Drug Firms' Payments and Physicians' Prescribing Behavior in Medicare Part D

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September 2017

Abstract

In a pervasive but controversial practice, drug firms frequently make monetary or in-kind payments to health care providers. Critics are concerned that drug firms are distorting prescribing behavior away from the best interests of patients, while defenders of the practice claim that payments arise from the need to educate providers about changing drug technologies. Using two different identification strategies, we investigate the effect of payments from drug firms on patient-level prescribing behavior in Medicare Part D. We find that patients whose prescribers receive payments from a drug firm tend to increase expenditure on that firm's drugs. Our methods account for the selection of prescribers into payments (which may result if, e.g., pharmaceutical firms target payments to high volume prescribers) and our finding holds even when we look over time within patients who move residences and change to a new prescriber. However, using hand-collected efficacy data on four major therapeutic classes, we also find that those receiving payments prescribe higher-quality drugs on average. In addition, we examine four case studies of major drugs going off patent. Prescribers receiving payments from the firms experiencing the patent expiry transition their patients just as quickly to generics as prescribers who do not receive such payments. Our results have implications for the regulation of interactions between drug firms and physicians such as the Physician Payments Sunshine Act.

*We are grateful for helpful comments from Judy Hellerstein, Seth Freedman, Sean Nicholson, Ashley Swanson, Benedic Ippolito, and seminar participants at Harvard University, Cornell University, University of Michigan, the 2015 International Health Economics Association meetings, the 2015 American Health Economics Conference, and the 2016 Association for Public Policy Analysis and Management Annual Meeting. Anup Das provided excellent research assistance. Colleen Carey acknowledges the financial support of the Robert Wood Johnson Foundation.

1 Introduction

Prescription drug firms spend tens of billions of dollars marketing their products to health care providers each year. These payments may lead prescribers to direct demand towards the firms that pay them. If so, then perhaps the senior medical adviser at Consumer Reports is right to declare that "a major conflict of interest is at work when a physician has accepted payments from a drug company whose products he or she then prescribes."[1] Alternatively, defenders of the practice may be correct that payments facilitate encounters that ultimately educate prescribers: "Pharma reps provide timely access to balanced, FDA-approved research and information. This 'delivery mechanism' organically complements and reinforces the information they receive from medical journals and conferences."[2] If this is the case, payments help prescribers to choose higher quality drugs for their patients. It is important to understand how payments affect both drug expenditures and the quality of drugs prescribed in order to evaluate recent public policies such as the Physician Payments Sunshine Act that mandated the disclosure of drug firms' payments to prescribers.

This paper presents empirical evidence that, although payments do raise expenditures on a firm's product, the quality of drugs prescribed does not fall and, in fact, appears to increase. We use a new, large dataset on payments from drug firms linked to patient-level drug claims from more than 1.8 million Medicare Part D enrollees. Our evidence is consistent with the claim that payments alter prescribers' behavior to favor products made by the paying firm. However, using a dataset of drugs' efficacies hand-collected from clinical trials, we also show that payments from drug firms lead providers to prescribe more efficacious drugs. These results suggest that interactions between drug firms and prescribers play a role in informing prescribers about the quality of prescription drugs.

We first demonstrate that payments from a drug firm raise expenditures on the products

[1] http://www.consumerreports.org/cro/news/2014/09/find-out-if-your-doctor-takes-payments-from-drug-companies/index.htm

[2] http://nurse-practitioners-and-physician-assistants.advanceweb.com/Article/Pharmaceutical-Sales-Reps-Value-Beyond-Samples.aspx

the firm makes. We use data on expenditures on the products made by each drug firm in 130 therapeutic classes from longitudinal, patient-level prescription drug claims in Medicare Part D from 2011 to 2013. We link prescribers to a record of recent payments that they have received from any of fourteen drug firms who were forced to disclose payments as part of legal settlements.

Two different empirical strategies take advantage of the distinct features of our data to identify the impact of payments on expenditures. First, we use variation in the timing of payments to evaluate how the same prescriber behaves within the same therapeutic class before and after receiving a payment. This specification controls for all unobservable factors that lead a prescriber to favor a particular firm's drug in a therapeutic class, and is robust to drug firms targeting physicians on any time-invariant characteristic such as specialty, geography, or average patient population. Second, we consider a specification that identifies the impact of payments on prescribing solely from patients who move and simultaneously change prescribers for a class. This strategy borrows the insight of Finkelstein et al. (2016) that changes in the behavior of those who move residences can be used to identify patterns in provider behavior. This method allows us to net out average expenditure over time of a patient in a therapeutic class on drugs made by each firm, flexibly controlling for any time-invariant patient-specific characteristics that affect demand for a particular drug. In each approach, we show that patients whose prescribers begin to receive payments from a drug firm tend to have higher expenditures on products made by that firm; within a patient $\times$ therapeutic class, changing prescribers raises expenditure on products of firms who pay the new prescriber. While we find that large payments (in the hundreds or thousands of dollars) have somewhat larger impacts on expenditure, small payments under \$50, which comprise the vast majority of payments made, still raise expenditure on a firm's products by an economically meaningful 4%.

We then examine whether payments from drug firms affect the efficacy of prescribed drugs. To explore this question, we hand-collect data from the outcomes of published clin-

ical trials for four major therapeutic classes. This dataset reflects the information used by prescribers themselves to infer drug quality as well as the information that drug firms are allowed to disclose to prescribers in the encounters that generate payments. Using the same types of variation as in our analysis of expenditures, we find that the quality of prescribed drugs rises modestly when a prescriber receives a payment. Consistent with inertia in drug choice among existing patients, the effects of the payment are strongest among patients who have not previously received a drug in the therapeutic class from this prescriber. Although there are undoubtedly instances of inappropriate interactions between doctors and pharmaceutical firms, our evidence suggests that the encounters that generate payments from drug firms to prescribers also play a role in the diffusion of information about drug quality.

Finally, past research (Engelberg et al., 2014) has found, and media reports (e.g. Gold, 2001) have asserted, that payments from pharmaceutical companies lead prescribers to keep patients on branded drugs even when a generic equivalent is available. If true, these payments are likely leading patients to pay higher out-of-pocket costs with no compensating increase in the quality of the drug. We analyze the impact of payments on four major patent expirations: Lipitor, Singulair, Seroquel, and Lexapro. As illustrated in Figure 3, prescribers who had received payments transition their patients to the generic just as quickly and thoroughly as prescribers who had not received payments. A difference-in-difference regression analysis shows no evidence that prescribers who receive payments from relevant firms transition to generics more slowly than those who do not.

After developing our empirical results, we interpret them using a model of profit-maximizing drug firms making payments that can both inform and persuade. A mixed strategy equilibrium indicates how firms with drugs of different quality should optimally make payments to physicians. We then compare how equilibrium payments affect the choice of drug and the efficacy of prescribed drugs under different assumptions about the informativeness vs. persuasiveness of payments. We find that even when payments may be both informative and persuasive, equilibrium payments can increase the quality of prescribed drugs. Our model

also predicts that small payments are more likely to arise when payments are relatively more informative.

Our paper builds on a long literature that explores whether pharmaceutical detailing affects the quantity, costs, and quality of physicians' prescribing. Although there are fairly robust positive correlations between being exposed to pharmaceutical companies' information and the quantity and cost of prescribed drugs, most studies rely upon cross-sectional or time-series data and make no attempts to address the endogeneity of interactions between pharmaceutical companies and physicians. Recent reviews of this literature conclude that little can be said regarding these relationships (Spurling et al., 2010; Henry, 2010; Scott Morton and Kyle, 2011).[3] We contribute to this literature by providing estimates of payments to physicians based on longitudinal data that address concerns about selection of patients to providers as well as selection of payments to prescribers.[4]

Our paper also contributes to the literature on physicians' learning about drug quality through detailing. A number of papers model physician learning about drugs via detailing or other sources in a Bayesian framework (e.g. Narayanan et al., 2005; Narayanan and Manchanda, 2009; Ching and Ishihara, 2010, 2012; Chintagunta et al., 2012). These papers often use detailed information on pharmaceutical promotion from a single firm for one therapeutic class and exploit time-series prescribing patterns for physicians to identify the underlying structural model, but they do not have a direct measure of prescribing quality from outside the model. Research with a direct measure has used reviews of prescribing by other physicians (Becker et al., 1972; Haayer, 1982), the variance in the number of prescriptions a

[3]Two studies had exogenous variation in information provision, but both used unconventional promotion techniques and failed to find any impacts on physicians' prescribing (Dolovich et al., 1999; Freemantle et al., 2000). Overall, Spurling and colleagues concluded that "The limitations of studies reported in the literature mentioned above mean that we are unable to reach any definitive conclusions about the degree to which information from pharmaceutical companies increases, decreases, or has no effect on the frequency, cost, or quality of prescribing" (Spurling et al., 2010, p. 19).

[4]Our work is also related to the literature on the impacts of direct-to-consumer advertising (DTCA) on the pharmaceutical market. Studies have tended to find that DTCA has market expanding effects and that these impacts tend to dominate any business-stealing effects (e.g. Iizuka and Jin, 2005; Shapiro, 2017b; Sinkinson and Starc, 2017). Although DTCA has grown since the mid-1990s, it is a small portion of total pharmaceutical promotional expenditures (Scott Morton and Kyle, 2011) and is not included in our data on payments to prescribers.

particular physician made (de Bakker et al., 2007), or adherence to some treatment guideline (Muijrers et al., 2005) to proxy for quality.[5] Each of these analyses is a simple cross-sectional design. Our paper complements this literature through our use of clinical endpoints as a measure of quality and our ability to account for time-invariant, prescriber-specific attributes that make some prescribers more likely to interact with pharmaceutical representatives than others.

The remainder of the paper is structured as follows. In Section 2, we provide background information on the payments that drug firms make to prescribers. We discuss our various data sources in Section 3. Section 4 contains our empirical strategy and results on the relationship between payments and prescription expenditures. Section 5 contains our empirical strategy and results for the impact of payments on the efficacy of drugs prescribed. Section 6 contains our empirical strategy and results for the impact of payments on the brand-generic choice as drugs go off patent. In Section 7, we present a simple model that helps to interpret our empirical work. Section 8 discusses the results and concludes.

2 Payments to Physicians

Interactions between members of the medical profession and drug firms are commonplace. In 2008, drug firms spent $12 billion promoting their products to physicians, nurse practitioners, and physicians' assistants (Congressional Budget Office, 2009). In the 2000s, there were a number of efforts to curb these provider-industry relationships for fear that they influenced prescribing at the cost of patient welfare. For example, in 2008, the Association of American Medical Colleges called on all academic medical centers to ban acceptance of industry gifts by doctors, faculty, students, and residents (Sears, 2008). In 2007, Senator Chuck Grassley proposed the "Sunshine Act" to force drug firms to publicly disclose interactions with

[5]The impacts of information from the government (Soumerai et al., 1987), "dear doctor" letters (Kazmierczak and Coley, 1997), the presentation of information during grand rounds (Spingarn et al., 1996), and being involved in a clinical trial (Andersen et al., 2006) on similar measures of quality have also been explored with mixed results.

physicians. After several years of promotion, the Sunshine Act was included as part of the Affordable Care Act and became law in 2010. As of August 1, 2013, all drug and medical device firms were compelled by the Sunshine Act to start tracking these payments and were required to report them for public release to the Center for Medicare and Medicaid Services.

Although these interactions have roused great public concern, the financial value of the individual interactions is actually fairly limited (these interactions are hereafter referred to as payments). A typical payment covers a meal provided in a physician's office. Figure 1 shows the distribution of payments that 15 drug firms, among them Pfizer, Eli Lilly, and other major pharmaceutical manufacturers, made to prescribers in 2012.[6] The great majority of payments are small in magnitude; the median payment is only $47. Given that the median earnings for primary care physicians are $220,942 and $396,233 for specialists,[7] even the payment at the 95th percentile is not particularly large, about 0.2% of a primary care physician's income.

There is a long theoretical literature in economics about the varied impacts of advertising.[8] The "persuasive" view goes back at least as far as Robinson (1933). In her book on imperfect competition, she discusses how advertising increases demand for a particular product in the context of a monopolistically competitive market. This tends to increase prices and reduce social welfare. On the other hand, proponents of the "information" view (beginning with Stigler, 1961) outline how advertising notifies consumers of products' existence, prices, or other qualities. This information tends to increase welfare via reduced search costs and increased competition. Empirical studies suggest a prescriber's behavior can be affected both by her own financial interests (Gruber and Owings, 1996; Dafny, 2005; Liu et al., 2009) as well as the welfare of her patients (Iizuka, 2007; Epstein and Ketcham, 2014). Because the theories do not have unequivocal predictions, how pharmaceutical firms' marketing affects the costs, quantity, and quality of prescribing is an empirical question with, as noted earlier,

[6]The data used to make this figure will be described in Section 3.
[7]Numbers from BLS: http://www.bls.gov/ooh/healthcare/physicians-and-surgeons.htm.
[8]For a thorough review of this literature, see Bagwell (2007).

little that has been established definitively (Spurling et al., 2010; Henry, 2010; Scott Morton and Kyle, 2011).

3 Data

3.1 Prescribing Behavior: Medicare Part D

We assess prescribing behavior using the prescription drug claims of a 5% random sample of enrollees in Medicare Part D from 2011 through 2013; both enrollees in Medicare Advantage Part D plans and free-standing Part D plans are included. Over the sample period, Medicare Part D provided subsidized private insurance for outpatient prescription drugs to about 28 million elderly and disabled enrollees and represents approximately one-quarter of US prescription drug expenditure. An advantage of this dataset over a commercial claims dataset is that nearly all individuals continue in the sample once enrolled, facilitating our longitudinal identification strategies.

For each Part D claim, we observe the exact drug purchased (ingredients, strength, and drug form, including extended release if applicable), its days supply, the full drug price paid by the patient's insurer to the drug firm (prior to discounts), and the National Provider Identifier of the prescriber.[9] We assign each drug to a therapeutic class using the 2011 Formulary Reference Guide provided to Medicare Part D plans. We obtain the portfolios of the fifteen drug firms in the *Pro Publica* data using the Structured Product Label, as recorded in the RxNORM Attributes file.

In order to analyze prescribing behavior, we organize prescribing into "decisions." A decision is a patient, with the assistance of a prescriber, consuming a drug in a particular therapeutic class in a year. For example, Jane Smith may consume a drug in therapeutic class k, prescribed by a Dr. White, in 2011. Structuring the analysis in this way has

[9]Historically prescriber identifiers in Part D data were encrypted; we take advantage of a regulatory decision in May 2014 that permitted decryption.

several advantages. Firstly, organizing the data into therapeutic classes recognizes that substitutability within classes is much higher than across classes. Secondly, Medicare beneficiaries commonly see different medical providers for different ailments or systems of the body. We acknowledge this by assigning for each "decision" the prescriber who accounts for the plurality of days supply for the patient in that therapeutic class. That is to say, if a patient obtains statins from her cardiologist and antidepressants from a psychiatrist, we assess the influence of payments to the psychiatrist on antidepressant choice and payments to the cardiologist on statin choice. The primary prescriber accounts for an average of 93% of total days supplied in each beneficiary $\times$ therapeutic class. Later, we assess robustness to this assignment.

In Table 1, we describe our dataset at the level of the patient. We are using the prescription drug claims of approximately 1.8 million Medicare enrollees. Patients each participate in an average of 8 decisions per year. In 40 percent of decisions, the patient's prescriber has been paid by one of the competing firms.

One of our identification strategies analyzes how consumption changes as patients change prescribers due to moving residences. The 160,000 patients, or about nine percent of the overall population, who move residences (change zip codes) are described in the second column of Table 1. They make a similar number of decisions, and a similar number of decisions involve a payment from a *Pro Publica* firm. Our identification arises from decisions that are repeated with a new prescriber: i.e., cases where a patient consumes in the therapeutic class both before and after the move but changes prescribers. We find that similar numbers of decisions are repeated among both the general population and the movers subset, but that movers are more likely to have a new prescriber.[10]

[10]We define movers as those who change zip codes, but even when we consider those who change states, only 51% have a new prescriber for a repeated decision. Patients may legally refill prescriptions for months or even years after the prescription was originally written, which helps explain why only some movers in our data change prescribers. In addition, geographic information in the data reflects the residence at the end of the year, so if an individual moves late in the year, most of the year's prescriptions will have been supervised by the old prescriber.

3.2 Payments from Drug Firms: *Pro Publica Dollars for Docs*

Our data on payments made by drug firms to prescribers come from the non-profit organization ProPublica. Between 2009 and 2013, as a result of lawsuit settlements, fourteen firms were forced to disclose the payments they had made to prescribers.[11] ProPublica collected these data from the drug firms' websites, compiling more than 2.1 million encounters where the firms gave prescribers meals, travel, speaking fees, consulting payments, honoraria, gifts, and research payments.[12] Most of these encounters involve in-kind rather than cash payments, so the data record the dollar value of the meal, gift, or other transfer. We use the prescriber's name and geographic location to obtain the National Provider Identifier, which we then match to the Medicare Part D prescription data. As seen in Figure 1, the great majority of payments made to the prescribers in our sample are small. The median payment from a company to a particular prescriber in 2012 equals only \$46. However, there are a small number of extremely large payments in the data that bring the average up to \$1,071.[13] The median payment provides a more representative picture of most payments than the average: it is not until the 73rd percentile that payments to a prescriber from an individual firm reach even \$100.

We define our key independent variable as a binary indicator for a prescriber for a particular decision in year t if the prescriber has ever received a payment from a firm that makes a branded product in the class. This definition contains three simplifications. Firstly, we dichotomize payment despite the fact that the value of the payments vary greatly, as seen above. We explicitly consider the impact of payments of different sizes in a separate analysis. Secondly, we do not allow the impact of payments to depreciate. Due to our short panel,

[11] The lawsuits were often due to the practice of promoting drugs for "off-label" consumption, uses not explicitly approved by the FDA. There is an expanding literature that explores the relationship between interactions with pharmaceutical firms and off-label prescribing. The latter could be thought of as a measure of the quality of prescribing. Policies that likely affect detailing (Larkin et al., 2014) and positive information shocks that shift detailing (Shapiro, 2017a) are both found to affect off-label prescribing, though the economic significance of the impacts vary.

[12] In our analysis we aggregate payment types because firms appear to categorize payments differently, and we have no prior on differential effects of payment types.

[13] The large payments, which can reach \$4.1 million, are for research.

we assume prescribers do not "forget" a payment encounter. To note, while our prescribing data cover 2011 to 2013, we use payment data from 2009 and 2010 in determining whether a physician has ever been paid. To the extent that physicians' stock of information about a drug does depreciate with time, our empirical strategies will estimate an average impact of the payments over the time period in our sample. Thirdly, we must assume that a payment influences the prescribing of all of a firm's branded products because our payments data simply record an encounter between a firm and a prescriber, not the specific therapies being promoted. Thus, we cannot narrow the impact of payments to the specific drug or drugs discussed. This likely causes us to understate the impacts of payments since we will be classifying many decisions as being influenced by payments when in reality, they are not. However, we do acknowledge that drug firms stop or dramatically reduce the provision of promotional materials for their drugs which face generic competition (Huckfeldt and Knittel, 2011). Because of this, we impose that a firm's payments in year t affect prescribing for all of the firm's products that do not have generic equivalents in year t. We then test explicitly in Section 6 whether payments influence behavior around the onset of generic competition.

In Table 2, we describe the Part D data associated with each of the *Pro Publica* firms; the remaining products are included in a "composite brands" or "composite generics" line. Firms are sorted by the percent of Part D expenditure they represent. Together, the *Pro Publica* firms represent 40 percent of total Part D expenditure over the sample period, or 54 percent of branded expenditure. The major drug firms make payments at some point to a large minority of prescribers, led by Pfizer who reaches a quarter of prescribers. Overall, two in five prescribers receive a payment from one of the *Pro Publica* firms, demonstrating that financial relationships with drug firms were very common over our time period. The third column of the table reports the percent of Part D decisions where the firm makes a branded product in that year. This column represents the potential scope of influence for a firm's payments. The final column reports the percent of these decisions where the firm has made at least one payment to that decision's prescriber. Pfizer, known for a robust

physician-oriented marketing program, again leads this column; in nearly half of the Part D decisions where Pfizer has a competing product, it has made a payment to the relevant prescriber by the year of the decision.

Finally, one of our identification strategies takes advantage of the fact that each year some prescribers are paid by a particular firm for the first time. The final column of the table above reports on prescribers who begin to be paid by a firm for the first time over our sample period. For example, about five percent of prescribers begin to be paid by Merck over our sample period, meaning that no payment had been recorded by 2011 but a payment is recorded in 2012 or 2013. In what follows, we will test whether the onset of payment for a prescriber is associated with a change in prescribing, relative to the prescriber's behavior in that therapeutic class prior to the payment.

3.3 Efficacy Measurements

This paper takes advantage of a novel dataset on drug efficacy. Together with an MD/PhD student, we identified four major therapeutic classes where there is a common and well-defined clinical endpoint for drug therapy. For each therapeutic class, we obtained a unidimensional efficacy measurement for every molecule from the medical literature, documenting the exact source. For example, within the drug class of statins, our measure of efficacy for each drug is the percent reduction in LDL cholesterol associated with use of that drug observed in clinical trials. In Table 3 we describe the four therapeutic classes and their efficacy measures.

There are a number of important drawbacks to our efficacy measures. First, bad clinical trial results may be censored by drug firms (Turner et al., 2008). This is a concern for us to the extent that firms differentially censor their results; if all drug firms censor to the same degree, then this simply raises the mean efficacy relative to a placebo, but does not change our interpretation. A second drawback is that we are using a single measure of efficacy for all individuals. There is almost certainly heterogeneity in the efficacy of a given drug across

individuals which we are not measuring (e.g., differences in LDL reductions or differences in side effects across individuals). Because efficacy will be a dependent variable in our analyses, these measurement errors will bias our findings to the extent that they are systematically correlated with our payment variable and they will tend to increase our standard errors even if uncorrelated.

Despite these drawbacks, our measures largely capture efficacy as viewed by the physicians writing prescriptions. In 2011, a nationally representative survey of 508 physicians by KRC Research found that in addition to a physician's clinical knowledge and experience, the next most important factors that were considered when prescribing a drug were the patient's response to a particular medicine, the patient's particular situation (e.g. potential drug interactions or contraindications), clinical practice guidelines (often based on clinical trial results), and articles in peer-reviewed medical journals (also often presenting results from clinical trials). Moreover, Sullivan et al. (2014) show that when asked about drug efficacy, physicians seek information about clinical studies. A 2014 survey of 245 physicians by Publicis Touchpoint Solutions found that physicians want information about clinical studies and evidence-based medicine from their interactions with pharmaceutical sales representatives. Together, these studies suggest that prescribers view clinical trial results as indicators of efficacy and that the efficacy of the drugs is an important determinant of which drug the physician prescribes.

4 The Effect of Payments to Prescribers on Expenditure

We now turn to assessing the impact of payments from drug firms to physicians on expenditures on the firms' drugs. We pursue two distinct empirical strategies to evaluate whether payments to prescribers affect prescription drug expenditures, each addressing a potential omitted variable or source of selection. The first approach examines changes in behavior for

a given prescriber, firm, and therapeutic class over time. This approach exploits variation in the timing of payments to prescribers and allows us to account for time-invariant firm-by-prescriber-by-therapeutic class factors that make some prescribers more likely to receive payments from a particular firm than others. The second approach focuses on patients who move residences and simultaneously switch prescribers for a given therapeutic class. As described by Finkelstein et al. (2016), Medicare patients who move can be used to identify physician practice patterns since the patient's time-invariant behavior can be netted out by a fixed effect.

To implement these strategies, we consider the options—firms' products—that a prescriber faces in each "decision" (patient × therapeutic class × year) he makes. We create an analytic dataset with one observation for each firm that competes within a decision. That is, for every prescription drug purchase in the Part D data, we create observations with zero expenditures for the drugs in the same therapeutic class that were not purchased. We combine expenditures on all the generics and all the brands made by non-*Pro Publica* firms (or made by a *Pro Publica* firm that now faces exact generic competition, such as Lipitor in 2013) within a therapeutic class into a composite generic and composite brand for each therapeutic class.

We illustrate how the expenditure dataset is organized in Table 4, returning to the decision by Dr. White of a statin for Jane Smith in 2011. Dr. White has five options: three products produced by firms reporting payments in the ProPublica dataset, a branded product produced by another firm (composite brand), or a generic (composite generic). By 2011, Dr. White has received payments from Pfizer and AstraZeneca; while under her care, Jane spends $400 on Pfizer products and $50 on a generic. This data structure recognizes the polychotomous decision prescribers face. We estimate the equation using linear methods.[14]

[14]Although the multinomial logit model based on a standard random utility framework seems natural, there are a number of drawbacks to implementing it specific to our setting. If we were to use the closed form choice probabilities, we would define each prescriber by therapeutic class by year as a "market" with each firm's drug as options within the market, and *payment* a characteristic of a product. One concern is that we lose the ability to include patient fixed effects. In addition, the model does not accommodate the fact that many drugs in each "market" receive zero share. While we could simply say that the set of drugs

4.1 Identification Strategy: Within a Prescriber Over Time

Fugh-Berman and Ahari (2007) discuss how drug firms commonly monitor physicians' prescribing and specifically target high-volume prescribers for payments. From the drug firms' perspectives, high-volume prescribers are more appealing targets for payments–even small changes in their prescription choices could lead to large monetary returns for the drug firm. This strategic behavior by drug firms tends to make the correlation between a prescriber's payments and her patients' expenditures positive even if payments have no effect on prescribers' choices. In addition, if a firm "rewards" prescribers who already prescribe the firm's drug in a particular therapeutic class, but the prescriber does not react to the payment, this specification will report no association in our context.

To address this type of selection, we use variation in the timing of payments to evaluate whether changes in prescribing of a firm's product within a therapeutic class occur after such payments have been made. We estimate

$$DrugExp_{ikjt} = \beta_1 Payment_{ikjt} + \delta_{pkj} + \delta_{kt} + \epsilon_{ikjt}. \quad (1)$$

$DrugExp_{ikjt}$ are the expenditures for beneficiary i in therapeutic class k on firm j's drugs in year t, $Payment_{ikjt}$ indicates whether the primary prescriber for beneficiary i in class k has been paid by firm j at any point up to time t, δ_{pkj} is a set of fixed effects for each combination of prescriber, p, therapeutic class, and drug firm, and δ_{kt} is a set of therapeutic class by year fixed effects to net out all annual-level changes in average expenditure for this therapeutic class. The fixed effect δ_{pkj} nets out the prescriber's average expenditure on this firm's products in this therapeutic class over the three years of our sample period. We cluster standard errors at the prescriber level to account for correlations over time and across patients in the residuals for a given prescriber.

available (the choice set) in each market is different to sidestep this issue, this would throw out information contained in a prescriber's choice to never prescribe a given firm's drug. Estimating the model without taking advantage of the closed form choice probabilities would necessitate the inclusion of hundreds of thousands of fixed effects in a nonlinear model. This poses considerable practical issues.

The results are presented in the first column of Table 5. We find that receiving a payment is associated with a $5.41 increase in the average expenditures of a prescriber's patients. Relative to the mean expenditure of $89.82, this represents 6% increase in expenditures. Expenditures can increase as the result of a change in the quantity of drugs consumed, the price of those drugs, or a combination of both. We find no increase in quantity following the receipt of a payment, suggesting that payments encourage substitution towards more expensive drugs.[15]

Research on prescription drug choice shows that, after an initial period where patients and physicians learn about these experience goods, patients tend to continue their current treatment either until cure or indefinitely (Dickstein, 2014; Crawford and Shum, 2005). As a result, we might expect payments to be more influential when a patient is not continuing therapy, but is rather beginning it for the first time or beginning it with a new prescriber. To explore this possibility, we separate patients into two groups. "New" patients are those who either switched prescribers in a given therapeutic class or those who had not been taking a drug in class k in year $t-1$ but began taking a drug in that class in year t. "Existing" patients are the complement. The next two columns present results for the subsamples of "New" and "Existing" patients. Interestingly, payments lead to similarly sized increases in expenditures for both groups of patients. However, qualitatively different therapeutic classes are represented by the two subsamples, since acute therapies are disproportionately represented in the "new" patients category.

Our fixed effect δ_{pkj} absorbs all time-invariant characteristics of the prescriber that affect the expenditure she prescribes of a firm's drug in a therapeutic class. However, residual selection on time-varying characteristics could still cause a spurious correlation between payments and expenditures. If a prescriber's patient pool is changing over time, then she may become a target for firm payments at the same time that she begins prescribing more heavily in the therapeutic class. To directly address this concern, we include in the fourth

[15]These results are available from the authors upon request.

column dummies for the prescriber's decile of expenditure prescribed in the therapeutic class last year. The decile is known to be used by drug firms in targeting prescribers;[16] we use the lag since this is most recent information that could possibly be available to firms, and to avoid simultaneity between the independent and dependent variables. Use of the lag limits this analysis to years 2012-2013, so for comparison we report in the fifth column our baseline analysis (without the lagged decile) using only those years. Our coefficient in this specification is smaller, but still economically meaningful. Adding the lagged decile does not result in a different coefficient from the results that use only 2012 and 2013.

As described in Section 3.1, we assign each patient to the prescriber who accounts for the plurality of their expenditure in the therapeutic class that year. As a robustness check, in the final column of this table, we use only observations where the patient receives drugs from only a single prescriber. These results are statistically indistinguishable from our baseline findings, and similarly-sized as a percent of the mean.

As seen in Figure 1, there is considerable variance in the size of payments made to prescribers. To assess whether the large payments are driving our results, we estimate separate impacts for different payment sizes. We do so by interacting the *payment* variable with dummies indicating the size of the prescriber's largest payment up to that year. The coefficient on *payment* represents the impact of payments less than $20, and the other coefficients represent the incremental impact of larger payments. The results are reported in Figure 2. A prescriber whose first payment is less than $20 still increases expenditure by $0.83 (significant at the ten percent level), nearly 1% of the mean expenditure. However, higher payments have nearly monotonically higher impacts, although the variance grows as the number of prescribers represented falls.

[16] See, e.g., `https://social.eyeforpharma.com/commercial/pharma-marketing-upside-segmentation` or `http://customerthink.com/crm_healthcare_cpr_pharma_marketing_disease_management/`.

4.2 Identification Strategy: Within a Patient Who Moves Residences

If patients who have high expenditures on particular drug firms' products are more likely to select prescribers once they begin receiving payments from those firms, then there would be a spurious positive correlation between payments and expenditures. To address this concern, we identify the impact of payments on prescribing by using patients who move residences and, as a result, change prescribers. This identification strategy has been used to address the selection of patients to health care providers by many previous studies (e.g. Finkelstein et al., 2016). This approach is invalid if patients change prescribers due to a shock to preferences for a particular firm's drug; using those who switch prescribers at the same time they move makes it less likely that the change in prescribers is due to such a shock.

We estimate

$$DrugExp_{ikjt} = \beta_2 Payment_{ikjt} + \delta_{ikj} + \delta_{kt} + \epsilon_{ikjt}. \tag{2}$$

Our primary independent variable of interest, $Payment_{ikjt}$, is 1 if patient i's primary prescriber for class k has received a payment from company j by year t. We limit the sample to patients who both move residences and change prescribers for a therapeutic class. We require both conditions to hold since using only movers alone would include variation in $Payment_{ikjt}$ generated by prescribers beginning to be paid (the subject of our previous identification strategy). We also include a set of therapeutic class by year fixed effects, δ_{kt}, to net out class-specific changes in prices or other class-specific time effects. If $\beta_2 > 0$, this indicates that patients who switch to prescribers who receive a payment from drug firm j increase their spending on pharmaceuticals produced by company j, or that patients who switch *away* from a paid prescriber to one who is not paid decrease their spending.

Our results are presented in the first column of Table 6. We find that when a beneficiary switches to a prescriber who receives a payment from firm j, her expenditures on drugs made by firm j increase by \$7.56. With average spending just under \$101, the \$7.41 represents

a 6.5% increase in expenditures. This is very similar to our previous estimated increase in spending due to receiving a payment.

The second column of Table 6 uses only 2012 and 2013 in order to provide a comparison for the third column, which includes controls for the lagged decile of expenditure in the therapeutic class (as dummies). In this case neither limiting to the latter two years nor including these controls results in a statistically different estimate for the impact of payment on prescribed expenditure. The fourth column uses all those who switch prescribers, rather than simply those who move residences, resulting in a nearly identical coefficient. The fifth column again tests for robustness of our method of assigning patients to their plurality prescriber in a therapeutic class. When combined with our restriction that the individual switches prescribers, this limitation restricts to only patients who receive all their drugs from prescriber A in year t and all their drugs from prescriber B in year $t+1$. A patient who, for example, moves in February and receives two months' supply from her old prescriber will be excluded. Still, our estimated impact is not statistically different from our baseline estimate.

As before, we test whether larger payments have different impacts on expenditures and report the results in Figure 2. Again, larger payments are associated with higher impacts, but for even relatively small payments (e.g. \$20-\$49) expenditures increase by economically meaningful amounts. In this specification, there is no impact of payments if the prescriber has never received a payment exceeding \$20.

These results are consistent with our findings from the previous empirical strategy and they suggest that we are not simply picking up a spurious correlation due to patients' choices of prescribers. Taken together, the results suggest that payments are influencing prescribers' behaviors in a way that increases expenditures. We now turn to estimating whether these increased expenditures are coming at the cost of quality.

5 Payments and Efficacy of Prescribed Drugs

Industry representatives have claimed that regular contact with drug firm representatives helps to keep prescribers up to date on the availability and quality of new drugs. If these interactions do result in prescribers having better information about which drugs are most efficacious, they may lead to an overall improvement in the quality of drugs prescribed. Alternatively, if the payments have no information component (or, worse still, if they mislead prescribers into incorrectly assessing the quality of drugs available), we may find no relationship or a negative relationship between payment receipt and drug quality. In this section, we evaluate whether payments lead prescribers to choose more efficacious drugs.

To estimate these models, we organize the data at the level of the decision: a patient consuming in a therapeutic class in a year. Our dependent variable is therefore a measure of the quality of drugs that a patient takes for this therapeutic class in this year. We begin by evaluating measures that can be compared across therapeutic classes. First, we examine the fraction of days supplied of patient i going to the most efficacious drug in therapeutic class k. We categorize a drug as "most efficacious" based on the efficacy measures described in Section 3.3. Second, within each therapeutic class, we transform our efficacy measure into a z-score by subtracting from each product's efficacy the average efficacy within that therapeutic class (weighted by total days supply) and dividing by the standard deviation of that measure. Then, we average the z-scores for each patient's claims within the therapeutic class by year to create a dependent variable that captures the patient's prescribed efficacy in the class relative to the average efficacy in that class.[17] This results in a summary measure of efficacy within a therapeutic class that is comparable across classes.

We note that our results from the previous section, that payments increase expenditures, continue to hold when the sample is restricted to the four therapeutic classes we use in our

[17] Because the average efficacy within the class is weighted by days supply, but the sample means presented in Tables 7 and 8 are averaged over patients with no weighting applied, the sample mean is slightly higher than zero.

analysis of quality.[18]

We estimate:

$$Efficacy_{ikt} = \gamma_1 PaymentInClass_{ikt} + \delta_{pk} + \delta_{kt} + \epsilon_{ikt} \tag{3}$$

where $PaymentInClass_{ikt}$ equals one if i's primary prescriber for class k has received a payment from *any* company that produces a drug within therapeutic class k by year t; that is, $PaymentInClass_{ikt}$ is not firm-specific. For this reason, γ_1 captures whether or not receiving any potentially informative payments affects the efficacy of drugs prescribed in the therapeutic class. If $\gamma_1 > 0$, it indicates that payments are associated with the prescription of higher efficacy drugs as measured by clinical trial results. δ_{pk} is a set of prescriber by therapeutic class fixed effects which control for the average efficacy prescribed by this provider in this therapeutic class between 2011 and 2013, and δ_{kt} captures time-varying changes in the average efficacy prescribed in class k across sample years. These fixed effects remove the cross-sectional variation in $PaymentInClass_{ikt}$; as a result, γ_1 is being identified by variation in the timing of payments to prescribers.

The estimates are presented in Panel A of Table 8. We find that payments are positively, significantly associated with the fraction of days supplied going to the highest quality drug. Patients whose provider receives a payment took the most efficacious drug for approximately 0.13 percentage points more of their days supplied than patients whose provider had not received a payment. Because just over 9 percent of a patient's days supplied were of the most efficacious drug available, this is a 1.4 percent increase in days of the highest quality drug. While this increase in quality is small on average, there could be heterogeneous effects for new and existing patients. In the next two columns of Table 8, we present results separately for these two groups. For new patients, payments increase the fraction of days the patient takes the highest quality drug by approximately 4 percent. For existing patients,

[18]In fact, the results are somewhat larger in magnitude. Furthermore, when restricting to these four chronic-use therapeutic classes, we find that the effect is significantly larger for new patients than for existing patients.

we do not see any impacts, although it is possible that drug quality or patient-specific drug fit are changing in ways that are not captured by our efficacy measure. We verify in the fourth column that our results are similar when restricting to those who see only a single prescriber for a therapeutic class in a year.

The next four columns show the effect of payment receipt on the standardized average quality of a drug within a therapeutic class. Here, we find a positive but not statistically significant association between provider payments and the average quality of drugs being prescribed. The next two columns show the results for new and existing patients. We find that the increase in efficacy is larger and statistically significant among new patients. For that group, the estimate implies that seeing a prescriber who has received a payment increases average quality by 0.01 standard deviations.

Panel B of Table 8 presents results for the class-specific measures of efficacy. The results are not systematically positive or negative. We find little impact of payments on the quality of prescribing for blood pressure medications or for 2nd generation anti-psychotics. We find positive impacts of payments on the quality of statins prescribed, particularly for new patients. Although our point estimates are negative for gastrointestinal agents, the implied magnitude of the impacts is negligible (0.05 *percent* reduction). In all cases, results are similar when we restrict the sample to those who see a single prescriber within each therapeutic class.

As in the expenditure analysis, we estimate the impact of payments on expenditures for patients who switch prescribers due to moving residences. This addresses the possibility that patients who tend to use high quality drugs also begin to patronize prescribers once they receive payments. To isolate this variation, we estimate a version of equation (3) where the prescriber by therapeutic class fixed effects, δ_{pk}, have been replaced with beneficiary by therapeutic class fixed effects, δ_{ik}, and we limit the sample to patients who move residences and change prescribers for a therapeutic class between 2011 and 2013. These results are presented in Tables 8 and 9.

Using either the fraction of days supplied that were for the highest quality drug or

the average efficacy z-score, we find that patients who switch from a prescriber without a payment to a prescriber with a payment see a significant increase in the quality of drugs they are prescribed. The magnitudes are modest, but they allow us to rule out any negative impacts on quality associated with payments. We also detect improvements in drug efficacy when analyzing patients who simply change prescribers but do not move residence. In models where we estimate therapeutic class specific effects, we find for the most part positive and statistically significant improvements in quality when patients switch to a physician who is paid by a company in that therapeutic class. Overall, these results indicate that drug quality improves when physicians interact with pharmaceutical companies.

6 Payments and Patent Expiry

In Part D, patients typically pay higher out-of-pocket prices for a branded drug when there exists a generic equivalent; therefore, prescribers acting as good agents for their patients should transition the patient to generics as soon as possible. At the same time, patent expiries represent substantial revenue losses to branded drug firms. Finding that prescribers who receive payments from a drug firm disproportionately keep patients on the firm's brands would be evidence that prescribers were privileging the drug firms' interests over their patients.[19] We choose four major drugs that lost patent protection and faced new generic competition over our sample period: Lipitor, Singulair, Lexapro, and Seroquel. These four drugs alone accounted for eight percent of Medicare Part D expenditures in 2011.[20]

Figure 3 depicts the generic transition for the four molecules we consider. On the left, we depict expenditure on the branded version of the molecule, and on the right we depict expenditure on the generic version. The red line is average expenditure by month among patients whose prescribers receive payments from the branded drug firm, and the blue line is all other prescribers; the confidence interval for each month's average expenditure is in gray.

[19]Prescribers can override automatic substitutions of a generic for the name-brand drug (see Hellerstein, 1998).

[20]See Appendix B. for more detailed information about these drugs.

There is a clear drop in expenditure on the branded version of the drug, and an increase in expenditures on the generic version of the drug, at the time of the patent's expiry for all cases we consider. The red line is sometimes above the blue line (e.g., Seroquel) prior to the patent expiry, reflecting the same prescribing pattern demonstrated in Table 5: receiving a payment from a drug firm is associated with greater expenditure on that firm's drugs. After the patent expiry, however, the red and blue lines cannot be distinguished. This figure therefore shows that prescribers who receive payments transition to generics just as quickly as those who do not.

We formalize this visual analysis in a regression framework by estimating

$$\begin{aligned} ExpOnBrandedDrug_{im} = \beta_0 + \beta_1 AnyPaymentfromBrand_i \\ + \beta_2 PatentExpired_m + \beta_3 AnyPaymentfromBrand_i \times PatentExpired_m \\ + \epsilon_{im}. \end{aligned} \tag{4}$$

This equation models expenditure in month m on the branded drug by patient i as a function of whether patient i's prescriber has received a payment from the branded drug firm, whether the branded drug's patent has expired, and the interaction of these two effects. Based on the figure, we expect β_2 will be large and negative; i.e., that monthly expenditures on the branded version of the drug will fall substantially after the patent has expired. Based on our analysis in Section 4, we also expect β_1 to be positive; that is, that payments on the branded drug prior to the expiration of the patent will be higher among patients whose prescribers receive payments. The coefficient on the interaction term, β_3, indicates whether the change in expenditures following the expiration of the patent is different for patients whose prescribers receive payments. If we find $\beta_3 > 0$, it would indicate that payments lead prescribers to transition their patients off of the branded version of the drug more slowly than prescribers who do not receive payments. This would suggest a persuasive role for payments and that prescribers are poor agents for their patients; in this case, prescribers would be prescribing a

more expensive version of a drug that is available at a much lower price. However, if we find $\beta_3 \leq 0$, this result would suggest that prescribers who receive payments move their patients off of the branded drug at least as quickly as other prescribers.

The results are presented in Table 11 in the first column under each drug name. We do not find evidence that expenditure on the branded drug falls more slowly for prescribers who receive payments than for other prescribers.[21] Indeed, for Seroquel and Lipitor, our estimates suggest that patients whose prescribers who receive payments actually transition off of the branded molecule *more* quickly than patients whose prescribers do not receive payments.

We estimate a similar model that replaces the dependent variable with expenditures on the generic version of the molecule. If payments were persuasive, then we would expect patients of prescribers receiving payments to transition to generics less quickly, i.e. $\beta_3 < 0$. The results are reported in the second column under each drug name in Table 11. For all four case studies, we find that expenditures on the generic version of the molecule increase more among patients whose prescribers receive payments from the drug company.[22]

Huckfeldt and Knittel (2011) show that pharmaceutical companies advertise branded reformulations of drugs facing generic competition immediately prior to the loss of patent protection. It may be the case that payments lead physicians to prescribe branded reformulations, or other branded molecules, more heavily. Among the four drugs we study, Seroquel and Lexapro have plausible branded substitutes. AstraZeneca offered a branded reformulation (Seroquel Extended Release) and Forest offered another branded anti-depressant,

[21] This result is counter to the one presented in Engelberg et al. (2014). However, this discrepancy appears due to the fact that we are using more precise data on the dates of patients' expenditures than their annual aggregates. This allows us to more accurately delineate the "pre" and "post" patent period. Appendix Figure C.1 depicts the generic transitions for the three drugs Engelberg et al. (2014) use in their analysis. Arimidex loses patent protection in June, 2010; Cozaar loses protection in April, 2010. Protonix lost patent protection in January, 2011. However, generic manufacturers had infringed on the patent beginning in 2008 and were ordered to stop selling their drug in April, 2010. As seen in these figures, prescribers who had received payments had higher expenditures on the branded drug while the patent was in effect, but prescribed almost identically to prescribers without payments when facing competition from generics.

[22] Results are similar when examining the impact of patent expiries across physicians practicing in states with and without generic substitution laws. These figures are available from the authors upon request.

Viibryd. Both were introduced prior to the expiration of patents of Seroquel and Lexapro.

We investigate substitution towards these branded alternatives in Figure 4. Although there is a visible "run up" in use of these branded alternatives prior to the patent expiry, there is no discernible difference in this pattern for physicians that do and do not receive a payment. This suggests that, at least in these two cases, payments are not driving substitution to similar but more expensive products following the expiration of a patent.

The results in Table 11 combined with the graphical evidence in Figures 3 and 4 demonstrate that prescribers who receive payments transition their patients off of the branded molecule and onto the generic molecule just as quickly as prescribers who do not receive payments. This suggests that, at least in this context, payments to prescribers are not causing them to act counter to their patients' interests.

7 Model

In this section, we outline a simple model that helps to interpret our empirical results. Suppose there are two firms and that each firm produces a drug which can be advertised to health care providers. The firms compete with each other to have providers prescribe their drug. Advertising by firm i occurs as a payment to a prescriber that can inform her about drug quality or persuade her to prescribe firm i's drug. For simplicity, let there be a single provider who chooses one of the two drugs for a single patient.

The providers's utility of prescribing drugs 1 and 2 is given by the following equations:

$$u_1 = \alpha_1^1 p_1(\mathbb{1}\left[p_1 \geq b\right]) + \alpha_1^2 p_2(\mathbb{1}\left[p_2 \geq b\right]) + q_1$$
$$u_2 = \alpha_2^1 p_1(\mathbb{1}\left[p_1 \geq b\right]) + \alpha_2^2 p_2(\mathbb{1}\left[p_2 \geq b\right]) + q_2$$

where p_i is the payment made from drug firm i to the prescriber, α_m^i describes how a

payment from i affects the prescriber's utility of prescribing drug m, and q_i describes how the perceived quality of firm i's product affects the utility of prescribing that product. $\mathbb{1}[p_i \geq b]$ is an indicator function equal to one when payment i is at least b and zero otherwise. The indicator functions reflect that fact that prescribers have a reservation value for their time and so require a payment of at least size b from firms. In practice, drug firms' representatives visit prescribers' offices to discuss their drugs and provide FDA-approved promotional materials that highlight clinical trial results. If the payment is below b, the prescriber refuses to meet the firm's representative and so is unaffected by any advertising amount lower than b.

What we refer to as quality, q_i, incorporates two elements: the prescriber's beliefs about the drug's quality as well how important quality is to the prescriber. The prescriber chooses drug 1 for the patient when $u_1 > u_2$, i.e. when

$$(\alpha_1^1 - \alpha_2^1)p_1(\mathbb{1}[p_1 \geq b]) - (\alpha_2^2 - \alpha_1^2)p_2(\mathbb{1}[p_2 \geq b]) + (q_1 - q_2) > 0. \tag{5}$$

Notice that $(\alpha_1^1 - \alpha_2^1)$ describes the degree to which firm 1's payments differentially increase the utility of prescribing 1's drug (with $(\alpha_2^2 - \alpha_1^2)$ the analogous preference for firm 2). We think of this difference in αs as describing the persuasiveness of the payments that firms make to prescribers. For simplicity, we will assume that payments from firms are all equally persuasive, that $(\alpha_1^1 - \alpha_2^1) = (\alpha_2^2 - \alpha_2^1) \equiv w$. As w increases, the utility of prescribing a drug from a firm that pays the prescriber increases.

In addition to possibly being persuaded, prescribers potentially care about the differential quality of the two firms' drugs, $q_1 - q_2 \equiv \beta$. Without loss of generality, we will assume that if prescribers were perfectly informed they would believe that firm 1's drug has higher quality than firm 2's drug. If the prescriber is aware of this difference and values prescribing more effective drugs, then $\beta > 0$. However, β could also be zero. Prescribers do not always know which drugs are most effective. In that case, we will assume that prescribers believe $q_1 = q_2$ and so $\beta = 0$. An alternative, though unlikely, possibility is that the prescriber does not

actually value prescribing the best drug to her patients. In that case, a drug's efficacy will not affect her utility at all and will imply that $\beta = 0$.

One potentially important reason for firms to advertise their drugs to prescribers is to provide information on drug quality. If the prescriber values prescribing the highest quality drug, then firm 1 has an incentive to reveal this information to the prescriber. We assume that a payment $p_i \geq b$ reveals to the prescriber that firm 1 produces the higher quality drug.[23]

On the supply side, drug firms optimally choose whether and how much to pay the prescriber. Drug firms choose their payments simultaneously without knowledge of the other firm's choice. If R_i is the revenue firm i receives from having its drug prescribed, its problem is

$$\max_{p_i} R_i D_i(p_i) - p_i \tag{6}$$

where p_i is the payment the firm makes to the prescriber and $D_i(\cdot)$ is the demand for its product. We assume that payments must be non-negative and that the higher quality drug receives a higher market price, $R_1 > R_2$. Demand for a firm's drug is given by

$$D_i = \begin{cases} 1 & if\ u_i > u_j \ \text{ for } i, j \in \{1, 2\} \\ 1/2 & if\ u_i = u_j \\ 0 & if\ u_i < u_j. \end{cases}$$

Given this structure, the problem is an extension of a standard all-pay auction (e.g. Hillman and Riley, 1989; Baye et al., 1996). Our model differs in two respects. First, the auctioneer (the prescriber) can have a preference over who wins the auction if she cares about quality ($\beta > 0$). This feature is similar to the model of electoral contests in Meirowitz (2008). In

[23]Note that a payment from either firm reveals the superiority of firm 1's drug in our model. This is consistent with regulatory restrictions on firms to disseminate only FDA-approved information and inference on the part of prescribers. Theory and empirical evidence on the endogenous disclosure of information (e.g. Lewis, 2011) suggest that prescribers will deduce that a firm is the lower quality firm if it makes a payment to the prescriber but does not disclose itself as the high-quality firm. The restrictions by the FDA prevent the lower-quality firm from falsely representing itself as the high-quality firm.

that paper, voters have preferences that make them inherently more likely to vote for a candidate from a particular political party and candidates choose levels of effort to exert (effort increases the probability a given voter casts her ballot for that candidate). The prescriber's preference for prescribing the higher quality drug is analogous to the voter's preference for a particular political party. Second, the prescriber does not necessarily know which firm produces the better drug, but the firms can change the prescribers' perceptions as part of their payments. There is no corresponding feature in Meirowitz (2008) in which a voter does not know which party she prefers until she receives some information from the candidate.

In our model, the drug firms play mixed strategies according to the cumulative distribution functions described in Proposition 7.1 below.

Proposition 7.1 *In equilibrium, when $b < R_2$, firms 1 and 2 play mixed strategies according to $G_1(p_1)$ and $G_2(p_2)$ respectively. These distributions are given by*

$$G_1(p_1) = \begin{cases} 0 & if\ p_1 < b \\ \frac{p_1+\beta/w}{R_2} & if\ p_1 \in [b, R_2 - \beta/w] \\ 1 & if\ p_1 > R_2 - \beta/w \end{cases}$$

$$G_2(p_2) = \begin{cases} \frac{1}{R_1}\left[R_1 - R_2 + b + \beta/w\right] & if\ p_2 \in [0, b + \beta/w) \\ \frac{1}{R_1}\left[R_1 - R_2 + p_2\right] & if\ p_2 \in [b + \beta/w, R_2] \\ 1 & if\ p_2 > R_2 \end{cases}$$

Proof See Appendix A.

As usual in all-pay auctions, there is not a pure strategy equilibrium. Intuitively, each firm wants to outbid the other by some small amount ϵ. This ratchets bids up until one of the firms hits the highest payment it is willing to make to a prescriber (R_2 for firm 2). Because $R_1 > R_2$, firm 1 can bid $R_2 + \epsilon$, win with certainty, and make positive profits. In this case, firm 2 will bid zero so that it does not lose profits. However, there is not an

equilibrium because once firm 2 bids zero, firm 1 will want to reduce its payment to ϵ to maximize profits.

Figure 5 plots the distributions of payments that each firm makes in equilibrium. We can see that the higher quality producer will not make a payment lower than the amount b that reveals it to have the better drug. On the other hand, there are many instances in which the lower quality firm will not make a payment at all, i.e. it has a significant mass at $p_2 = 0$. Conditional on making a payment, each firm distributes its payments uniformly over an interval. Firm 2 will make payments all the way up to how much it earns when it wins the auction, R_2. However, firm 1's highest payment can be lower than that because it always reveals itself as producing the better drug. As a result, its largest payment is $R_2 - \beta/w$.

In equilibrium, the relationship between marketing to prescribers and prescribers' behavior depends upon the parameters governing persuasiveness (w), how important the quality of the drug is (β), and the minimum payment necessary to inform a prescriber about drug quality (b). For some drugs or some prescribers, $b > R_1 > R_2$. In this case, the prices for the drugs are so low relative to the physician's opportunity cost of time that neither firm finds it worth making a payment to the prescriber. However, when there is scope for payments, the probability that firm 1's drug is prescribed is given by

$$\frac{1}{R_1}\frac{1}{R_2}\left\{\left(R_1 - \frac{1}{2}R_2\right)R_2 + \left(\sqrt{\frac{1}{2}\frac{\beta}{w}} + \sqrt{\frac{1}{2}}\ b\right)^2\right\} \tag{7}$$

Because this quantity is greater than one-half, firm 1's drug is prescribed more frequently than firm 2's drug. Then for a sample of data that likely contains situations where it is profitable to make payments and situations where it is not, the model suggests, and our analysis confirms, that firms that make payments are more likely to have their drugs prescribed and thus have greater revenues (expenditures in our analysis). It is straightforward to show that this correlation becomes stronger as the relative importance of information to persuasion (β/w) increases. However, even if prescribers do not care about quality at all

($\beta = 0$), firm 1's drug is still more likely to be prescribed than firm 2's drug.[24] Intuitively, even though quality does not impact prescribing, the benefit to firm 1 of winning is larger than that for firm two (because $R_1 > R_2$) and so it is willing to make greater payments, which increase the probability that its drug is prescribed.

Because drug quality is closely tied to a drug's price, the model suggests, and our estimates once again largely confirm, a positive impact of payments on the quality of the drugs prescribed. It is worth noting that even if physicians do not care about drug quality, the higher quality drug will still be more likely to be prescribed in equilibrium.

Thus, the model's predictions echo our empirical findings regarding how payments affect expenditures and the quality of drugs prescribed. In addition, the model suggests a relationship between the size of payments made and the roles of information and persuasion in these payments. Notice that as information becomes important relative to persuasion, as β/w increases, firm 1 puts increasing mass on the smallest payments ($p_1 = b$) and firm 2 becomes increasingly likely to not make a payment. For a given b, this suggests that smaller payments are likely to indicate that information is the primary purpose of payments to prescribers and payments significantly larger than b tend to occur in an environment where persuasion is relatively important. As we saw in Figure 1, the vast majority of payments are small and the median payment is only \$43. Although there are some very large payments made that could reflect a persuasive effect, these could also simply reflect a distribution of time costs across physicians.

Our results on patent expiry fit more neatly into a slightly modified version of the model presented above. In this case, we can consider the branded drug to have had a monopoly before patent expiry and then to be exposed to a competitor with exactly the same quality, but a lower price after expiry. If payments are not persuasive, then physicians are indifferent between prescribing the branded and generic versions of the drug. Given that every state has some version of a generic-substitution laws, the majority of patients would end up receiving

[24] With this simplification, our model fits within the framework of Hillman and Riley (1989). Their results imply that firm 1's drug is more likely to be prescribed than firm 2's.

the generic version of the drug. However, if payments are persuasive, then the branded firm's drug will be more likely to be prescribed. Because our analysis of patent expirations finds that payments before expiry do not lead to greater expenditures on the branded drug after expiry, the evidence suggests that payments are not primarily persuasive.

8 Conclusion

In this paper, we test the impact of payments from drug firms on prescribing behavior using a novel combination of patient-level prescription drug claims linked to each prescriber's history of payments from drug firms. Using two empirical approaches that account for both selection of prescribers into payments and of patients to prescribers, we find that prescribers raise expenditures on products made by firms from whom they have received payments. However, using a hand-collected dataset on drug efficacy, we find evidence that those who receive payments prescribe higher-quality drugs. We also find that prescribers who receive payments from a drug firm transition their patients just as quickly to generics in the wake of a patent expiry among that firm's products. Consistent with defenses offered by drug firms and some prescribers, we find evidence that the transmission of information about drug quality and availability is an important component of the encounters that result in payments.

Our results suggest that, at least in principle, laws that discourage physician-drug firm interactions may reduce consumer welfare as health care providers become less informed about the quality of drugs available to patients. However, without better measures of consumers' value of higher efficacy drugs, we cannot make conclusive statements about the direction of any welfare effects of such policies. Further research on the topic may shed light on this question.

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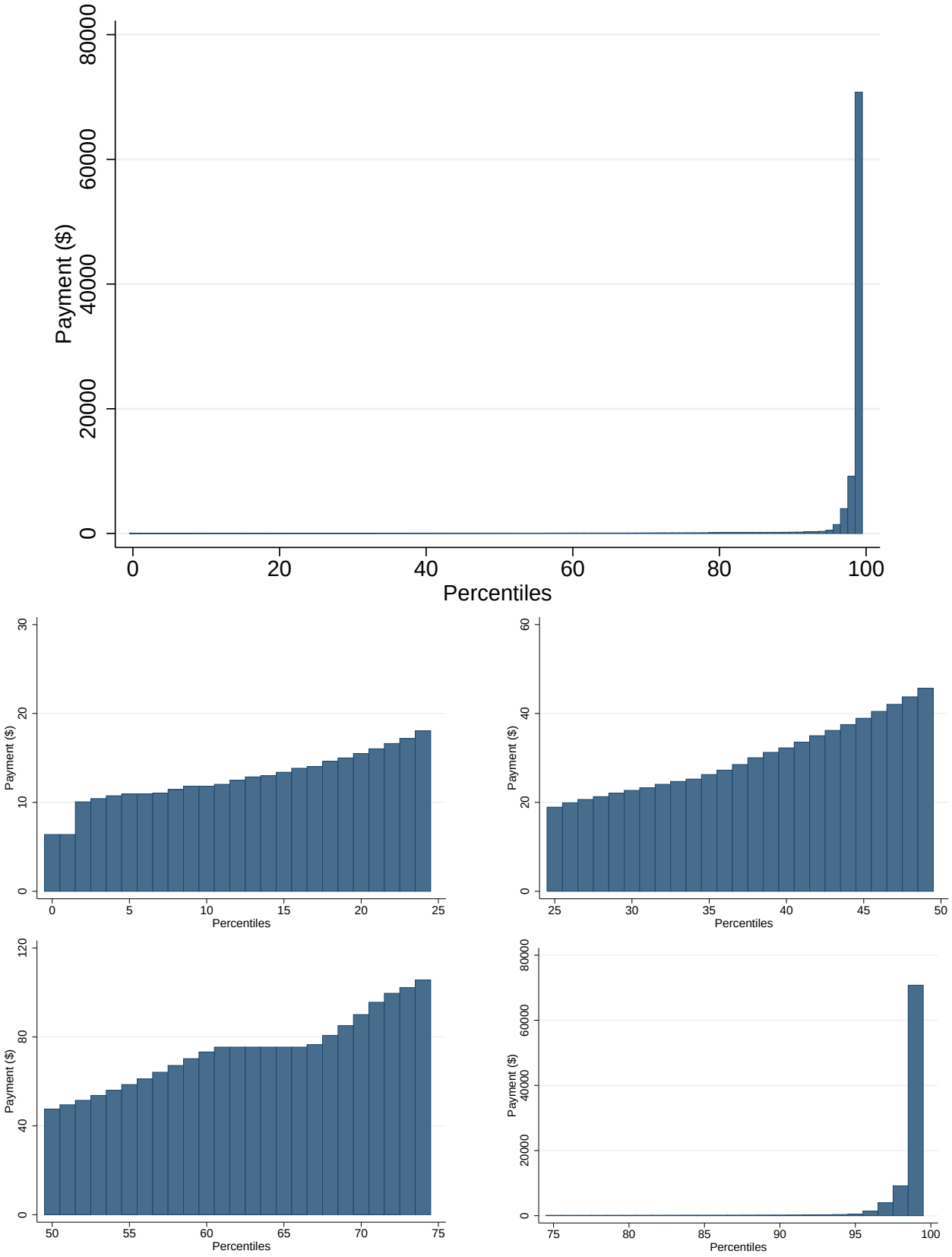
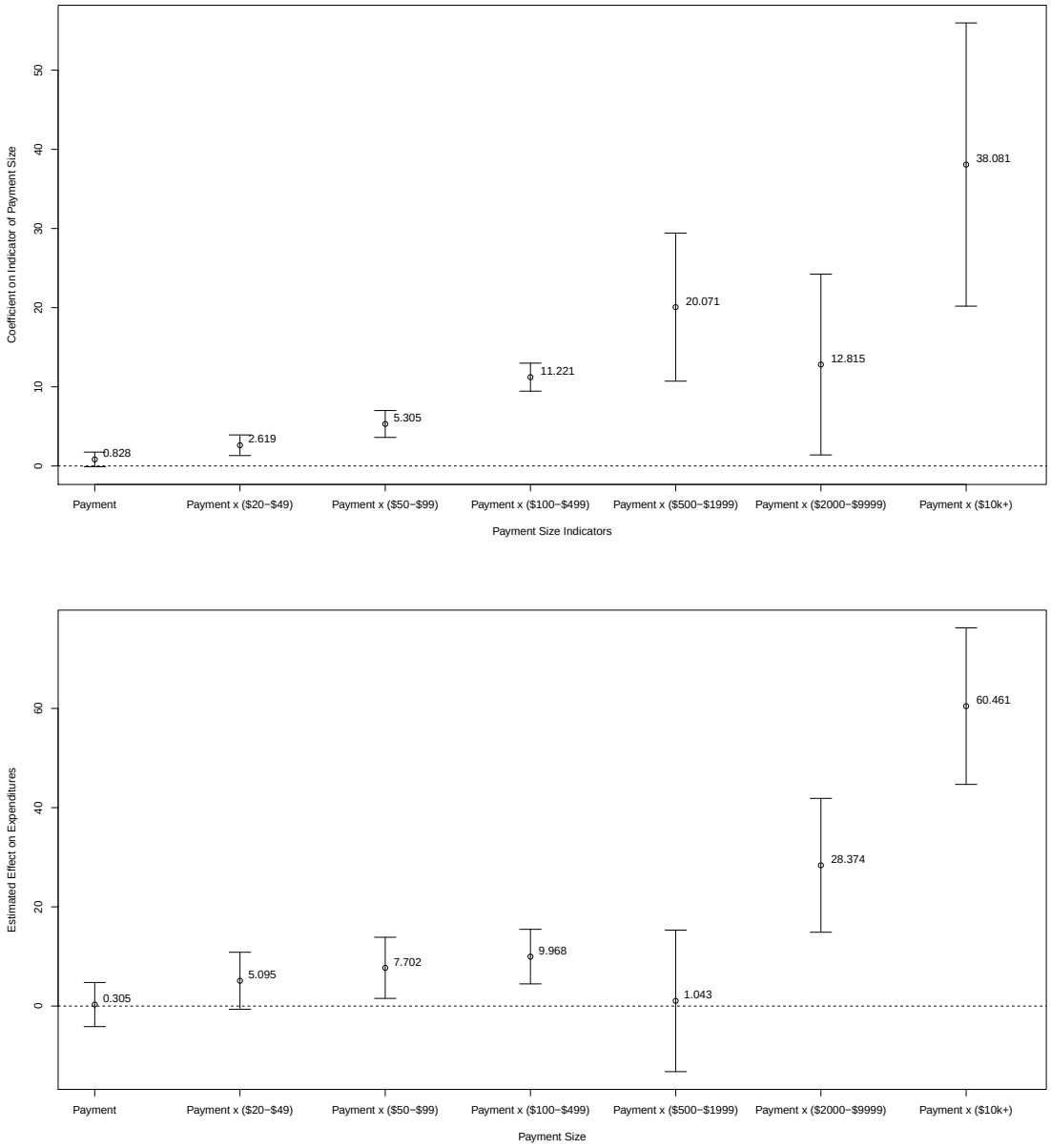
Figure 1: Distribution of Payments Overall and for Portions of the Distribution



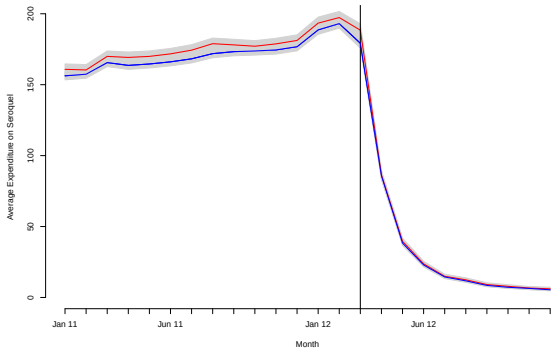
Notes: Full distribution shown in top figure. Quarters of distribution shown in four subfigures. Y-axis/scale changes for each subfigure.

Figure 2: Impact of Payments on Expenditure by Payment Size

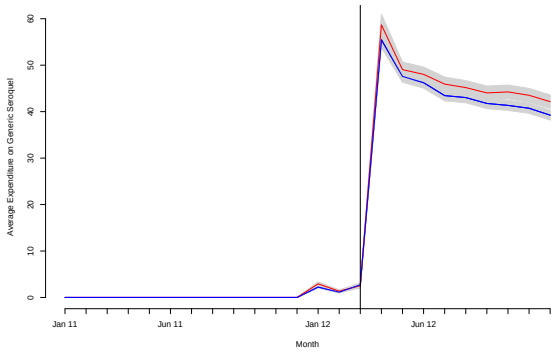


Notes: These figures report the results of adding interactions for largest payment received from the firm up to year t to Equations 1 (top panel) and 2 (bottom panel). The first coefficient represents the impact of payments less than \$20, while each successive coefficient represents the incremental impact of a larger payment. The bars represent the 95 percent confidence interval.

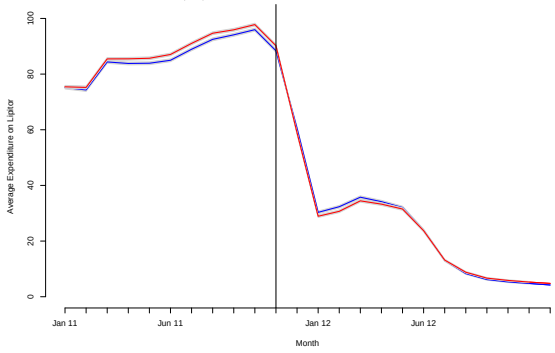
Figure 3: Generic Entry by Payment from Expiring Brand Pharmaceutical Company (Red = Some Payment, Blue = No Payment)



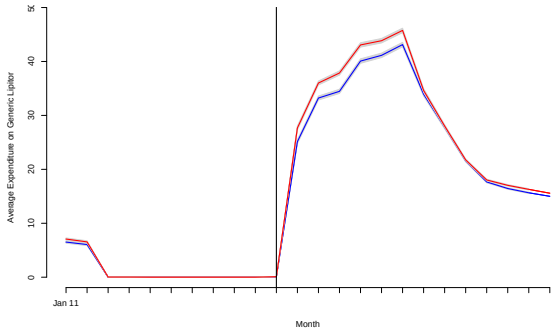
(a) Use of Seroquel



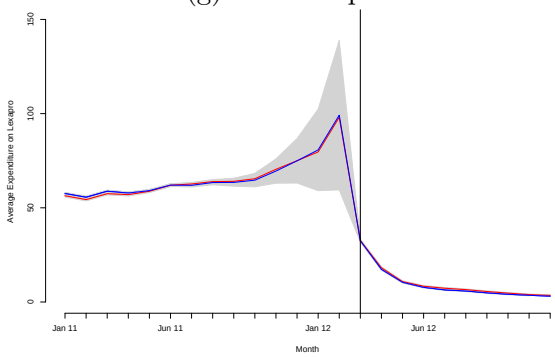
(b) Use of Generic Seroquel



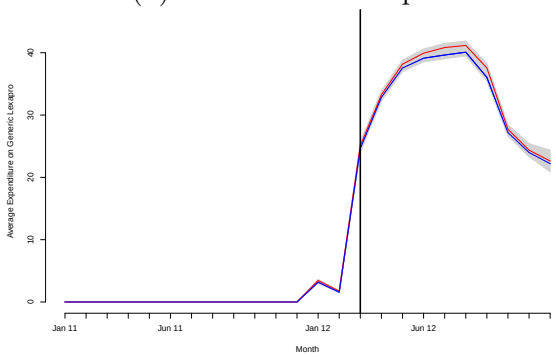
(g) Use of Lipitor



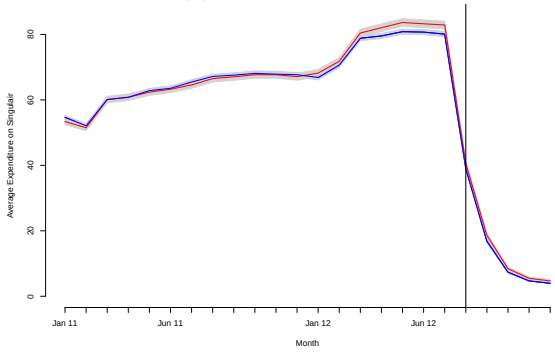
(h) Use of Generic Lipitor



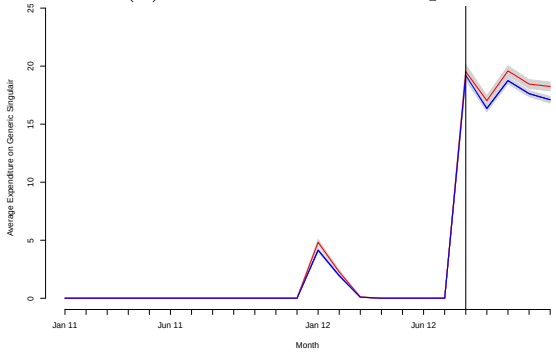
(c) Use of Lexapro



(d) Use of Generic Lexapro



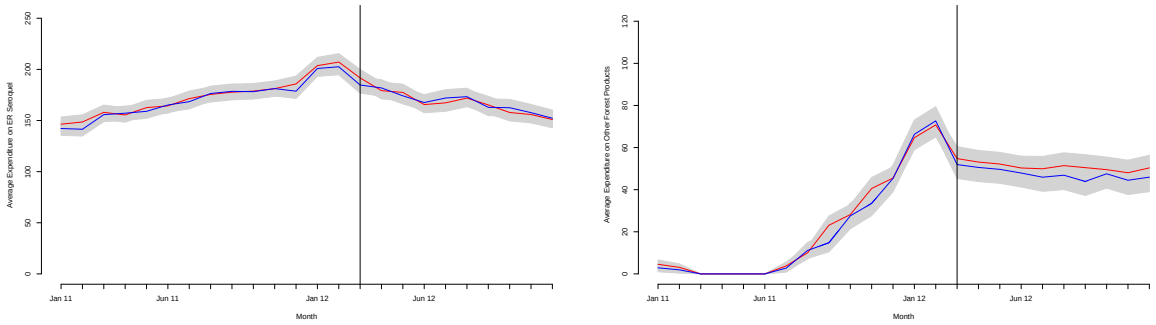
(e) Use of Singulair



(f) Use of Generic Singulair

Each figure reports average monthly expenditure in 2011 and 2012 in Medicare Part D for four molecules experiencing patent expiries. The vertical line shows the month of patent expiry. The red line denotes expenditure for patients whose prescriber for the molecule has received a payment from the firm that makes the branded version. The blue line denotes expenditure for patients whose prescriber has never been paid by that firm. The left column shows expenditure on the branded version of the molecule, while the right column shows expenditure on the generic equivalent.

Figure 4: Generic Entry by Payment from Expiring Brand Pharmaceutical Company (Red = Some Payment, Blue = No Payment)

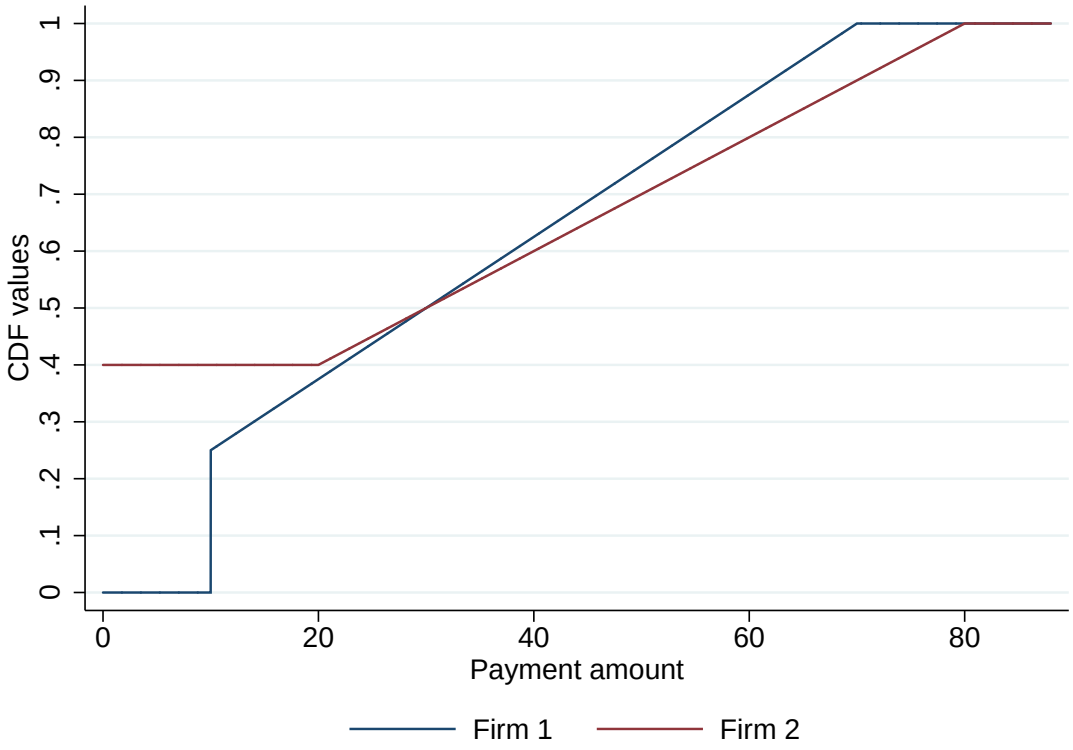


(a) Use of Seroquel ER

(b) Use of Viibryd

Each figure reports average monthly expenditure in 2011 and 2012 in Medicare Part D for branded molecules that are plausible substitutes for the molecules experiencing patent expiries. The vertical line shows the month of patent expiry. The red line denotes expenditure for patients whose prescriber for the molecule has received a payment from the firm that makes the branded version. The blue line denotes expenditure for patients whose prescriber has never been paid by that firm.

Figure 5: Equilibrium Distributions of Payments Implied by Model



Notes: Mixing distribution for each firm plotted for $R_1 = \$100, R_2 = \$80, b = \$10, \beta = 20, w = 2$.

Table 1: Summary Statistics: Medicare Beneficiaries 2011-2013

	All	Movers
Number of Patients	1,798,450	164,414
Number of Decisions Per Year	7.79	8.38
Of Decisions, Percent With Payment	39.72	39.05
Of Decisions, Percent Repeated	41.95	42.43
Of Repeated Decisions, Percent With New Prescriber	31.20	43.64

This table reports on our sample of Medicare beneficiaries. The first column reports on all beneficiaries (used in the first identification strategy, within a prescriber) and the second column reports on the subset of those who change residences between 2011 and 2013 (used in the second identification strategy, within a patient). The first row reports the total number of beneficiaries. The second column reports the average number of "decisions", meaning selection of a drug within a therapeutic class in a year. The third row reports the percent of decisions where the prescriber has been paid by a firm making a branded drug in the class. The fourth row reports the percent of decisions that are repeated in successive years, which allows them to contribute to identification. The final row reports the percent of repeated decisions with a new prescriber, which allows them to contribute to identification in the within-patient strategy.

Table 2: Summary Statistics: Payments from *Pro Publica* Firms to Medicare Part D Prescribers, 2011-2013

	Percent of Part D Expenditure	Percent of Prescribers Ever Paid	Percent of Decisions Where Firm Competes	Of Decisions Where Competes, Percent Where Prescriber is Paid	Percent of Prescribers Newly Paid
AstraZeneca	8.0	12.9	6.1	45.3	1.5
Merck	5.1	11.1	6.1	18.9	5.2
Eli Lilly	4.9	10.7	4.1	42.3	1.6
Novartis	4.9	6.8	5.3	16.2	2.7
Pfizer	4.1	23.3	6.8	47.2	1.4
AbbVie	3.1	8.0	4.3	15.5	4.7
Johnson & Johnson	3.0	12.8	3.6	25.3	3.6
Forest	2.9	10.9	3.7	26.2	5.4
GlaxoSmithKline	1.8	6.7	7.5	11.0	2.7
Allergan	1.3	5.0	2.3	24.8	1.0
Cephalon	0.3	2.9	0.3	25.8	0.1
UCB	0.3	2.1	1.8	5.4	1.0
Valeant	0.2	1.8	2.6	7.4	0.4
EMD Serono	0.1	0.1	0.1	1.1	0.0
composite brands	34.0	0.0	22.9	0.0	0.0
composite generics	25.4	0.0	22.6	0.0	0.0

This table reports on the firms whose payments to prescribers are recorded by *Pro Publica*. Products not made by a reporting firm are represented in the last two rows. The first column reports the share of Part D expenditure represented by the firm's branded products. The second column reports the percent of Part D prescribers ever paid by a firm. The third column reports the percent of decisions (choice of a drug in a therapeutic class in a year) where the firm makes a branded product. The next column reports the share of such decisions where the firm has paid the prescriber for the decision. The final column reports the share of Part D prescribers who are paid for the first time by this firm between 2011 and 2013.

Table 3: Efficacy: Therapeutic Classes and Clinical Outcomes

Class	Efficacy measure
HmG CoA Reductase Inhibitors (statins)	Percent reduction in LDL cholesterol
Angiotensin II Receptor Antagonists	Reduction in systolic blood pressure
Proton Pump Inhibitors	Percent with esophageal healing
2nd Generiation Antipsychotics	Reduction in Positive & Negative Syndrome Scale

Table 4: Example of Expenditure Data

Year	Prescriber	Payment up to Year	Firm	Patient	TC	Exp.
2011	White	0	Eli Lilly	Jane Smith	k	0
2011	White	1	Pfizer	Jane Smith	k	\$400
2011	White	1	AstraZeneca	Jane Smith	k	0
2011	White	0	composite brand	Jane Smith	k	0
2011	White	0	composite generic	Jane Smith	k	\$50
2012	Green	1	Eli Lilly	Jane Smith	k	\$450
2012	Green	0	Pfizer	Jane Smith	k	0
2012	Green	0	AstraZeneca	Jane Smith	k	0
2012	Green	0	composite brand	Jane Smith	k	0
2012	Green	0	composite generic	Jane Smith	k	0

Example of data setup for patient Jane Smith seeing providers White and Green. The estimation of Equations (1) and (2) use this data arrangement.

Table 5: Impact of Payments on Expenditure Within a Prescriber Over Time

	Baseline	New Patients	Existing Patients	Lagged Decile	12&13 only	Single Prescriber
Payment	5.414***	4.365***	5.000***	2.208***	1.866***	4.684***
	(0.400)	(0.583)	(1.055)	(0.684)	(0.685)	(0.445)
Prescriber X TC X Firm FEs	Y	Y	Y	Y	Y	Y
TC X Year FEs	Y	Y	Y	Y	Y	Y
Lagged Decile				Y		
R-squared	0.606	0.468	0.708	0.633	0.633	0.645
Mean of LHS	89.8	76.1	124.4	89.8	89.8	78.2
Observations (in millions)	114.6	82.1	32.5	78.2	78.2	88.8

Table reports the results of estimating Equation (1) on the Part D beneficiaries' spending from 2011 to 2013. Each column includes fixed effects that flexibly account for the average expenditure for a prescriber on drugs made by a particular firm in a particular therapeutic class; in addition, a fixed effect nets out the average expenditure in a therapeutic class each year. "Payment" is 1 if the prescriber has received a payment from that firm in the year of the observation or in any previous year. Given these fixed effects, the impact of payment is identified from prescribers who begin to be paid part way through the sample. The second and third columns break the sample into patients who are being prescribed a drug in this therapeutic class by this prescriber for the first time ("new") and those who were prescribed a drug in this therapeutic class by this prescriber last year ("existing"). The fourth column drops 2011, for comparison with column five, which adds as controls dummies for the prescriber's lagged decile of spending within the therapeutic class. The fifth column uses only observations where the prescriber accounts for the entirety (rather than the plurality) of an individual's expenditure within the therapeutic class.

Table 6: Impact of Payments on Expenditure Within a Patient Over Time

	Baseline	12 & 13 only	Lagged Decile	All Switchers	Single Prescriber
Payment	7.576***	7.075***	5.617***	7.440***	9.572***
	(1.298)	(1.590)	(1.608)	(0.445)	(2.065)
Patient X TC X Firm FEs	Y	Y	Y	Y	Y
TC X Year FEs	Y	Y	Y	Y	Y
Lagged Decile			Y		
R-squared	0.776	0.853	0.853	0.799	0.805
Mean of LHS	116.1	115.4	115.4	100.9	80.82
Observations	4,582,048	3,165,778	3,165,778	32,197,450	2,470,411

Table reports the results of estimating Equation (2) on the Part D beneficiaries' spending from 2011 to 2013. Each column includes fixed effects that flexibly account for the average expenditure for a patient on drugs made by a particular firm in a particular therapeutic class; in addition, a fixed effect nets out the average expenditure in a therapeutic class each year. "Payment" is 1 if the prescriber has received a payment from that firm in the year of the observation or in any previous year. To avoid variance in Payment generated by physicians who begin to get paid, we limit the sample to patients who change prescribers. In our baseline specification, we further limit to those who change zip codes; in the fourth column we use all those who change prescribers. The second column drops 2011, for comparison with the third column, which adds dummies for the prescriber's lagged decile of spending within the therapeutic class. The final column limits to cases where the prescriber accounts for the entirety (rather than the plurality) of a patients consumption in a therapeutic class.

Table 7 : Impact of Payment on Drug Efficacy Within a Prescriber Over Time

Panel A								
Therapeutic Class:	*All*				*All*			
	Fraction Days Supply Most Effiacious	Fraction Days Supply Most Effiacious	Fraction Days Supply Most Effiacious	Fraction Days Supply Most Effiacious	Average Efficacy (Z-Score Index)	Average Efficacy (Z-Score Index)	Average Efficacy (Z-Score Index)	Average Efficacy (Z-Score Index)
sample:	All	New Patients	Existing Patients	Single Prescriber	All	New Patients	Existing Patients	Single Prescriber
Payment	0.0013**	0.0041***	0.0003	0.0015*	0.0024	0.0125**	-0.0041	0.0017
SE	(0.0007)	(0.0016)	(0.0009)	(0.0008)	(0.0024)	(0.0056)	(0.0031)	(0.0027)
Observations	4,639,658	1,984,039	2,655,619	3,539,605	4,639,658	1,984,039	2,655,619	3,539,605
mean of LHS	0.091	0.089	0.092	0.089	0.017	0.019	0.015	0.009
Panel B								
Therapeutic Class:	*Cardiovascular Agents (Angiotensin II Receptor Antagonists)*				*2nd Generation Anti-Psychotics*			
	Reduction in Systolic Blood Pressure	Reduction in Systolic Blood Pressure	Reduction in Systolic Blood Pressure	Reduction in Systolic Blood Pressure	PANSS	PANSS	PANSS	PANSS
sample:	All	New Patients	Existing Patients	Single Prescriber	All	New Patients	Existing Patients	Single Prescriber
Payment	0.0004	-0.0013	0.0035	-0.0007	0.0487	0.1294	-0.0213	-0.0026
SE	(0.0069)	(0.0181)	(0.0094)	(0.0081)	(0.0347)	(0.0806)	(0.0473)	(0.0439)
Observations	785,810	328,177	457,633	604,902	284,121	149,399	134,722	185,328
mean of LHS	9.26	9.24	9.28	9.28	13.82	13.76	13.9	13.74
Therapeutic Class:	*Cardivascular Agents (HMG CoA Reductase Inhibitors)*				*Gastrointenstinal Agents (Proton Pump Inhibitors)*			
	% Reduction in LDL Cholesterol	% Reduction in LDL Cholesterol	% Reduction in LDL Cholesterol	% Reduction in LDL Cholesterol	% Patients with Esophageal Healing	% Patients with Esophageal Healing	% Patients with Esophageal Healing	% Patients with Esophageal Healing
sample:	All	New Patients	Existing Patients	Single Prescriber	All	New Patients	Existing Patients	Single Prescriber
Payment	0.0622**	0.2326***	-0.0383	0.0537*	-0.0440**	-0.0617	-0.0359	-0.0339
SE	(0.0256)	(0.0628)	(0.0319)	(0.0293)	(0.0197)	(0.0397)	(0.0287)	(0.0231)
Observations	2,259,182	858,564	1,400,618	1,764,207	1,310,545	647,899	662,646	985,168
mean of LHS	36.44	36.68	36.29	36.39	86.58	86.54	86.62	86.50

This table reports the results of estimating Equation 6 on the efficacy of drugs purchased by Part D beneficiaries in 2011 to 2013. Each column includes fixed effects that absorb the average drug quality for a prescriber in a particular therapeutic class and fixed effects that net out the average expenditure in a therapeutic class each year. "Payment" is 1 if the prescriber had received a payment from a firm in the class by the current year. The impact of a payment is identified by prescribers who begin to be paid. Additional columns break the sample into patients who are being prescribed a drug in this TC by this prescriber for the first time ("new") and those who were prescribed a drug in this TC by this prescriber last year ("existing").

Table 8: Impact of Payment on Drug Efficacy Within a Patient Over Time

	Fraction Days Supply Most Effiacious Baseline	Fraction Days Supply Most Effiacious All Switchers	Fraction Days Supply Most Effiacious Single Prescriber
Payment	0.0031***	0.0019***	0.0030
SE	(0.0010)	(0.0004)	(0.0023)
Patient X TC Fes	X	X	X
TC X year FEs	X	X	X
Observations	234,641	1,759,098	300,581
R-squared	0.859	0.881	0.855
mean of LHS	0.099	0.099	0.090
	Average Efficacy (Z-Score Index) Baseline	Average Efficacy (Z-Score Index) All Switchers	Average Efficacy (Z-Score Index) Single Prescriber
Payment	0.0152***	0.0094***	0.0160**
SE	(0.0032)	(0.0012)	(0.0072)
Patient X TC Fes	X	X	X
TC X year FEs	X	X	X
Observations	234,641	1,759,098	300,581
R-squared	0.865	0.89	0.866
mean of LHS	0.033	0.033	0.004

This table reports the results of estimating Equation 6 on the efficacy of drugs purchased by Part D beneficiaries in 2011 to 2013. The sample is limited to switchers. Each column includes fixed effects that absorb the average drug quality for a prescriber in a particular therapeutic class and fixed effects that net out the average expenditure in a therapeutic class each year. "Payment" is 1 if the prescriber had received a payment from a firm in the class by the current year. The impact of a payment is identified by beneficiaries who who switch prescribers.

Table 9: Impact of Payment on Drug Efficacy Within a Patient Over Time, by Therapeutic Class

	Cardiovascular Agents (Angiotensin II Receptor Antagonists)		*2nd Generation Anti-Psychotics*	
	Baseline	All Switchers	Baseline	All Switchers
Payment	0.0164	0.0135***	0.0763**	0.0427**
SE	(0.0105)	(0.0036)	(0.0385)	(0.0166)
Patient X TC Fes	X	X	X	X
TC X year FEs	X	X	X	X
Observations	29,670	270,211	28,628	117,798
R-squared	0.903	0.91	0.831	0.876
mean of LHS	9.19	9.22	14.21	14.01
	Cardivascular Agents (HMG CoA Reductase Inhibitors)		*Gastrointenstinal Agents (Proton Pump Inhibitors)*	
	Baseline	All Switchers	Baseline	All Switchers
Payment	0.0976***	0.0785***	0.0680***	0.0270***
SE	(0.0339)	(0.0121)	(0.0238)	(0.0089)
Patient X TC Fes	X	X	X	X
TC X year FEs	X	X	X	X
Observations	105,683	856,523	70,660	514,566
R-squared	0.876	0.895	0.840	0.872
mean of LHS	36.44	36.54	86.75	86.72

This table reports the results of estimating Equation 6 on the efficacy of drugs purchased by Part D beneficiaries in 2011 to 2013. The sample is limited to those who change prescribers over time. Each column includes fixed effects that absorb the average drug quality for a prescriber in a particular therapeutic class and fixed effects that net out the average expenditure in a therapeutic class each year. "Payment" is 1 if the prescriber had received a payment from a firm in the class by the current year. The impact of a payment is identified by beneficiaries who switch prescribers.

Table 11: Effect of Patent Expiry on Patient Expenditures

	Seroquel		*Lipitor*	
	Expenditure on Branded	Expenditure on Generic	Expenditure on Branded	Expenditure on Generic
Payment	4.786**	0.0639**	1.544***	0.107***
	(2.227)	(0.0284)	(0.252)	(0.0287)
Patent Expired	-133.0***	39.92***	-58.72***	24.83***
	(1.126)	(0.493)	(0.186)	(0.0943)
Payment × Patent Expired	-3.287*	2.103***	-1.769***	1.347***
	(1.872)	(0.814)	(0.260)	(0.133)
N (Beneficiary x Month)	1,088,808	1,088,808	3,299,496	3,299,496
R-squared	0.087	0.088	0.189	0.132
	Singulair		*Lexapro*	
	Expenditure on Branded	Expenditure on Generic	Expenditure on Branded	Expenditure on Generic
Payment	0.490	0.0536***	1.076	0.0299**
SE	(0.481)	(0.0116)	(3.942)	(0.0146)
Patent Expired	-53.78***	17.49***	-56.17***	31.99***
SE	(0.263)	(0.122)	(3.063)	(0.239)
Payment × Patent Expired	0.677	0.684***	-0.496	0.698*
SE	(0.476)	(0.220)	(3.936)	(0.386)
N (Beneficiary x Month)	1,446,504	1,446,504	1,249,464	1,249,464
R-squared	0.090	0.088	0.001	0.139

Results of estimating Equation (4) on a random 5 percent sample of Medicare beneficiaries in 2011 and 2012. SEs clustered at the prescriber level. Any Payment is a binary indicator for ever having received a payment from the drug firm that produces the branded molecule experiencing patent expiry.

Appendices

A. Proof of Proposition

The proof for Proposition 7.1 is shown below.

Let G_i denote the distribution of payments made by firm i. We begin by describing the support of G_i. Because physicians require at least b for the payment to affect their utility, there is no incentive for payments from either firm in the region $p_i \in (0, b)$. We will assume that $b < R_2$ so that both firms have an incentive to make payments to the physician. There is no incentive for $p_2 > R_2$ because a payment in that region will not increase the probability of winning the physician's business, but it will increase costs and so reduce profits. Given that, a similar argument shows that payments $p_1 > R_2 - \beta/w$ are never made. For firm 2, $p_2 \notin [b, b + \beta/w)$ because payments in this region do not increase the probability that firm 2 wins the physician's business over $p_2 = 0$, but they are higher cost. As such, they are dominated and not in the support of G_2. These arguments indicate that the support of G_2 is $\{0\} \cup [b + \beta/w, R_2]$.

The expected profits for firm 2 when setting payment p_2 are

$$E\pi_2(p_2) = \begin{cases} R_2 \frac{1}{2} G_1(0) & \text{if } p_2 = 0 \\ G_1(0) R_2 + (1 - G_1(0))\, R_2 G_1(p_2 - \beta/w) - p_2 & \text{if } p_2 \geq b + \beta/w \end{cases} \tag{8}$$

This leads us to the following lemma.

Lemma A..1 *(i) Firm 2 makes zero profits in equilibrium ($E\pi_2(p_2) = 0$). (ii) Firm 1 does not play $p_1 = 0$ in equilibrium, i.e. $G_1(0) = 0$.*

Proof Note that $E\pi_2(R_2) = G_1(0)R_2 + (1 - G_1(0))\, R_2 G_1(p_2 - \beta/w) - R_2 = 0$. For firm 2 to play a mixed strategy, it must be that $E\pi_2(p_2) = 0 \ \forall \ p_2$ in the support of G_2. This establishes (i). (ii) follows from $E\pi_2(0) = (1/2)R_2 G_1(0) = 0$.

Lemma A..1 implies that the support of G_1 is $[b, R_2 - \beta/w]$. As such, in equilibrium, firm 1 always reveals that it is the higher quality firm. The following lemma derives the exact forms of G_1 and G_2.

Lemma A..2 *Firm 1 plays a mixed strategy according to*

$$G_1(p_1) = \begin{cases} 0 & if \ p_1 < b \\ \frac{p_1 + \beta/w}{R_2} & if \ p_1 \in [b, R_2 - \beta/w] \\ 1 & if \ p_1 > R_2 - \beta/w \end{cases}$$

Proof From Lemma A..1, we know that firm 2 makes zero profits in equilibrium. This in turn implies that $E\pi_2(p_2) = 0$ and thus $R_2 G_1(p_2 - \beta/w) - p_2 = 0 \Rightarrow G_1(p_2 - \beta/w) = p_2/R_2$. A change of variables completes the proof.

Lemma A..3 *Firm 2 plays a mixed strategy according to*

$$G_2(p_2) = \begin{cases} 0 & if\ p_2 < 0 \\ \frac{1}{R_1}\left[R_1 - R_2 + b + \beta/w\right] & if\ p_2 \in [0, b + \beta/w) \\ \frac{1}{R_1}\left[R_1 - R_2 + p_2\right] & if\ p_2 \in [b + \beta/w, R_2] \\ 1 & if\ p_2 > R_2 \end{cases}$$

Proof We have seen that firm 1 makes profits $R_1 - R_2 + \beta/w$ in equilibrium. This in turn implies that $E\pi_1(p_1) = R_1 - R_2 + \beta/w$ and thus $R_1 G_2(p_1 + \beta/w) - p_1 = R_1 - R_2 + \beta/w \Rightarrow G_2(p_1 + \beta/w) = \frac{1}{R_1}(R_1 - R_2 + \beta/w + p_1)$. A change of variables combined with the previously obtained support of G_2 completes the proof.

B. Drugs Going Off Patent

We look at four molecules that began to face generic competition in 2011 or 2012.

- Seroquel (quetiapine), made by AstraZeneca, began to face generic competition in March 2012. Quetiapine is an 2nd generation or "atypical" antipsychotic frequently used in Part D to treat schizophrenia. In 2011, it accounted for 2.9% of total Part D expenditure. AstraZeneca introduced Seroquel XR in 2007 and it is protected by patents until 2017; we treat Seroquel XR as an independent good and exclude expenditure on it from both our pre and post observations.

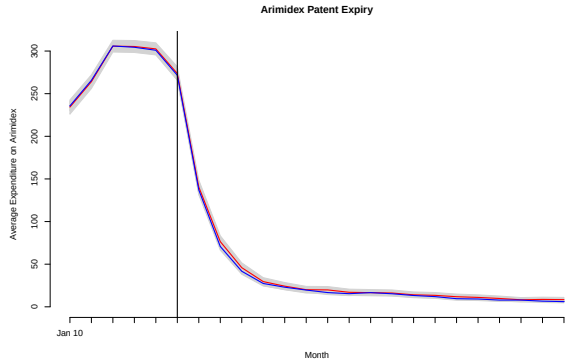
- Lipitor (atorvastatin), made by Pfizer, began to face generic competition in November 2011. Atorvastatin is a statin (HMG CoA Reductase Inhibitors) that treats high blood pressure. In 2011, it accounted for 3.2% of total Part D expenditure. Lipitor is the highest-revenue drug of all time; in 2011, it accounted for approximately 14% of Pfizer's revenues.

- Singulair (montelukast), made by Merck, began to face generic competition in August 2012. Montelukast is an antileukotriene used to treat asthma. In 2011, it accounted for 1.0% of total Part D expenditure.

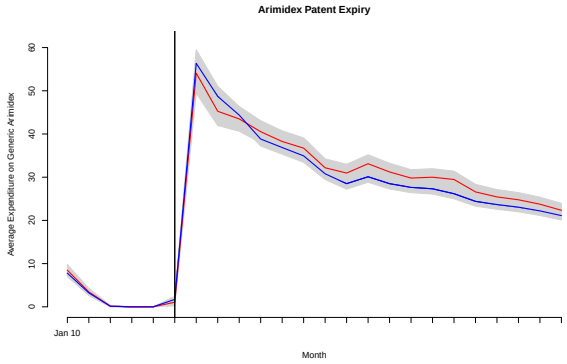
- Lexapro (escitalopram), made by Forest, began to face generic competition in March 2012. Escitalopram is an antidepressant. In 2011, it accounted for 0.9% of total Part D expenditure. Escitalopram is an enantiomer (mirror image) of citalopram (Celexa), which was approved in branded form (Celexa) in 1998 and in generic forms in 2003. Lexapro is unusual in its disproportionate importance to its manufacturer; Lexapro accounted for about half of Forest's revenues in the years prior to expiry.

C. Additional Figures and Tables

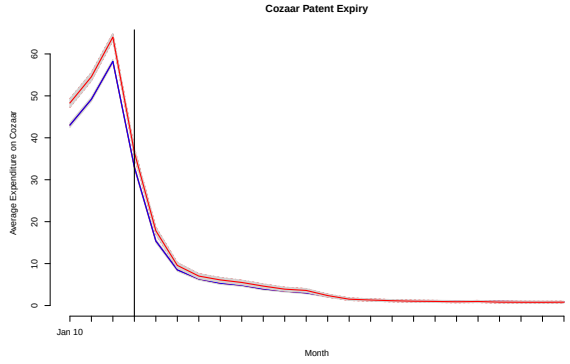
Figure C.1: Generic Entry by Payment from Expiring Brand Pharmaceutical Company (Red = Some Payment, Blue = No Payment)



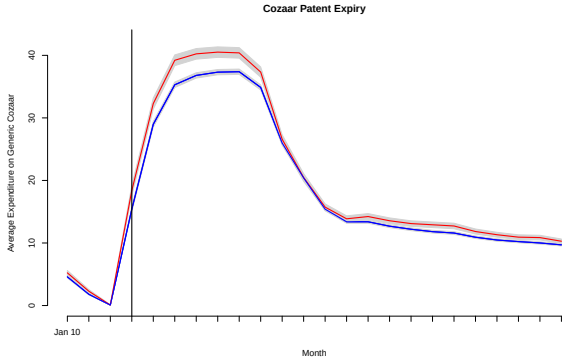
(a) Use of Arimidex



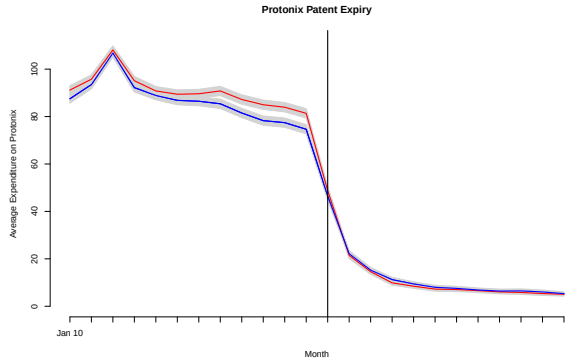
(b) Use of Generic Arimidex



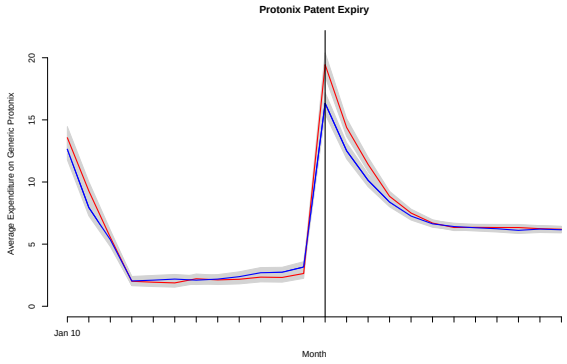
(c) Use of Cozaar



(d) Use of Generic Cozaar



(e) Use of Protonix



(f) Use of Generic Protonix

Notes: Arimidex lost patent protection June, 2010. Cozaar lost protection April, 2010. Protonix faced generic competition at start of 2010; U.S. federal court ordered generic makers to stop selling in April, 2010; Protonix lost remaining patent protection in January, 2011.