalog, EQ 2

Figure 2.6: Effect of DTC on Outside Option Shares

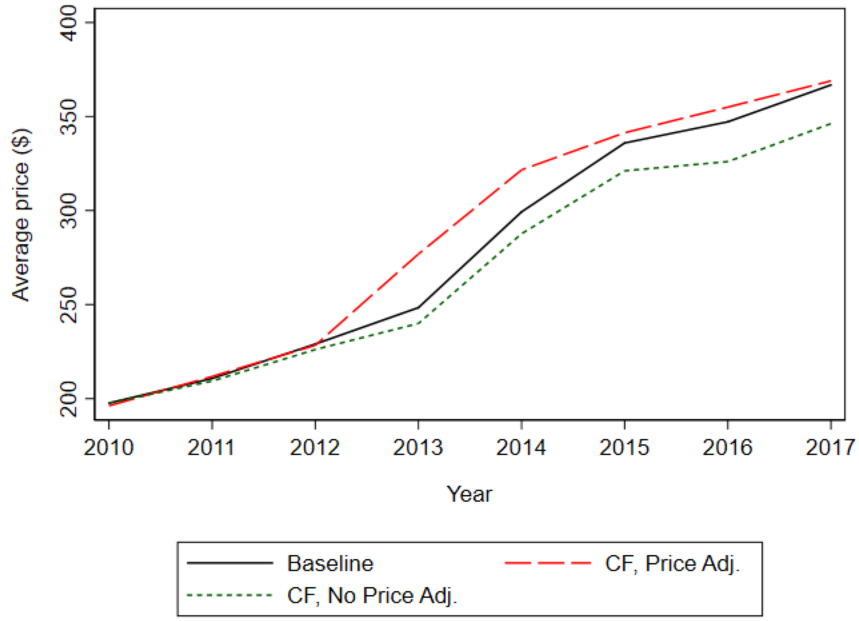


(a) EQ 1

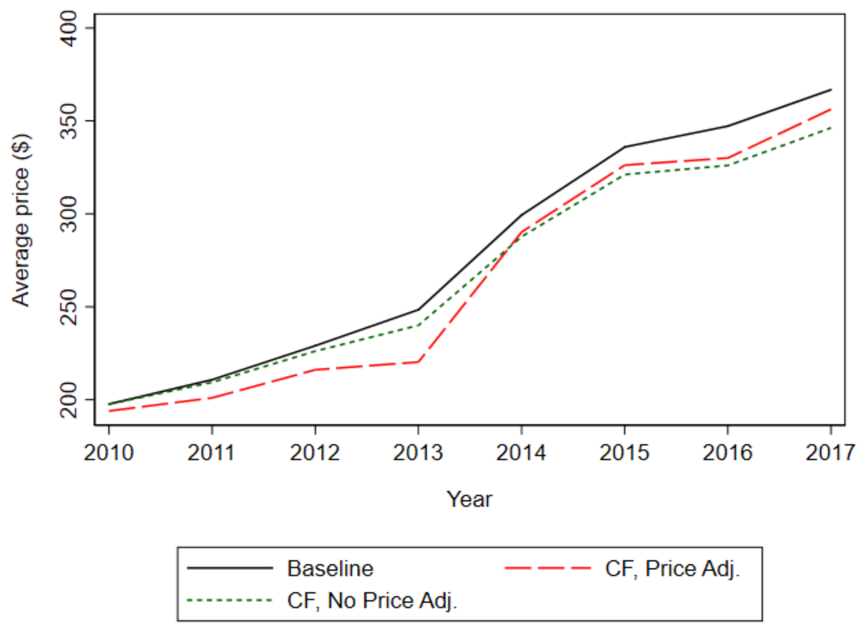


(b) EQ 2

Figure 2.7: Average Drug Prices after a Ban on DTC with Simulated Rebates



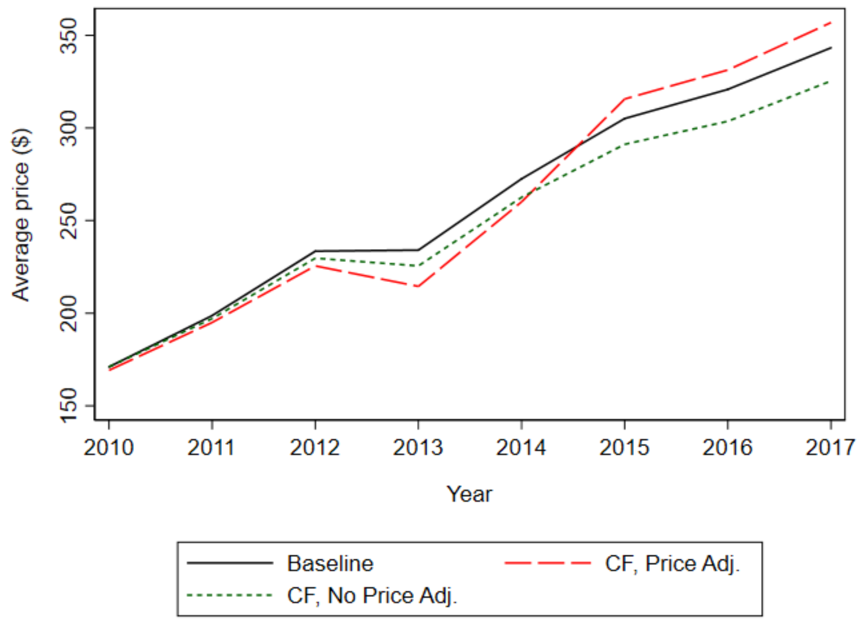
(a) Prices rise



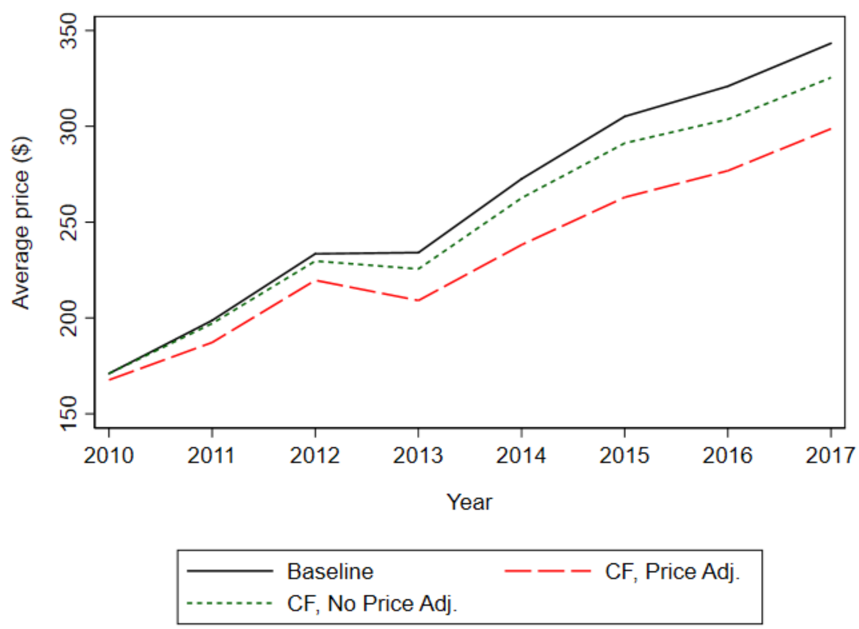
(b) Prices fall

Notes: Rebates were simulated by reducing insurer prices by 12% and re-estimating the bargaining model. The estimated bargaining weight is 0.90.

Figure 2.8: Average Drug Prices after a Ban on DTC, $b = 0.5$



(a) Prices rise



(b) Prices fall

Table 2.1: Effect of Advertising on Drug Prices

	OLS	2SLS
$\ln(1+Ad_{jmt})$	0.0230	-0.1163
	(.0009)	(0.0137)
$\ln(1+Ad_{-jmt})$	.0078	0.0607
	(.0008)	(0.0147)
Observations	273,046	273,046
R^2	0.7948	0.7751

Notes: Includes product, CBSA, and year fixed effects. Standard errors are clustered at the CBSA level.

Table 2.2: Effect of Advertising on Drug Prices by Intensity of Entry

	2010-2013	2014-2017
	$\ln(P_{jmt})$	$\ln(P_{jmt})$
$\ln(1+Ad_{jmt})$	-0.0915	-0.3122
	(0.0166)	(0.0483)
$\ln(1+Ad_{-jmt})$	0.0367	0.0233
	(0.0128)	(0.0274)
Observations	153,231	119,815
R^2	0.8145	0.7884

Notes: Includes product, CBSA, and year fixed effects. Standard errors are clustered at the CBSA level.

Table 2.3: Cost and Bargaining Estimates

b	0.7112
	(0.0061)
Mean MC	$191.2
	(118.1)
Mean gross margin	42.07%
	(29.63)

CHAPTER III

Airline Competition, Oil Price Pass-Through, and Carbon Taxes

3.1 Introduction

Cost pass-through – the rate at which a cost change translates to a price change – is an important concept in many areas of economics, ranging from industrial organization (e.g., merger efficiencies) to international trade (e.g., exchange rate pass-through) and public finance (e.g., tax incidence). In particular, energy cost pass-through has important implications for environmental policy. In this paper, we use the Australian airline industry to study how fuel cost shocks are passed through to airfares and how the pass-through rate depends on the competitiveness of the route. Airlines are an intriguing setting to study pass-through due to imperfect competition and differentiated products, leading to the possibility of price discrimination. Furthermore, from a policy standpoint, carbon dioxide emissions from the airline industry are projected to grow rapidly (Tabuchi, 2019). This industry is therefore an important part of the debate on strategies to address global climate change.

Fuel costs make up a significant portion of airlines' total costs and could potentially be passed on to consumers in the form of higher airfares.[1] Additionally, the level of competition on a route likely affects how much of the cost is passed on. Pass-through in this context is important because the effect of higher fuel costs should be equivalent to the effect of a carbon tax (Cullen and Mansur, 2014). The pass-through rate we find could then help policymakers evaluate the likely effects of a carbon tax on the airline industry. Finally, by evaluating how pass-through differs

[1]Fuel costs are 15-20% of total airline expenses (DOT, 2019).

with the number of competitors on a route and the type of product, we can shed light on the nature of competition in this industry.

This paper uses a novel dataset of Australian airfare data from Sabre Corporation and schedule data from the Official Airline Guide (OAG). The airfare data are monthly, an important advantage over the publicly available, quarterly Databank 1B US data. The schedule data tell us exactly which aircraft each carrier used on each of its routes; we use this to construct engineering estimates of fuel costs that are specific to each carrier and route in each month.

This paper has two main contributions. First, we estimate fuel cost pass-through in an industry characterized by differentiated products and imperfect competition. Importantly, we use aircraft engineering characteristics to construct precise fuel cost measures at the carrier-route-month level. We find average pass-through rates in excess of 100%. We also study how the pass-through rate varies by the number of competitors on a route. Theoretically, the relationship could go either way. A simple model of linear demand and constant marginal cost tells us that pass-through is 100% in perfect competition and 50% for a monopolist. If we further assume symmetric Cournot competition for the oligopoly case, pass-through rises monotonically from the monopoly rate to the perfectly competitive rate as the number of firms grows. On the other hand, other demand forms such as CES can have pass-through that is greater than 100% and decreasing with competition. This is therefore an empirical question. We find that pass-through increases with competition in the airline industry.

Second, we study whether pass-through varies by product. Because each firm offers multiple products (e.g. non-stop vs. one-stop flights), there is potential for pass-through to be different across products within the same firm. In fact, we should expect this to be the case due to different demand elasticities for different products. Specifically, we consider economy vs. business class flights and non-stop vs. one- and multi-stop flights. We find that fuel cost pass-through is lower for business class consumers relative to economy consumers on monopoly routes. By contrast, non-stop flights have higher pass-through than one- and multi-stop flights. One interpretation of these results is that they reveal a tension between differing pricing incentives. On the one hand, airlines have a price discrimination incentive to distort prices for "low-quality" products (e.g. economy class) more than "high-quality" products (e.g. business class). On the other hand, standard pricing models show that markups will be higher for relatively inelastic consumers; intuitively, we might expect that passengers traveling on non-stop flights are less elastic than passengers on flights with stops. These results suggest that consumer heterogeneity and pricing incentives of multi-product firms can explain our baseline results of pass-through that is greater than 100% and increasing with competition. To our knowledge, this pattern of results is novel in the pass-through literature.

In answering these questions, our paper contributes to several literatures. A large literature in industrial organization studies market structure in the airline industry (Borenstein, 1989; Berry, 1992; Goolsbee and Syverson, 2008; Ciliberto and Tamer, 2009). These papers estimate the impact of market dominance, entry, and the threat of entry. Another strand of this literature considers welfare effects of shorter-run decisions such as pricing, capacity, and codeshare agreements (Berry and Jia, 2010; Armantier and Richard, 2008). Finally, there is a large literature that studies how price discrimination varies with competition in the airline industry (Borenstein and Rose, 1994; Gerardi and Shapiro, 2009; Chandra and Lederman, 2015). None of these papers consider fuel cost pass-through, which is an important parameter for environmental policy.

There has recently been renewed theoretical and empirical interest in pass-through. Weyl and Fabinger (2013) theoretically characterize several principles of pass-through under different market structures. Their main finding in general cases of imperfect competition is that pass-through depends crucially on the curvature of demand. Our reduced-form analysis imposes little structure on the curvature of demand, so we are not pre-determining pass-through with restrictive functional form assumptions. Unfortunately, this also means we cannot formally say anything about welfare, since in the Weyl and Fabinger (2013) framework this depends on both pass-through and a conduct parameter. We view our work as complementary to papers that structurally model the airline industry.

Our work also contributes to the empirical literature on energy cost pass-through. Agrawal et al. (2017) use Weyl and Fabinger (2013)'s framework to estimate tax incidence and competition in the US airline industry. Agarwal et al. (2014) find a pass-through rate of 100% in the US airline industry using aggregate ticket prices and fuel costs, but do not study heterogeneity or competition. Fabra and Reguant (2014); Miller et al. (2017); and Ganapati et al. (2016) study energy cost pass-through in homogeneous product industries (electricity, cement, and a subset of manufacturing, respectively). All three studies find high rates. Ganapati et al. (2016) find a pass-through rate of 70% for manufacturing. Fabra and Reguant (2014) find that over 80% of emissions cost shocks are passed on to electricity prices. Miller et al. (2017) find that fuel costs are more than fully passed on to cement prices.

Some studies have examined the relationship between pass-through and competition. Miller et al. (2017) find that competition reduces pass-through in the cement industry. They explain this result using a symmetric oligopoly model with log-convex demand based on Weyl and Fabinger (2013). Consistent with this, Ganapati et al. (2016) compare several manufacturing industries and find that pass-through appears to be greatest in the least-competitive industry they study. On the other hand, Cabral et al. (2014) find that pass-through increases with competition in the Medicare Advantage insurance market. Given that different studies have found different results, the relationship between pass-through and competition is an empirical question. The interaction between pass-through and price discrimination has been under-studied in this literature.

Pass-through has also been studied extensively in contexts other than energy. In the international trade literature, Goldberg and Hellerstein (2013) estimate a structural model of the beer industry to explain incomplete exchange-rate pass through. That paper studies a differentiated product industry, but only in a single market (Chicago), whereas our setting allows us to use different markets to study how pass-through varies with competition.

A separate literature at the intersection of industrial organization and environmental economics finds that the welfare effects of environmental regulation can be quite different from what standard models predict in imperfectly competitive markets (Ryan, 2012; Fowlie et al., 2016). These papers consider the cement industry; by contrast, we study the airline industry, which is also a major source of emissions that are projected to grow rapidly.

The rest of the paper is organized as follows. In Section 3.2, we provide background on the Australian airline industry. In Section 3.3, we describe our data. Section 3.4 discusses the empirical model. Section 3.5 presents our main results. Section 3.6 concludes.

3.2 Background: Australian Airline Industry

This paper focuses on the domestic Australian air market. Australia is a particularly nice setting for our study because it is a relatively isolated country, decreasing the potential for outside events to substantially influence it.[2] Flying is the obvious way to travel between many of Australia's cities due to the lack of viable alternative transportation options. Many highways do not have frequent rest stops like those in the United States, and the rail network is much less developed than Europe's. Additionally, airline data are available at a higher frequency than similar publicly-available US data.

Australia's air market has two major full-service airlines – Qantas and Virgin – as well as a set of regional competitors and low-cost airlines. The regional and low-cost airlines have varying degrees of independence from the full-service airlines. While some operate fully independently, others have been purchased by Qantas or Virgin and become wholly-owned subsidiaries and/or are members of the same airline alliance. The latter relationship allows cross-marketing of each other's flights.[3] Table 3.1 shows each major airline's market share during our sample period.

Jet fuel is a key component of airlines' costs and can constitute up to 20% of total costs (DOT, 2019). Jet fuel is a refined product that is made from crude oil. Consequently, its price is closely tied to the price of crude oil. The ease of transporting oil and its products means that prices are determined in world markets. World oil markets are very thick and no individual participant can substantially affect prices. We therefore treat jet fuel as an exogenous cost over which airlines have no control.

Australia introduced carbon tax legislation in 2011. The legislation was subsequently passed and took effect on July 1, 2012. It was later repealed on July 17, 2014, but the repeal was backdated to July 1, 2014. We will treat July 1, 2012 through July 1, 2014 as months that airlines were expecting to pay the carbon tax. While most industries paid a tax of just under \$25AUD/ton, jet fuel was taxed at 6 Australian cents per liter. This tax was equivalent to roughly \$21.50/ton of carbon.[4] Due to the fact that this carbon tax was relatively modest and short-lived, we elect not to focus on it in our empirical work.

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[2] By contrast, air travelers in the Netherlands have outside options at Dusseldorf Airport (Germany) and Brussels Airport (Belgium).

[3] For example, one could purchase from Qantas a flight that is operated by Northern Air Cargo.

[4] This is within the range of estimates of the social cost of carbon, albeit at the lower end.

Airlines have two primary ways to respond to changing jet fuel costs. Adjusting airfares is the easiest and most flexible way – many airfares are changed multiple times per week. Airlines can also alter their service offerings through the set of routes that they offer and/or the frequency with which each route is offered. However, this adjustment process generally takes considerably longer as airlines would have to purchase access to gates. We therefore focus on airlines' price responses to changing fuel costs.

3.3 Data Description & Summary Statistics

Our airline price and passenger dataset was purchased from Sabre Corporation. It consists of detailed monthly data for all domestic air travel in Australia from 2010 through 2017.[5] The raw data are aggregated so that everybody who flew on a given airline during a given month for an exact one-way itinerary in a cabin class is combined. For example, all passengers who flew discount economy on Qantas from Sydney to Perth via Canberra in January 2010 are grouped into one observation. For each observation, we see the number of passengers and total revenue in the month *traveled* rather than the month in which the ticket was purchased (we explain below how we handle this constraint). The full sample consists of many routes with inconvenient layovers and very few passengers. Consequently, we drop observations where the airline has less than 1% market share for a route-month. These dropped observations are likely not viable competitors for most passengers. Total fare data are inclusive of all taxes, fees, and surcharges.

Airline schedule data were purchased from OAG. The data contain the complete schedule of all domestic flights within Australia during our time period. We observe the frequency, time, aircraft, and number of seats available for each route. Figure 3.1 shows capacity in terms of thousands of seats per day for the two major carriers.

We construct the average per seat cost of jet fuel (P^{JF}_{irjt}) for each carrier-route-product-month by multiplying three terms together:

$$P^{JF}_{irjt} = P^{Barrel}_{t} \times Dist_{irj} \times FuelEff_{irjt} \tag{3.1}$$

the average price of a barrel of jet fuel (P^{Barrel}_{t}) in month t, carrier i's average fuel efficiency ($FuelEff_{irjt}$) in month t for product j on route r, and distance ($Dist_{irj}$)

[5]Having the universe of tickets vs. a subsample is another advantage of our data over the DB1B.

for product j on route r.[6] The average cost of jet fuel varies with all three terms – different aircraft can have large differences in fuel efficiency, longer routes require more fuel than shorter routes, and the price of jet fuel varies over our time period. We now briefly discuss the source and construction of each term.

We collect daily jet fuel price data (P_t^{Barrel}) from Platts (accessed via Bloomberg) at the US Gulf Coast and average by month to match our ticket data. Because we do not know the date each ticket is sold, we assume that the average ticket is purchased one month in advance and therefore lag our fuel prices by one month. As discussed above, because oil is traded on global markets, we assume that the Gulf Coast price is a good proxy for the price Australian airlines face. Jet fuel prices ranged between 45 and 163 US cents per liter during our sample period. Figure 3.2 plots average airfares and jet fuel prices. Both series are de-trended by year (to account for macro trends) and month (to account for seasonality). Total airfare tracks jet fuel closely for most of the sample.

Distance ($Dist_{irj}$) is one of the variables provided in our data from Sabre Corporation. Distance varies across routes and across products within routes – one-stop and non-stop itineraries will have different distances – and is an important source of fuel cost variation. Figure 3.3 provides a graphical representation of the variation from distance. The y-axis denotes the residual from a regression of jet fuel costs on month-of-sample fixed effects, while the x-axis shows each observation's distance. Distance is positively and meaningfully correlated with our fuel cost estimates.

Finally, for each observation we assign an average fuel efficiency ($FuelEff_{irjt}$) based on the aircraft flying that route. Fuel efficiency data for each aircraft are gathered from internet research.[7] Fuel economy varies widely by type of aircraft. Generally, larger aircraft use less fuel per seat-mile. Additionally, there can be large differences within aircraft class. For example, the 98-seat Embraer E-Jet-190 uses 3.81 L/100km/seat while the 82-seat Bombardier Dash 8 Q400 uses 2.79 L/100km/seat. We also adjust for the fact that seats in premium cabin classes (business and first) take up more floor space in the airplane and therefore have a higher per seat fuel cost (Bofinger and Strand, 2013).

[6] A route is a directional origin-destination pair, i.e. Sydney–Melbourne is a different route than Melbourne–Sydney. A non-stop flight from Sydney to Melbourne and a one-stop flight from Sydney to Melbourne are different products serving the same route.

[7] Wikipedia aggregates and cites estimates for many aircraft. Additional data are gathered for aircraft not listed there.

Table 3.2 summarizes our data at a slightly aggregated level: we combine passengers with different intermediate stops and passengers in different cabin classes. An observation is at the month-airline-route level (e.g., all seats on Qantas-operated flights from Sydney to Melbourne in January 2012, including routes with stops).

Recall from the discussion in Section 3.2 that the two dominant airlines – Qantas and Virgin – partly or wholly own regional airlines. In particular, Jetstar is a wholly-owned subsidiary of Qantas for the entire sample period. Consequently, we treat any Jetstar flight as being operated by Qantas; it would not be accurate to treat Jetstar as a competitor for Qantas because Qantas likely internalizes the profit impacts of Jetstar's pricing. Similarly, Tiger Airways was fully owned by Virgin after October 2012; we therefore treat any Tiger Airways flight after that date as being operated by Virgin.

Code-sharing is common in Australia, as it is in the United States. For the purposes of estimating pass-through, we are interested in the identity of the operating (rather than the marketing) airline because the operating airline is the one that makes pricing decisions. Therefore, we calculate the number of competitors on a route, as well as carrier fixed effects, based on the operating airline.

3.4 Empirical Strategy

3.4.1 Specification

Our empirical strategy seeks to estimate the degree to which jet fuel costs are passed through to airfares and how this relationship varies with competition. We estimate various forms of equation (3.2) below. Our dependent variable ($Airfare_{irt}$) is the weighted (by passengers) average airfare for a given route (r), airline (i), and month(t). For example, one observation in this specification is the weighted average of airfares for all itineraries that traveled from Sydney to Melbourne on Qantas during January 2010. This means that we aggregate across cabin classes and different itineraries (for example, non-stop itineraries and itineraries that have a stop in Canberra).

$$Airfare_{irt} = \alpha + \beta_1 Comps_{rt} + \beta_2 P^{JF}_{irt} + \beta_3 Comps_{rt} \times P^{JF}_{irt} + \omega Q_t + \delta M_t + \mathbf{X}_{rt} + \epsilon_{irt} \quad (3.2)$$

On the right-hand side, we have the weighted (by passenger) average cost of jet fuel for each carrier-route-month (P^{JF}_{irt}, aggregating P^{JF}_{irjt}), the number of competitors on a route ($Comps_{rt}$), and the interaction of these two terms. Construction of the jet fuel variable is discussed in Section 3.3. The number of competitors is calculated by counting the number of airlines that have at least 1% market share and fly between the origin and destination, regardless of the number of stops. When we investigate heterogeneity across products, we disaggregate $Airfare_{irt}$ and P_{irt}^{JF} to the appropriate level.

We expect β_1 to be negative and β_2 to be positive. The sign of β_3 is ambiguous ex ante, as seen by the mixed results in the existing literature. Our coefficients of interest are β_2 and β_3. The average pass-through rate on a given route can be calculated as $\beta_2 + \beta_3 \times Comps_{rt}$.

3.4.2 Identification

Because airlines typically sign long-term contracts with airports for gate access, and air schedules are set far in advance, we assume that the number of competitors on a route is fixed in the short run. While the number of competitors may be endogenous, it will not vary endogenously with the price of jet fuel – it takes time for an airline to change their route schedule and to enter new markets.

The price of jet fuel is determined in a world market and will not be affected by Australian firms' decisions. However, unobserved macroeconomic demand shocks could make the price of jet fuel endogenous – if demand shocks increase both the demand for air travel and the price of jet fuel, our estimate of the pass-through rate would be biased upwards. To control for unobserved macroeconomic shocks, we include quarter-of-sample (Q_t) fixed effects. Demand for air travel is also highly seasonal (e.g. during the summer and holidays), so we include calendar month (M_t) fixed effects.[8]

Some specifications include a set of state- and route-specific controls ($\mathbf{X}_{rt}$). We construct the geometric mean of the origin and destination's local government area (LGA) populations, densities, and building values.[9] We also use the average of the origin and destination LGA's net migration. We use the geometric mean of origin and destination states' population, wages, business expenditures, mineral exploration,

[8]We also include the monthly national unemployment rate as a more fine-grained control in some specifications.

[9]An Australian LGA is roughly equivalent to a US MSA.

and petroleum exploration.[10] These controls will address route-specific demand and cost shifts.[11] We include origin and destination fixed effects and route fixed effects in some specifications. In the most restrictive specifications with route fixed effects, identification of our parameters of interest comes from shocks to jet fuel prices and entry and exit within routes. This is similar to the identification strategy used by Miller et al. (2017).

Our analyses are weighted by the number of passengers flying each route. We take this approach because we are primarily interested in the major routes. Flights on small planes that only run once a week are a small part of carbon emissions and may not be broadly representative. Standard errors are clustered at the monthly level.

3.5 Results

Table 3.3 presents our first set of primary results. The second row reports the pass-through rate for a monopoly route, while the third row reports how the pass-through rate varies with additional competitors. Our preferred specification is in the last column, which includes the most restrictive set of controls and fixed effects. The estimates show that pass-through in the presence of a monopoly is roughly 138% on average, with each additional competitor increasing pass-through by 46%. These estimates are relatively stable across all specifications. The sign on the coefficient for number of competitors is negative in all cases, which is a useful sanity check and indicates that our controls are doing well at capturing demand differences across routes. As Miller et al. (2017) explain, a pass-through rate greater than 100% is possible when there is a high degree of heterogeneity in consumers' willingness to pay (WTP). The intuition behind this argument is that when costs increase, firms abandon low-WTP consumers and price only to high-WTP consumers, leading to a large price increase. Conversely, when costs decrease, low-WTP consumers enter the market, leading to large price decreases. Intuitively, a high degree of heterogeneity in WTP is a feature we would expect to find in the airline industry.

[10]The geometric mean is better than the arithmetic mean at capturing variation when locations have very different values. For example, consider how the arithmetic and geometric means differ for: a city of one million people and a town of ten thousand vs. a city of one million and a town of twenty thousand. The arithmetic means will be nearly identical, while the geometric means will be further apart. For airline demand, the latter is likely more informative. We use the arithmetic mean for net migration because net migration can be negative, invalidating the geometric mean.

[11]Some states in Australia experienced a resource boom during our sample period, which is why we control for mineral and petroleum exploration.

Recall that the airfare variable we use is inclusive of taxes, fees, and surcharges. To confirm that these factors are not driving our pass-through results, we re-run the baseline regression with base airfare on the left-hand side. The results, shown in Table 3.4, are very similar to the results with total airfare.

Table 3.5 reports results for non-stop flights and flights with stops.[12] These are differentiated products across which we might expect pass-through to vary. Indeed, pass-through on flights with stops is 77% for a monopoly, with a 17% premium for each additional competitor. For non-stop flights, however, pass-through is 133%, with a 46% increase for each additional competitor. One interpretation of these results is that passengers on non-stop flights are less price-elastic than passengers on flights with stops, as we might intuitively expect. This set of results, then, is in line with airlines' incentives to price higher to relatively inelastic consumers.

The finding of a pass-through rate less than 100% which increases with competition – as we find for flights with stops – is well in line with results found in the literature and theoretically established by Weyl and Fabinger (2013). The result for non-stop flights is more interesting. Miller et al. (2017) use the Weyl and Fabinger (2013) model to argue that when pass-through exceeds 100%, it should decrease with competition. In their context, they consider markets for a single product which serves both low- and high-WTP consumers, but here, airlines target low- and high-WTP consumers with different products. With more competition, some high-WTP consumers might choose the "low-quality" good (here, flights with stops) as prices fall. This would leave only the consumers with the highest WTP consuming the "high-quality" good (non-stop flights), so pass-through increases with competition for these flights because airlines are pricing to higher-WTP consumers. The logic is similar to why branded drug prices can increase after generic entry (Frank and Salkever, 1997; Ching, 2010). This argument relies on more airlines offering flights with stops as competition increases. We test this prediction by regressing the number of airlines offering flights with stops on the total number of airlines, controlling for the same factors as in our pass-through regressions. Table 3.6 shows these results. The first column runs the regression at the airline-route-month level and includes airline fixed effects. The second column runs the regression at the route-month level. In both cases, there is a positive and significant coefficient on the total number of airlines. Thus, more competition is indeed associated with more non-direct flights, supporting the argument above.

[12] We drop distance controls from the non-stop regression with route fixed effects as these will be collinear.

Table 3.7 shows how pass-through varies for economy and business class seats. We find that business class pass-through is lower on monopoly routes at 52% vs. 145% for economy. Interestingly, this differs from the previous set of results if we consider business class to be a "high-quality" product targeted to high-WTP consumers. Following the intuition for the pass-through regressions with stops, it could be that business class passengers are more price-elastic than economy class passengers. This seems unintuitive since business class seats are generally more expensive, but certain models of demand (e.g., logit) imply that elasticity increases with price. Another, perhaps more likely, interpretation is that economy class passengers are low-WTP consumers for whom airlines will distort price more in order to respect the high-WTP business class passengers' incentive compatibility constraints. In other words, airlines are engaging in second-degree price discrimination through business class and economy tickets, distorting economy ticket prices to steer high-WTP consumers to business class. The fact that business class pass-through is much lower than economy class only on monopoly routes, where airlines presumably have much more power to price discriminate in this way, lends support to this intuition.

Consistent with the previous results, we find that ticket prices increase with competition for both cabin classes. The fact that pass-through rates start converging when there is more competition supports the idea that second-degree price discrimination is harder without a monopoly. Economy pass-through might increase with competition, however, because airlines still have an incentive to steer high-WTP consumers to business class by distorting economy ticket prices.

3.6 Conclusion

We find that the pass-through of fuel costs to ticket prices in the Australian airline industry exceeds 100% on average and increases with the amount of competition on a route. While it is unusual to have both results simultaneously, they are possible in this industry due to the presence of multi-product firms and heterogeneous consumers. Supporting this idea, we find important heterogeneity in the pass-through rates for different products, reflecting a tension between incentives to price higher to less elastic consumers and to engage in second-degree price discrimination. From a public policy standpoint, the results suggest that a carbon tax on the airline industry would be over-shifted onto consumers.

In this paper, we have presented reduced-form evidence on heterogeneity in pass-through rates across different products and markets. Future work could take a more structural approach and estimate demand for different consumer groups, as well as airline pricing and capacity decisions, to better disentangle the various forces at play. This would allow calculation of welfare changes due to changes in jet fuel prices and a carbon tax. Overall, the results presented here underscore the importance of taking industry-specific features into account when interpreting pass-through. The effects of public policies like a carbon tax will greatly depend on pre-existing market structure; intuition from simpler models will not always carry over.

Figure 3.1: Seat Capacities by Carrier, 2010-2017

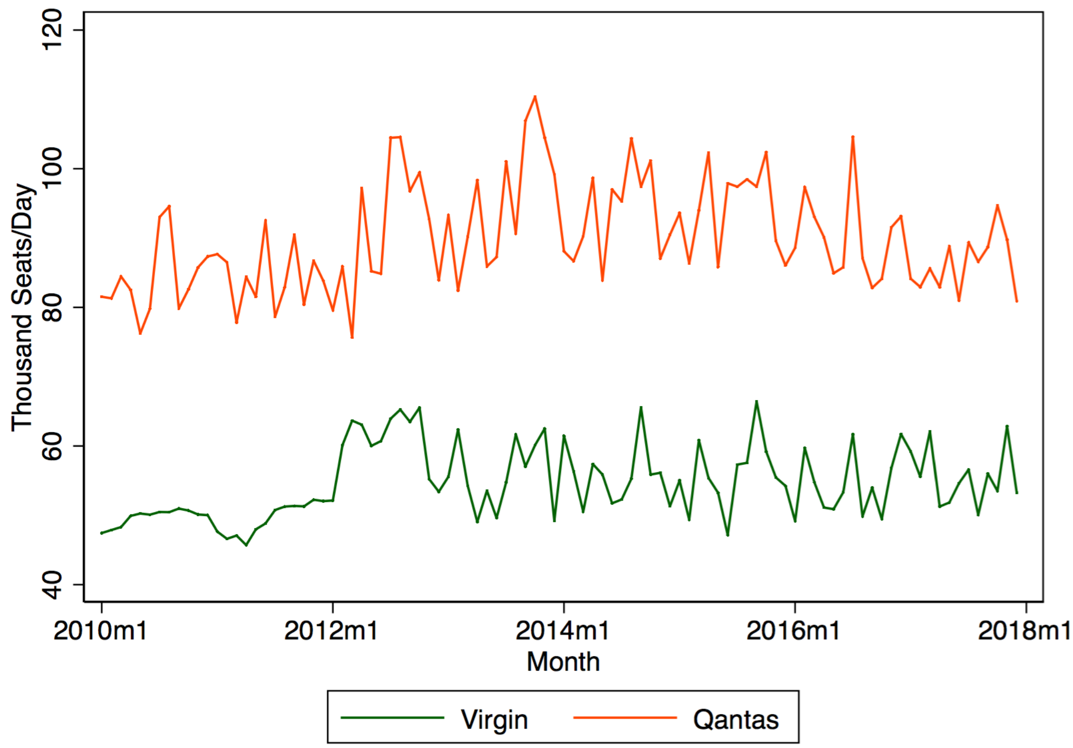
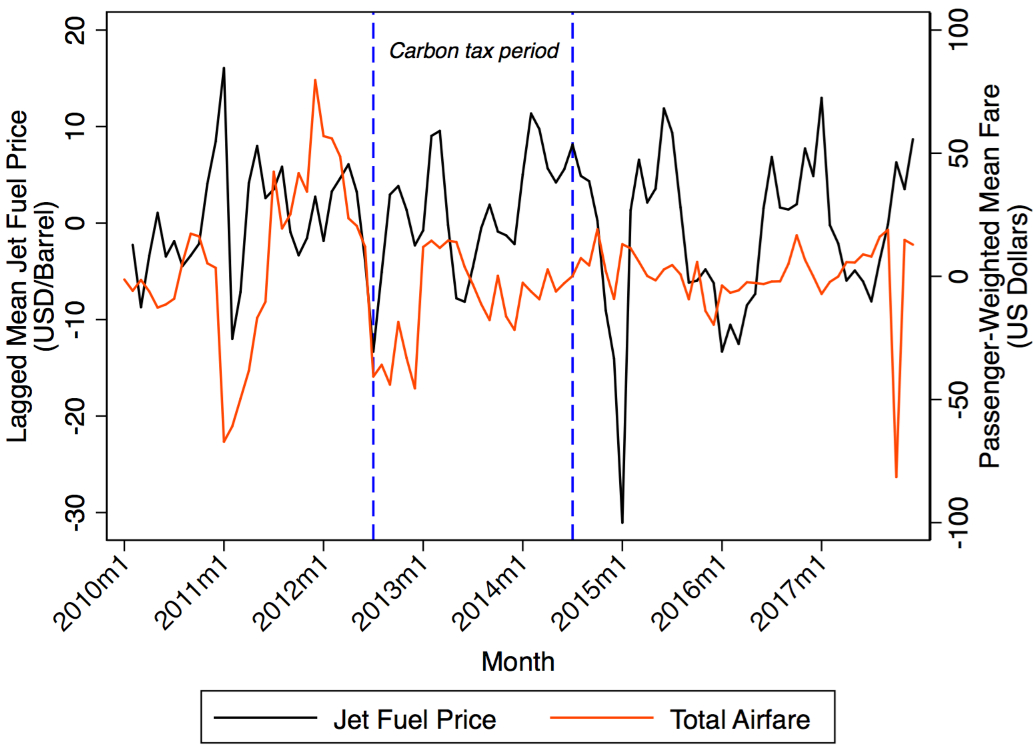
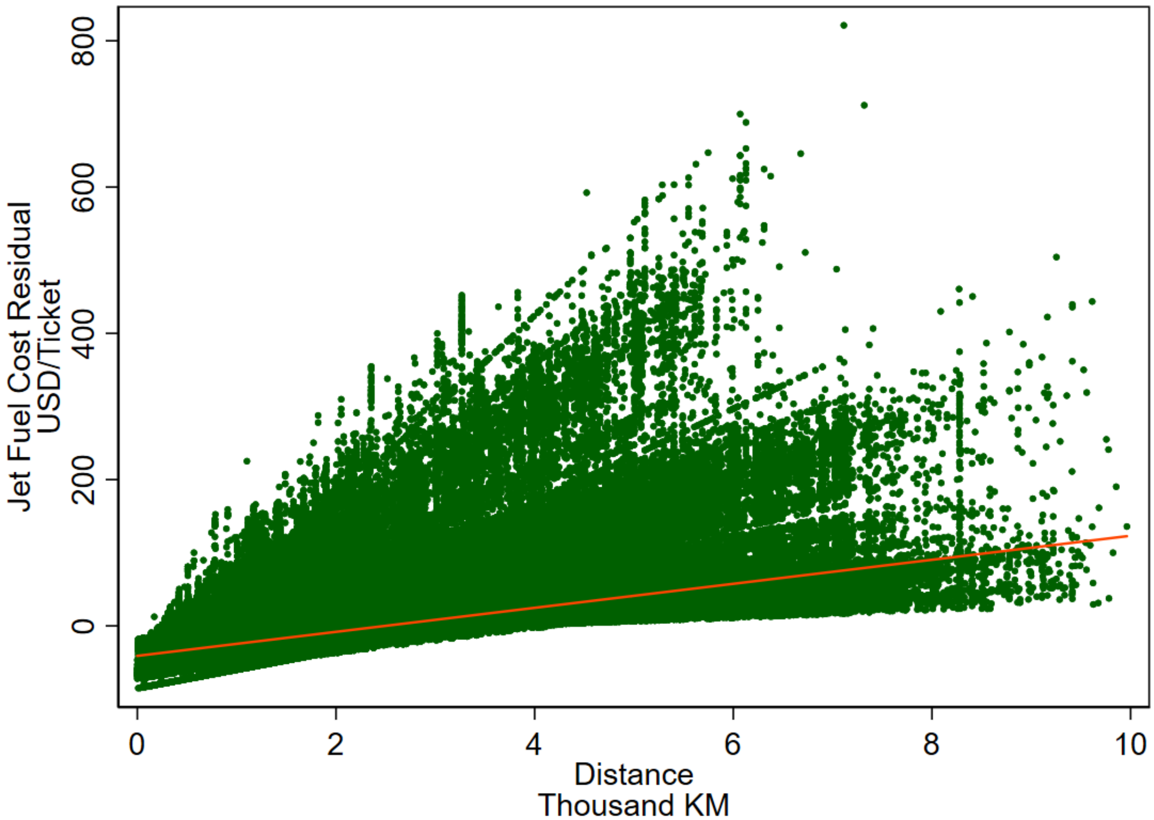


Figure 3.2: Airfares and Jet Fuel Prices, 2010-2017



Notes: Airfares are averages across Australia for a given month. Jet fuel prices are from the US Gulf Coast.

Figure 3.3: Jet Fuel Costs and Distances, 2010-2017



Notes: This is a scatterplot of estimated jet fuel cost residuals and itinerary distances. Residuals are calculated after regressing jet fuel costs on month-of-sample fixed effects. The orange line is a line of best fit and demonstrates that the residuals are positively correlated with itinerary distance. Distance is positively and meaningfully correlated with our fuel cost estimates.

Table 3.1: Market Shares of Major Airlines

	Market Share	Total Passengers (Millions)
Qantas	37.10	187.52
Virgin	28.01	141.58
Jetstar	21.08	106.54
Tiger	5.65	28.54
Cobham Aviation	2.91	14.71
Regional Express	2.31	11.70
Skywest	0.51	2.58
Airnorth	0.48	2.42
Alliance	0.42	2.10
Skytrans	0.26	1.32

Notes: There are ten different airlines that operate with some degree of independence during our sample. Qantas and Virgin are the major full-service airlines. Jetstar is a low-cost wholly-owned subsidiary of Qantas. It competes with Qantas on many routes. Tiger was an independent low-cost airline until 2013 when Virgin purchased 60% of the airline. Virgin purchased the remaining 40% in 2014. The other six airlines are regional players that focus on less-serviced routes.

Table 3.2: Air Travel Summary Statistics

	Full Sample		Non-Stop Flights	
	mean	st.dev.	mean	st.dev.
Passengers	2695.64	10510.71	4390.74	11124.82
Average Total Fare (USD)	286.99	163.01	190.55	81.86
Average Fuel Cost (USD)	27.20	21.76	13.72	12.14
Distance ('000 KM)	1.73	1.27	0.76	0.65
Average Capacity Factor	0.69	0.12	0.70	0.15

Notes: Observations are at the month-route-airline level in the left two columns. For example, one observation is all passengers that flew from Sydney to Melbourne in January 2010 on Qantas. There are 112,965 total observations.

Table 3.3: Regression Results: Baseline Pass-Through

	O-D FE	More FE	State/Route Controls	Route FE
Number of Competitors	-5.751***	-5.818***	-2.178	-4.236*
	(2.060)	(2.114)	(2.292)	(2.460)
Jet Fuel Cost	1.454***	1.464***	1.323***	1.383***
	(0.184)	(0.178)	(0.181)	(0.196)
Jet Fuel * Competitors	0.557***	0.565***	0.479***	0.455***
	(0.107)	(0.109)	(0.112)	(0.100)
Thousand KM, Avg	29.504***	28.831***	49.106***	418.165***
	(2.517)	(2.465)	(2.885)	(71.081)
Distance Squared	-0.722	-0.676	-4.838***	-93.383***
	(0.708)	(0.688)	(0.786)	(17.996)
Quarter FE	Yes	Yes	Yes	Yes
Month-of-Year FE	Yes	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes
Airline FE	No	Yes	Yes	Yes
State/Route Controls	No	No	Yes	Yes
Route FE	No	No	No	Yes
R squared	0.807	0.813	0.820	0.827
Observations	22688	22688	21921	21922

Notes: The dependent variable is the average airfare at the month-airline-origin-destination level. For example, one observation is all passengers traveling from Sydney to Melbourne on Qantas in January 2010. Competitors are at the operating-airline level, and at least 1% market share is required to be designated a competitor. Prices are in 2010 USD. Standard errors are clustered at the month level. Jet fuel prices are lagged by one month. Weights are assigned according to the number of passengers in an observation. Only the top 100 routes are included.

Table 3.4: Regression Results: Baseline Pass-Through, Base Fare

	Base Fare
Number of Competitors	-3.799
	(2.715)
Jet Fuel Cost	1.584***
	(0.259)
Jet Fuel * Competitors	0.444***
	(0.156)
Thousand KM, Avg	356.414***
	(78.890)
Distance Squared	-81.509***
	(19.657)
Quarter FE	Yes
Month-of-Year FE	Yes
Origin FE	Yes
Destination FE	Yes
Airline FE	Yes
State/Route Controls	Yes
Route FE	Yes
R squared	0.772
Observations	21922

Notes: The dependent variable is the average base airfare (not inclusive of taxes, fees, and surcharges) at the month-airline-origin-destination level. For example, one observation is all passengers traveling from Sydney to Melbourne on Qantas in January 2010. Competitors are at the operating-airline level, and at least 1% market share is required to be designated a competitor. Prices are in 2010 USD. Standard errors are clustered at the month level. Jet fuel prices are lagged by one month. Weights are assigned according to the number of passengers in an observation. Only the top 100 routes are included.

Table 3.5: Regression Results: Pass-Through by Stops

	Stops	Non-Stop
Number of Competitors	-0.244	-4.153*
	(4.306)	(2.473)
Jet Fuel Cost	0.770***	1.328***
	(0.172)	(0.193)
Jet Fuel * Competitors	0.167	0.461***
	(0.114)	(0.102)
Thousand KM, Avg	18.258***	
	(6.040)	
Distance Squared	-1.422*	
	(0.818)	
Quarter FE	Yes	Yes
Month-of-Year FE	Yes	Yes
Origin FE	Yes	Yes
Destination FE	Yes	Yes
Airline FE	Yes	Yes
State/Route Controls	Yes	Yes
Route FE	Yes	Yes
R squared	0.606	0.827
Observations	26449	21753

Notes: The dependent variable is the average airfare at the month-airline-origin-destination-number of stops level. For example, one observation is all non-stop passengers traveling from Sydney to Melbourne on Qantas in January 2010. Competitors are at the operating-airline level, and at least 1% market share is required to be designated a competitor. Prices are in 2010 USD. Standard errors are clustered at the month level. Jet fuel prices are lagged by one month. Weights are assigned according to the number of passengers in an observation. Only the top 100 routes are included.

Table 3.6: Regression Results: Number of Airlines Offering Flights with Stops

	Airline-level	Route-level
Number of Airlines	0.341***	0.288***
	(0.022)	(0.020)
Thousand KM, Avg	3.292***	
	(0.587)	
Distance Squared	-0.485***	
	(0.109)	
Quarter FE	Yes	Yes
Month-of-Year FE	Yes	Yes
Origin FE	Yes	Yes
Destination FE	Yes	Yes
Airline FE	Yes	No
State/Route Controls	Yes	Yes
Route FE	Yes	Yes
R squared	0.659	0.745
Observations	21922	6723

Notes: The dependent variable is the number of airlines offering flights with stops on a route-month. The first column is at the airline-route-month level, whereas the second column is at the route-month level. At least 1% market share is required to be designated a competitor. Standard errors are clustered at the month level. Weights are assigned according to the number of passengers in an observation. Only the top 100 routes are included.

Table 3.7: Regression Results: Pass-Through by Cabin Class

	Coach	Business
Number of Competitors	-3.514	-18.747***
	(2.367)	(5.294)
Jet Fuel Cost	1.446***	0.521**
	(0.223)	(0.240)
Jet Fuel * Competitors	0.416***	0.830***
	(0.101)	(0.123)
Thousand KM, Avg	332.579***	373.738***
	(71.926)	(100.477)
Distance Squared	-80.560***	-14.202
	(18.538)	(19.132)
Quarter FE	Yes	Yes
Month-of-Year FE	Yes	Yes
Origin FE	Yes	Yes
Destination FE	Yes	Yes
Airline FE	Yes	Yes
State/Route Controls	Yes	Yes
Route FE	Yes	Yes
R squared	0.809	0.832
Observations	27444	14299

Notes: The dependent variable is the average airfare at the month-airline-origin-destination-cabin class level. For example, one observation is all business class passengers traveling from Sydney to Melbourne on Qantas in January 2010. Competitors are at the operating-airline level, and at least 1% market share is required to be designated a competitor. Prices are in 2010 USD. Standard errors are clustered at the month level. Jet fuel prices are lagged by one month. Weights are assigned according to the number of passengers in an observation. Only the top 100 routes are included.

BIBLIOGRAPHY

ADA (2018). Statistics about diabetes. `http://www.diabetes.org/resources/statistics/statistics-about-diabetes`. Accessed: Oct. 30, 2019.

Agarwal, S., Chomsisengphet, S., Mahoney, N., and Stroebel, J. (2014). A simple framework for estimating consumer benefits from regulating hidden fees. *The Journal of Legal Studies*, 43(S2):S239–S252.

Agrawal, D. R., White, Q., and Williams, J. (2017). Tax incidence and market power: Evidence from the airline industry.

Antos, J. R. and Capretta, J. C. (2019). Assessing the effects of a rebate rollback on drug prices and spending. `https://www.healthaffairs.org/do/10.1377/hblog20190308.594251/full/`. Accessed: Oct. 10, 2019.

Armantier, O. and Richard, O. (2008). Domestic airline alliances and consumer welfare. *The RAND Journal of Economics*, 39(3):875–904.

Aron-Dine, A., Einav, L., Finkelstein, A., and Cullen, M. (2015). Moral hazard in health insurance: Do dynamic incentives matter? *Review of Economics and Statistics*, 97(4):725–741.

Bagwell, K. (2007). The economic analysis of advertising. *Handbook of industrial organization*, 3:1701–1844.

Bailey, T. (2013). Options for combination therapy in type 2 diabetes: comparison of the ada/easd position statement and aace/ace algorithm. *The American journal of medicine*, 126(9):S10–S20.

Berry, S. and Jia, P. (2010). Tracing the woes: An empirical analysis of the airline industry. *American Economic Journal: Microeconomics*, 2(3):1–43.

Berry, S. T. (1992). Estimation of a model of entry in the airline industry. *Econometrica*, pages 889–917.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262.

Bofinger, H. and Strand, J. (2013). *Calculating the carbon footprint from different classes of air travel*. The World Bank.

Borenstein, S. (1989). Hubs and high fares: Dominance and market power in the US airline industry. *The RAND Journal of Economics*, pages 344–365.

Borenstein, S. and Rose, N. L. (1994). Competition and price dispersion in the US airline industry. *Journal of Political Economy*, 102(4):653–683.

Braithwaite, D. (1928). The economic effects of advertisement. *The Economic Journal*, 38(149):16–37.

Cabral, M., Geruso, M., and Mahoney, N. (2014). Does privatized health insurance benefit patients or producers? Evidence from medicare advantage.

CDC (2017). National diabetes statistics report, 2017.

Chandra, A. and Lederman, M. (2015). Revisiting the relationship between competition and price discrimination in the airline industry.

Ching, A. T. (2010). A dynamic oligopoly structural model for the prescription drug market after patent expiration. *International Economic Review*, 51(4):1175–1207.

Chintagunta, P. K., Goettler, R. L., and Kim, M. (2012). New drug diffusion when forward-looking physicians learn from patient feedback and detailing. *Journal of Marketing Research*, 49(6):807–821.

Ciliberto, F. and Tamer, E. (2009). Market structure and multiple equilibria in airline markets. *Econometrica*, 77(6):1791–1828.

Collard-Wexler, A., Gowrisankaran, G., and Lee, R. S. (2019). nash-in-nash bargaining: a microfoundation for applied work. *Journal of Political Economy*, 127(1):163–195.

Crawford, G. S., Lee, R. S., Whinston, M. D., and Yurukoglu, A. (2018). The welfare effects of vertical integration in multichannel television markets. *Econometrica*, 86(3):891–954.

Crawford, G. S. and Yurukoglu, A. (2012). The welfare effects of bundling in multichannel television markets. *American Economic Review*, 102(2):643–85.

Cullen, J. A. and Mansur, E. T. (2014). Inferring carbon abatement costs in electricity markets: A revealed preference approach using the shale revolution. Technical report, National Bureau of Economic Research.

Dalton, C. M., Gowrisankaran, G., and Town, R. (2015). Myopia and complex dynamic incentives: Evidence from medicare part d. *NBER Working Paper*, 21104.

DOT (2019). What the cost of airline fuel means to you. `https://www.transportation.gov/administrations/assistant-secretary-research-and-technology/what-cost-airline-fuel-means-you`. Accessed: Mar. 31, 2020.

Ellison, G. and Ellison, S. F. (2011). Strategic entry deterrence and the behavior of pharmaceutical incumbents prior to patent expiration. *American Economic Journal: Microeconomics*, 3(1):1–36.

Entis, L. (2019). Why does medicine cost so much? here's how drug prices are set. `https://time.com/5564547/drug-prices-medicine/`. Accessed: Jul. 20, 2019.

Fabra, N. and Reguant, M. (2014). Pass-through of emissions costs in electricity markets. *The American Economic Review*, 104(9):2872–2899.

FDA (2015). The impact of direct-to-consumer advertising. `https://www.fda.gov/drugs/drug-information-consumers/impact-direct-consumer-advertising`. Accessed: Oct. 10, 2019.

Fowlie, M., Reguant, M., and Ryan, S. P. (2016). Market-based emissions regulation and industry dynamics. *Journal of Political Economy*, 124(1):249–302.

Frank, R. G. and Salkever, D. S. (1997). Generic entry and the pricing of pharmaceuticals. *Journal of Economics & Management Strategy*, 6(1):75–90.

Ganapati, S., Shapiro, J. S., and Walker, R. (2016). Energy prices, pass-through, and incidence in US manufacturing.

Gerardi, K. S. and Shapiro, A. H. (2009). Does competition reduce price dispersion? New evidence from the airline industry. *Journal of Political Economy*, 117(1):1–37.

Goldberg, P. K. and Hellerstein, R. (2013). A structural approach to identifying the sources of local currency price stability. *The Review of Economic Studies*, 80(1):175–210.

Goolsbee, A. and Syverson, C. (2008). How do incumbents respond to the threat of entry? Evidence from the major airlines. *The Quarterly Journal of Economics*, 123(4):1611–1633.

Gowrisankaran, G., Nevo, A., and Town, R. (2015). Mergers when prices are negotiated: Evidence from the hospital industry. *American Economic Review*, 105(1):172–203.

Grennan, M., Myers, K., Swanson, A., and Chatterji, A. (2018). Physician-industry interactions: Persuasion and welfare. Technical report, National Bureau of Economic Research.

Guo, T., Sriram, S., and Manchanda, P. (2017). The effect of information disclosure on industry payments to physicians. *Available at SSRN 3064769*.

Ho, K. and Lee, R. S. (2017). Insurer competition in health care markets. *Econometrica*, 85(2):379–417.

Inzucchi, S. E., Bergenstal, R. M., Buse, J. B., Diamant, M., Ferrannini, E., Nauck, M., Peters, A. L., Tsapas, A., Wender, R., and Matthews, D. R. (2015). Management of hyperglycemia in type 2 diabetes, 2015: a patient-centered approach: update to a position statement of the american diabetes association and the european association for the study of diabetes. *Diabetes care*, 38(1):140–149.

KFF (2017). Health insurance coverage of the total population. `https://www.kff.org/other/state-indicator/total-population/`. Accessed: Oct. 10, 2019.

Miller, N. H., Osborne, M., and Sheu, G. (2017). Pass-through in a concentrated industry: Empirical evidence and regulatory implications. *The RAND Journal of Economics*, 48(1):69–93.

Narayanan, S., Manchanda, P., and Chintagunta, P. K. (2005). Temporal differences in the role of marketing communication in new product categories. *Journal of Marketing Research*, 42(3):278–290.

Raz, I. (2013). Guideline approach to therapy in patients with newly diagnosed type 2 diabetes. *Diabetes Care*, 36(Supplement 2):S139–S144.

Ryan, S. P. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica*, 80(3):1019–1061.

Scott Morton, F. M. (1999). Entry decisions in the generic pharmaceutical industry. *The Rand Journal of Economics*, pages 421–440.

Scott Morton, F. M. (2000). Barriers to entry, brand advertising, and generic entry in the us pharmaceutical industry. *International Journal of Industrial Organization*, 18(7):1085–1104.

Shapiro, B. T. (2018). Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants. *Journal of political economy*, 126(1):381–437.

Sinkinson, M. and Starc, A. (2018). Ask your doctor? direct-to-consumer advertising of pharmaceuticals. *The Review of Economic Studies*, 86(2):836–881.

Tabuchi, H. (2019). 'worse than anyone expected': Air travel emissions vastly outpace predictions. `https://www.nytimes.com/2019/09/19/climate/air-travel-emissions.html`. Accessed: Mar. 31, 2020.

Telser, L. G. (1964). Advertising and competition. *Journal of political Economy*, 72(6):537–562.

Weyl, E. G. and Fabinger, M. (2013). Pass-through as an economic tool: Principles of incidence under imperfect competition. *Journal of Political Economy*, 121(3):528–583.