Pricing Power and New Prescription Drugs

Guneet Kaur Nagpal
Deepak Jena
Atul Nerkar
Rajdeep Grewal

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Guneet Kaur Nagpal is a doctoral candidate in marketing (guneet_kaur@kenan-flagler.unc.edu), Deepak Jena is a doctoral candidate in management (deepak_jena@kenan-flagler.unc.edu), Atul Nerkar is Professor of Strategy and Entrepreneurship and Allred Distinguished Scholar (atul_nerkar@unc.edu), and Rajdeep Grewal is the Townsend Family Distinguished Professor of Marketing (grewalr@unc.edu), all at Kenan-Flagler Business School, University of North Carolina, Chapel Hill NC, 27599.

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ABSTRACT

The pricing of prescription drugs comes under persistent public scrutiny, yet limited empirical evidence details the determinants of these price levels. This study provides a price function specification for newly launched drugs, with marginal cost and pricing power components. The sources of pharmaceutical firms' pricing power include patent protection, marketing spending, firm reputation, and number of players in the market. A novel data set details 328 prescription drugs introduced in the United States between 1984 and 2003 in 30 therapeutic categories. The results indicate that 15% of the price variation stems from the identified sources of pricing power; each source has a statistically significant influence. Priority drugs and orphan drugs invoke higher prices; drug prices increase with the number of patents. Firm reputation due to more recent drug introductions also results in higher prices, and early entrants tend to command higher prices than later ones. Finally, pharmaceutical firms often are criticized for their marketing spending, but the results indicate a negative relationship between marketing and drug prices, consistent with a penetration pricing strategy to reach more patients. This study thus contributes to contemporary prescription drug pricing debates, by revealing the extent to which pricing power influences launch price decisions.

1. Introduction

Despite the societal importance of drug innovations, pharmaceutical firms face immense, often negative public scrutiny, largely centered on the (high) price of new prescription drugs. For example, when Bristol Myers Squibb priced Opdivo in 2015, one of the first tumor immunotherapy prescription drugs, at $256,000 annually per oncology patient, the media attention was substantial (Loftsus and Winslow 2015). Such scrutiny of prescription drug prices is not new; the launch of Herceptin, a metastatic breast cancer treatment drug, by Genentech in 1998, stirred pricing debates about its annual costs of $70,000 (equivalent to $101,718 in 2015 dollars; Fleck 2006). Consecutively, the pricing power of pharmaceutical firms has evoked great anxiety among policymakers, media, and consumers (e.g. Davis 2016; Walker 2016). This anxiety highlights the need to understand the factors that explain the prices of new prescription. According to the industrial organization literature, it is the barriers to market entry that increase a firm's pricing power, such that the firm can charge higher prices without losing its customers (Porter 2004; Sutton 2007; Tirole 2015).

In the pharmaceutical industry the sources pricing power include patent protection, marketing efforts, and firm reputation. Patent protections, which reflect R&D investments, limit the options available in the market and potentially influence price elasticity, depending on the portfolio of patents attached to a new drug and their exclusivity period before expiration (Hemphill and Sampat 2011).[1] Policy makers suggest that larger portfolio of patents for a longer duration allows firms to charge premium prices (Lyman 2012), though this assertion has not been tested empirically at the launch stage of drug. Marketing spending, such as detailing efforts

[1] For example, Allegra launched at $34 (for 180 mg twice a day) in 1996, with three patents attached to it and an exclusivity period of 17 years; Zyrtec instead launched at $39 (for 10 mg once a day) and had just one patent attached to it, with an exclusivity period of 6 years.

and journal advertising targeted at physicians, and direct-to-consumer advertising (DTCA), creates brand loyalty (Sutton 2007), though critics suggest that pharmaceutical firms strategically focus their marketing spending on drugs that are likely to command higher prices (Robbins 2016).[2] Firms also might build their reputations by introducing innovations consistently, which potentially enables them to extract higher rents due to their superior drug portfolios and thus negotiation skills (Worstall 2015). Despite the widespread interest and controversy around patent protection, marketing spending, and firm reputation as the significant sources of pricing power among pharmaceutical firms, systematic empirical scrutiny of these pricing power sources has been lacking.

To investigate the influence of these variables on new drug pricing, we motivate an empirical model specification, based on the primitives of maximizing firm profits and consumer utility demand functions. The resulting price function, comprised of marginal cost and pricing power, relates new drug prices to patent protection, marketing spending, firm reputation, number of players in the market (market concentration),[3] and drug characteristics. To estimate the pricing model, we also compile a novel data set from IMS Health, the U.S. Food and Drug Association (FDA), and other sources. This data set comprises of 328 newly launched prescription drugs introduced in the U.S. market over a period of 20 years (1984–2003) in 30 therapeutic categories. After correcting for endogeneity concerns, we determine that 15% of pricing variation derives from the sources of pricing power that we identify. Consistent with extant literature, we find that the priority drugs, defined as those expected to have a particularly strong impact on the treatment

[2] For example, in 2013 Johnson & Johnson spent $17.5 billion on marketing, compared with $8.2 billion on R&D.
[3] The historic conceptualization of market concentration uses the Herfindahl-Hirschman index (HHI), which is the sum of the squared market shares of top firms in a market. However, market share information is seldom available, so scholars have used the number of players as a surrogate measure (e.g., Chen and Rizzo 2012; Singh and Zhu 2008). The HHI represents asymmetry in competition among firms; the number of players is a good candidate for representing market concentration when firms are homogenous in their size and capabilities (e.g., Beckert and Mazzarotto 2010; Evans, Froeb, and Werden 1993).

of a disease, such that the FDA prioritizes their approval, and orphan drugs, which are developed to treat a rare disease, are priced higher than standard drugs and non-orphan drugs. Among the patent protection variables, we find that an additional patent attached to a drug influences the launch price, but the length of the patent's exclusivity period does not. Increased spending on detailing and DTCA is associated with lower launch prices; the firm's reputation instead is associated with higher prices. As expected, the drugs entering a category earlier are priced higher than those entering later.

With this research, we seek to contribute to new product pricing literature in general and prescription drug pricing research in particular. We thus build on a broader product pricing literature that investigates product characteristics (e.g., Davis 2005) and the number of incumbent competitors (e.g., Singh and Zhu 2008) as sources of pricing power and examine more comprehensive conceptualizations of these factors. Furthermore, despite widespread considerations of the effects of pricing power for new drugs (e.g., Berndt 2002; Steele 1964), empirical studies focus almost exclusively on drug characteristics (e.g., Lu and Comanor 1998; Lucarelli and Nicholson 2009) and competitors in the market (e.g., Chen and Rizzo 2012; Shajarizadeh and Hollis 2015), such that they overlook other potential components that further influence the competitive market structure of a therapeutic category (e.g., Kannan and Sanchez 1994). Therefore, we address how patent protections, marketing spending, and firm reputation offer substantial power for explaining the launch prices of new prescription drugs. The findings in turn can inform both drug marketers and policymakers, who actively seek to understand the magnitude of the effects of various sources of pricing power on drug prices. To achieve these contributions, we start this text by reviewing relevant literature. We then develop our empirical model specification and present our data. Finally, we outline the results and their implications.

2. Literature Review

Our research relies on three domains of pricing research: new product pricing, pricing power, and drug pricing literature streams.

2.1. New Product Pricing

Two main perspectives appear in studies of new product pricing. First, rooted in Dean's (1969) early discussion of pricing strategies for new products, some studies distinguish skimming from penetration pricing. For example, Schmalensee (1982) reveals that uncertainty about new products leads firms to charge low introductory prices, to penetrate the market. Shapiro (1983) instead notes that optimism about product quality prompts firms to charge higher prices at the launch, then reduce the new product's price over time, which is popularly known as the price skimming strategy. According to Nair (2007), new video game pricing decisions depend on consumers' likely willingness to pay and their expectations about future price declines. Furthermore, Liu (2010) finds that lower launch prices increase the rate of product diffusion for game consoles but that consumer heterogeneity and network effects have opposing influences. Second, other studies highlight how new product prices might signal their quality. For example, Bagwell and Riordan (1991) find that firms have an incentive to increase the quality of their new products, to help consumers justify the prices they pay. Daughety and Reinganum (2008) show that when consumers have incomplete information, it is more profitable for vertically differentiated firms to price their products higher than it would be in a complete information setting.

We build on these strands of new product pricing literature by conceptually specifying a pricing model for a new product at the launch stage, with two influential components: marginal

costs and pricing power. We specifically seek to obtain an empirical estimate of the influence of various sources of pricing power on the launch prices of new prescription drugs.

2.2. Pricing Power

Studies that rely on the structure–conduct–performance paradigm test the relationship between market structure (sources of pricing power) and prices, such as Cotterill's (1986) consideration of grocery items; Keeler, Melnick, and Zwanziger's (1999) study of hospital services; Emmons and Prager's (1997) analysis of the cable television industry; and Davis's (2005) study of the motion picture industry. Two key generalizations emerge from this literature stream. First, most empirical studies assume that market concentration defines the market structure and is the sole of source of pricing power (e.g., Davis 2005; Emmons and Prager 1997). However, industrial organization literature offers some evidence that price markups over marginal costs (which are signals of pricing power) do not correlate with market concentration, such that other structural variables that might erect entry barriers for new firms should be included to operationalize pricing power (Martins, Scarpetta, and Pilat 1996). Second, market structure seemingly appears randomly assigned to firms, yet Singh and Zhu (2008) argue that pricing power results from strategic decisions, based on demand, competitors, and cost conditions. Therefore, the sources of pricing power may be endogenous (e.g.,Manuszak and Moul 2008).

We acknowledge this insight (Singh and Zhu 2008) and leverage research into sources of pricing power (e.g., Borenstein 1989; White 2013) to propose a comprehensive conceptualization of pricing power, in which the number of other players represents the quantity of competition in the market with similar firms, but the market structure also depends on the barriers to entry represented by three structural variables relevant to the pharmaceutical industry—namely, patent

protection, marketing spending, and firm reputation. Similar to Singh and Zhu (2008), we acknowledge and address the endogeneity concerns for these sources of pricing power.

2.3. Pharmaceutical Drug Pricing

A rich tradition of empirical literature uses hedonic price regression models to predict drug pricing (see Table 1). For example, Suslow (1996; antispasmodic drugs) and Lucarelli and Nicholson (2009; colorectal cancer drugs) find that manufacturers set higher prices for higher quality drugs. In contrast, for antidepressants (Chen and Rizzo 2012) and arthritis drugs (Cockburn and Anis 2001), the results are the opposite, such that higher quality drugs enter these markets with lower prices. These differences seemingly stem from the distinct therapeutic categories; in their investigation across therapeutic categories, Lu and Comanor (1998) show that price depends on the treatment alternatives available in the market, such that drugs that contribute important therapeutic gains are priced around 3.2 times higher than substitute products. An underlying assumption across all these studies is that drug characteristics represent the main influences on pharmaceutical drug prices. Yet a general consensus among industry experts also suggests that pricing power in the prescription drug category goes beyond product characteristics (Berndt 2002), a view that has not received sufficient empirical scrutiny.

[Insert Table 1]

With regard to the four pricing power variables we study—patent protection, marketing spending, firm reputation, and number of players—prior literature has indicated how the pricing of a previously launched drug depends on the expiration date for its patent (Lichtenberg and Philipson 2002). But whereas Caves, Whinston, and Hurwitz (1991) assert that firms lose pricing power after the expiration of their patents, Frank and Salkever (1991) suggest that firms could increase drug prices after this expiration, as part of their brand differentiation strategy. As these

examples indicate, there is no clear consensus about how patents and other sources of market power affect the launch pricing of new prescription drugs. Although Chen and Rizzo (2012) consider the impact of patent exclusivity length on drug pricing, their study focuses solely on the antidepressant category and investigates the effects as drugs are nearing their patent expiration date. To extend these insights, we investigate two aspects of patent protection, that is, both the number of patents, which indicates the breadth of the patent portfolio for the new drugs, and patent exclusivity, which indicates the period during which competing generic drugs cannot enter the market without breaching the patent. Marketing spending and firm reputation, though often cited as causes of anxiety among policymakers, have not been studied empirically in terms of their influences on the launch prices of prescription drugs. Finally, a few studies examine the influence of the number of players in non-U.S. drug markets in which governments impose price-cap regulations (Ekelund and Persson 2003 in Sweden; Shajarizadeh and Hollis 2014 in Canada) and find non-significant impacts. However, as noted previously, Chen and Rizzo (2012) identify such an effect for antidepressants in the U.S. market. To advance this stream of literature, we consider the influence of the number of market players across 30 prescription drug categories launched in the United States. By studying the influence of all these sources of pricing power for new prescription drugs, we develop a more comprehensive perspective.

3. Price Function for New Products

To develop a price function specification for newly launched prescription drugs, we start with the assumption that observed launch prices are the result of a Nash equilibrium in which each firm seeks to maximize its profits $\{ p_j q_j - c_j(j, q_j, Z_j)\}$, given the strategies of its competitors. For a specific therapeutic category, the demand for drug $j \epsilon J$, priced at p_j, is given

as q_j. The cost-based determinants, represented by $Z_j$that influence the total cost $c_j(.)$. The profit maximizing first order condition for drug j has the following expression:

$$(1) \qquad p_j = \frac{\partial c_j}{\partial q} + \frac{q_j}{-\left(\frac{\partial q_j}{\partial p_j}\right)}.$$

The right-hand side of Equation (1) thus features two economically meaningful terms: the marginal cost $\frac{\partial c_j}{\partial q}$ that arises when the quantity produced increases by one unit and the markup term $\frac{q_j}{-\left(\frac{\partial q_j}{\partial p_j}\right)}$ that varies inversely with the elasticity of demand and allows firms to increase their prices above the marginal cost. We make functional form assumptions for these marginal cost and demand functions to derive our price function specification.

Following Berry, Levinsohn, and Pakes (1995), we assume a log-linear specification for marginal costs, such that costs depend on observed (by consumers and researchers) product characteristics (i.e., x_j, which indicates whether the drug is a line extension of an existing drug formulation or a new formulation), observed (by consumers and researchers) sources of pricing power (y_j, such as marketing spending), and unobserved (observed by consumer but unobserved by researchers) product characteristics and sources of pricing power (ω_j, to represent pre-launch buzz about the drug that can bestow pricing power to the innovating firm). Formally,

$$(2) \qquad \ln\left(\frac{\partial c_j}{\partial q}\right) = x_j\beta + y_j\Gamma + \omega_j,$$

where β and Γ are the parameter vectors that we seek to estimate, and $Z_j = (x_j, y_j, \omega_j)$.

The $\frac{q_j}{-\left(\frac{\partial q_j}{\partial p_j}\right)}$ term is popularly known as Lerner's index in industrial organization literature (e.g., Bresnahan 1989; Schamalensee 1989), which can be interpreted as the pricing power as it

reflects the markup of product prices over marginal costs. To derive this term, we assume a quasi-linear[4] demand equation (see also Bajari and Benkard 2005):

$$(3) \qquad \ln(q_j) = \beta ln(x_j) + \delta ln(p_j),$$

where the product characteristics x_j and the price variable p_j influence demand. By differentiating Equation (3) with regard to p_j, we obtain:

$$(4) \qquad \frac{q_j}{\left(\frac{\partial q_j}{\partial p_j}\right)} = \frac{p_j}{\delta}.$$

Next, from Equations (1)–(4), we can express the marginal cost in Equation (2) as:

$$(5) \qquad \ln(\frac{\partial c_j}{\partial q}) = \ln(p_j - \frac{q_j}{-\left(\frac{\partial q_j}{\partial p_j}\right)}).$$

Substituting terms from Equation (4) into Equation (5) produces:

$$(6) \qquad \ln\left(\frac{\partial c_j}{\partial q}\right) = \ln\left(p_j + \frac{p_j}{\delta}\right) = \ln(p_j(1 + \frac{1}{\delta})).$$

Because $\ln(p_j(1 + \frac{1}{\delta}))$ can be expressed as $\ln(p_j) + \ln(1 + \frac{1}{\delta})$, using Equations (2) and (6), the pricing equation can be expressed as:

$$(7) \qquad \ln(p_j) = \alpha + x_j\beta + y_j\Gamma + \omega_j,$$

where $\alpha = -ln(1 + \frac{1}{\partial})$ is an intercept term.

Industrial organization literature also links pricing power to multiple structural variables (Martins, Scarpetta, and Pilat 1996), though most studies operationalize pricing power with a measure of market concentration, such as the number of players (N_j) (e.g., Balakrishnan and Ouliaris 2006; Davis 2005; Singh and Zhu 2008), and predict that pricing power increases as N_j decreases. We augment this operationalization with other sources of pricing power that have

[4] The resulting logarithmic price function equation, $ln(p_j) = \alpha + x_j\beta + y_j\Gamma + \omega_j$, also could be derived by assuming a linear demand equation, $q_j = x_j\beta + \partial p_j$.

been documented in prior literature as barriers to entry (White 2013). Consequently, we express our price function model with the following form:

$$(8) \qquad ln(p_j) = \alpha + x_j\beta + N_j\lambda + L_j\kappa + \omega_j \,,$$

where L_j refers to sources of pricing power other than the number of players in the market; y_j = (N_j, L_j); and $\beta, \lambda,$ and κ are the parameters of interest that we seek to estimate.

4. Data and Model Specification

4.1. Data

To estimate the price function for new prescription drugs, we use data on 328 newly launched prescription drugs in the U.S. market between 1984 and 2003. We collected these data from two primary sources: IMS Health's New Product Spectra and the FDA Orange Book.[5] The IMS's Spectra database reports monthly data on new prescription drugs for one year from their launch. For each new drug, classified into 30 therapeutic categories and 157 subcategories, it provides information about the manufacturer, product launch date, characteristics (e.g., acute/chronic, number of indications), monthly sales, marketing spending, and the prices. From the FDA Orange Book, we obtain data about the patents for the drugs in IMS Spectra.[6] In Table 2, we present category-level summary statistics for the drugs in our study sample.

[Insert Table 2 here]

[5] As we detail subsequently, we also collected data on instrumental variables to alleviate endogeneity concerns from three other sources: (1) the number of employees in pharmaceutical firms from the Osiris database, (2) producer price index for the advertising industry from the Bureau of Labor Statistics, and (3) number of pages in medical journals (*Journal of American Medical Association* and *New England Journal of Medicine*) dedicated to drug advertisements, as provided by Gettings et al. (2014).

[6] Patents are granted by the U.S. Patent and Trademark Office (USPTO) during the development of a drug; drug manufacturers are required by law to furnish details about patents associated with their drugs to be listed in the Orange Book. The Orange Book contains the patent number and expiration date of each patent associated with drug claims or method (www.fda.gov).

4.1.1. Product Attributes

We gather information about six new drug characteristics. First, we use a dummy variable that indicates whether a drug treats a chronic or acute condition (CHR). Acute conditions are severe and sudden in onset; chronic conditions indicate long-developing syndromes. Because chronic conditions require regular refills, these patients likely are more sensitive to price changes. For example, our data include information about Ultram, an analgesic that treats chronic pain, such as a bad back, and about Zomig, another analgesic that treats acute conditions, such as migraine headaches.

Second, we count the number of indications, which reflects how many conditions the FDA has approved the drug for treating (IND). For example, Pepcid obtained FDA approval for three gastrointestinal indications: short-term treatment of active duodenal ulcer, maintenance therapy for duodenal ulcer, and treatment of pathological hyper-secretory conditions. In contrast, the competing drug Propulsid was approved for just one indication, nocturnal heartburn in patients with gastroesophageal reflux disease.

Third, we use a dummy variable that indicates whether the main drug compound is an established molecule or not (EST). For example, in the respiratory therapy category, the main compound of Nasarel is not an established molecule, but the main compound for Flovent (i.e., fluticasone) was launched two years earlier, as the drug Flonase.

Fourth, we use a dummy variable to code whether the drug is a line extension, such that it offers a new form, strength, or delivery mode for an established molecule (EXT). For example, ProzacWeekly, an immunological agent, was launched with a new dosage form in 2001 (weekly version of the original Prozac). Similarly, in 2001 Remeron SolTab, a psychotherapeutic drug,

appeared on the market as an orally disintegrating tablet version of the original Remeron (mirtazapine) tablet.

Fifth, we use a dummy variable pertaining to whether a drug is an orphan drug (ORP); orphan drugs treat rare diseases and thus usually go through a fast-tracked regulatory review process and target niche markets. For example, Letairis treats pulmonary arterial hypertension, and Panretin is another orphan drug that treats AIDS-related Kaposi's sarcoma.

Sixth, another dummy variable indicates whether the drug underwent a standard or priority review (PS). The FDA suggests drugs for priority review when they offer potentially substantial therapeutic advancements over available therapies. Similar to Sorescu, Chandy, and Prabhu (2003), we use this variable to indicate efficacy. For example, Arava received priority review due to its pivotal efficacy in treating adult rheumatoid arthritis.

4.1.2. Pricing Operationalization

Consistent with most extant literature, we use the wholesale price at pharmacies to represent the price of prescription drugs (e.g., Cockburn and Anis 2001; Suslow 1996). A few studies use the retail prices charged to consumers (without insurance coverage) (Chen and Rizzo 2012; Narayanan, Desiraju, and Chintagunta 2004), but because our interest is in the pharmaceutical firm's strategic pricing decision, not consumer demand or price sensitivity, we believe the wholesale price is the more plausible measure. Considering the multiplicity of players involved in the pricing decision, we use the term "consumer"[7] as a composite entity, comprising patients, physicians, insurers, and pharmacy benefit managers.

[7] In the pharmaceutical industry, there are a multiple of actors involved while paying for the drug. In particular, consumers of prescription drugs rarely make consumption decisions on their own. Rather, physicians determine which drug to prescribe, and insurers and pharmacy benefit managers administer drug benefits and determine the out-of-pocket costs of various alternatives. The objective functions of these varied actors do not always align.

By using the price per prescription as the unit level, we mirror the Consumer Price Index and some pharmaceutical studies (e.g., Berndt and Aitken 2011; Lichtenberg and Philipson 2002; Narayanan, Desiraju and Chintagunta 2004). Despite arguments by health economists (Crown, Ling, and Berndt 2002) against using price per prescription, in favor of price per day, we lack access to price per day data and thus cannot compare the results obtained by using these two types of price data.[8] So that we can compare the prices of drug brands within and across therapeutic categories, the price per prescription offers a better unit, in that it can account for different brands in a same therapeutic category being prescribed for acute or chronic conditions with different dosages in terms of forms, strengths, and frequency. Thus, this research approach facilitates the comparison of prices across brands. As an illustration, consider two arthritis drug brands, Kineret and Humira. The former must be consumed daily, but the latter is taken once a week or every two weeks. The prices per day for these drugs would not be a viable price unit for comparing their prices. Furthermore, drugs that address chronic versus acute conditions require significantly different consumption times (i.e., number of days), so a price per day measure would be misleading. On the basis of these rationales, we use price per prescription in our model.

4.1.3. Pricing Power Variables

We use two measures to operationalize patent protection with data from the FDA Orange Book. First, we obtain the patent exclusivity term (EXC), which quantifies the duration of protection the drug claims to possess (Hemphill and Sampat 2011). This duration equals the difference between the day the product was approved by the FDA and the day the last patent on the drug expires (a drug may be protected by multiple patents, each with its own expiration date).

[8] Crown, Ling and Berndt (2002) have argued that price per day of treatment is a better measure than price per prescription because in the latter case, an increase in price per prescription could mean an increase in the number of days of treatment per prescription rather than an actual price increase. We are studying the price at the launch, not the change in price over time, so this point is not a critical issue for our study.

The shorter this duration, the more pressing the pharmaceutical firm's need to launch and distribute the product as quickly and widely as possible. For drugs covered by one or more patents at the time of approval, we identified the last expiring patent from their portfolios; for drugs that were not covered by any patent at the time of approval but were protected by other regulatory exclusivity functions (e.g., new drug formulation, pediatric exclusivity, orphan drug exclusivity; Voet 2014), we identified the latest exclusivity date.

Second, we assess the richness of the patent portfolio according to the number of unexpired patents connected with the focal drug ($NPAT$). A focal drug product enjoys a higher degree of protection with more unexpired patents. Beyond the patents covering the active compound, new drugs may enjoy patent coverage on their chemical variants, formulations, medical use, and other relatively minor aspects (Hemphill and Sampat 2011; Voet 2014). We use the drug's patent portfolio, according to the number of unique patents covering the drug product at the time of FDA approval, to measure the degree of protection. We also classify patents in the drug portfolio into four categories: compound, formulation, use, or others. For example, at the time of its launch, Allegra had around 17 years of remaining patent exclusivity and three patents attached to it, two of which pertained to the compound (piperidine derivatives) and one related to its treatment (allergic rhinitis). Similarly, Alimta had two patents and an exclusivity period of 8 years, such that its compound patent relates to N (Acyl)glutamic acid derivatives, and its use patent refers to a method to "inhibit the growth of GAR-transformylase-dependent tumors."

Marketing spending also can increase pricing power by erecting barriers to competitive entry and providing favorable information about the new drug to consumers (e.g., Brekke and Kuhn 2006; Ching et al. 2016). Consistent with extant literature (e.g., Fischer and Albers 2010; Narayanan, Desiraju, and Chintagunta 2004), we focus on the physician- and patient-focused

marketing efforts of pharmaceutical firms in our price function specification, as measured by detailing (DET), journal advertising (JRN), and direct-to-consumer advertising ($DTCA$). To determine marketing spending at the launch stage, we use total expenditures on each form of marketing spending in the first 12 months after the drug launch. Detailing includes the combined costs of sales activities by pharmaceutical representatives for office-based and hospital-based promotions to physicians. On average, one sales call involves two to four product contacts. For the dollar estimates, we use a 2001 average cost per call of $128 for office-based physicians and $117 for hospital-based physicians (New Product Spectra Manual). The journal advertising measure is an estimate of the cost of product advertising in medical journals, tabulated by linking observable advertising characteristics (e.g., position, color, circulation) to rates and charges published in Standard Rates and Data. Finally, DTCA spending reflects combined expenditures on television, newspaper, magazine, and outdoor media. Because DTCA was permitted in the United States only after 1996, for drugs released before this date, we assume the DTCA costs are null. As an example from our database, Allegra received $1.2 million of detailing support and $.85 million for DTCA.

To measure pharmaceutical firm reputation, we rely on the number of new drugs each firm introduced in the three years before the launch of a specific drug (REP). For example, between 2000 and 2002, Allergan launched three pharmaceutical drugs in the market, while AstraZeneca launched seven in the same time period. Firm reputation suggests the technical expertise and R&D strength of the firm, in terms of its ability to produce effective medicines and generate competitive advantages for its drugs, which should enhance its pricing power.

For the fourth source of pricing power, consistent with extant literature (e.g., Singh and Zhu 2008), we use the number of players as a surrogate for market concentration. Each of the 30

therapeutic categories in our database can be divided into subcategories, based on the drug mechanism,[9] and we calculate the number of players at this subcategory level. For example, Lamisil and Diflucan are the second and third drugs to enter the subcategory of anti-fungal agents; following their respective entries, the number of players in this category was two and three. We anticipate that fewer players implies greater pricing power (e.g., Dafny 2010; Kalyanaram, Robinson, and Urban 1995).

4.2. Model Specification for New Prescription Drugs

We leverage the price function from Equation (8) and apply it to the data describing the product attributes x_j, number of competitors N_j, and pricing power variables L_j, such that for brand j in therapeutic category m:

$$(9) \quad ln(p_{jm}) = \beta_0 + \beta_1 CHR_{jm} + \beta_2 IND_{jm} + \beta_3 EST_{jm} + \beta_4 EXT_{jm} + \beta_5 ORP_{jm} + \beta_6 PS_{jm} + \gamma N_{jm} + \kappa_1 NPAT_{jm} + \kappa_2 EXC_{jm} + \kappa_3 DET_{jm} + \kappa_4 JRN_{jm} + \kappa_5 DTC_{jm} + \kappa_6 REP_{jm} + \tau_m + \omega_{jm},$$

where τ_m is a category-specific indicator variable, and ω_{jm} is the unobserved error term.

5. Identification Challenges and Strategy

Our primary research objective is to estimate the causal link between the launch prices of prescription drugs and sources of pricing power. One naïve way to identify this causal link would rely on an exogeneity assumption, namely, that the error term is uncorrelated with the product characteristics and/or pricing power variables. This assumption holds, provided there is no omitted variable that influences price and simultaneously is correlated with any pricing power variable (e.g., Angrist and Pischke 2010). However, it is difficult to defend this exogeneity assumption effectively. For example, an omitted variables bias could arise because marketing

[9] This mechanism refers to the manner in which the drug's therapeutic agent or key molecule acts. It evokes a physiological or biochemical process within the body, thus producing a given response.

spending (e.g., detailing) is a (non-random) strategic decision at the time of the launch (e.g., Manchanda, Rossi, and Chintagunta 2004). We do not observe the rules for the marketing spending decisions at the time of the launch, so such an omitted variable bias is salient. These decision rules could include private information about drug quality or excess production capacity, which the pharmaceutical firm likely takes into consideration when choosing its marketing spending and prices. To account for this potential bias in our estimation, we consider how biases might could arise from product characteristics and price power variables, then develop a strategy to address the issue.

5.1. Identification Challenges

Identification challenges emerge for five variable categories: (1) product characteristics, (2) patent protection, (3) marketing spending, (4) firm reputation, and (5) number of players. For our new prescription drug study context, we document evidence of exogeneity for the variables other than marketing spending; we address the potential endogeneity of marketing spending explicitly in Section 5.2.

5.1.1. Product Characteristics

Differentiation based on product characteristics should enable a firm to price discriminate (Cabral 2017). The variables we use to assess the product characteristics are whether the drug addresses a chronic condition, number of indications cured by drugs, whether the drug's key molecule is established, whether the drug is a line extension, whether the drug is an orphan drug, and whether the drug received priority or standard review. This set of product characteristics is exhaustive (e.g., Chen and Rizzo 2012; Shajarizadeh and Hollis 2014); we believe that no critical product characteristic is omitted (Berry, Levinsohn, and Pakes 2004). Furthermore, these product characteristics are predetermined, sometimes even decades before the pricing decision.

5.1.2. Patent Protection

The exclusivity of new drug patents is not an independent decision of the pharmaceutical firm but a joint decision of the FDA and U.S. Patent and Trademark Office (USPTO). These terms vary substantially, from 1 to 20 years, and firms cannot simply speed up the patent approval process to obtain longer patents for their new drugs. Thus, patent exclusivity is exogenous.

Regarding the number of patents attached to a newly launched drug, the final decision comes from the FDA and USPTO, though the application for patents represents a strategic choice by the firm. More patents garner better protection, so firms apply for as many patents for a drug as they can, spanning the conditions it treats, the new molecules it includes, or its novel formulation. However, our main model already controls for these product attributes (i.e., number of indications, whether the molecule is a line extension, whether the molecule is established), which also may influence the number of patents for which the firm files. Finally, we include pharmaceutical firm fixed effects, to capture the innate tendency of each firm to apply for more patents. Thus, our data should reasonably identify the effect of the number of patents on launch prices.

5.1.3. Marketing Spending

Marketing mix decisions about detailing, journal advertising, and DTCA likely are endogenous, because these decisions, together with the pricing decisions, depend on expected sales (e.g., Iizuka and Jin 2005; Manchanda, Rossi, and Chintagunta 2004), which produces a simultaneity problem for the pricing estimation. For example, a firm seeking to penetrate the market might adopt a low price and spend more promoting the drug, relative to its competitors. We discuss our identification strategy to correct for this endogeneity in Section 5.2.

5.1.4. Firm Reputation

We operationalize firm reputation with a count of the number of innovations launched by the firm in three years before the launch of the focal drug. Here although launching more drugs and a building better reputation of firm although have temporal precedence over the outcome variable, i.e. price setting (Mittal 2016), however reputation building is unlikely to stem from a deliberate and focused decision by the firm to launch premium priced drugs in future. Therefore, firm reputation is exogenous and a preexisting variable.

5.1.5. Number of Players

The number of players in the market usually serves as a proxy for market structure in the structure–conduct–performance paradigm (Davis 2005). As Singh and Zhu (2008) argue, an observed market structure is an outcome of the firm's strategic entry decisions, based on demand, cost, and competition considerations. However, for prescription drugs, unlike other product categories, the order of entry in a therapeutic category cannot be precisely determined by the firm, because of the significant influence of regulators (i.e., FDA) and competing firms. In its attempt to enter the market early, the firm might speed up its clinical trials to expedite the FDA's approval process. However, vast variation in the amount of time a drug spends in each preapproval phase (i.e., 1–6 years in preclinical; 6–11 years in clinical trials; DiMasi, Hansen, and Grabowski 2003) and low success rates for new drugs (.01%; Phrma.org 2015; Thomke and Kuemmerle 2002) mean that firms have little control over market entry decisions. Thus, for new prescription drugs, market structure (number of competitors) is exogenous.

5.2. Identification Strategy

As we noted, the marketing spending variables likely suffer from endogeneity, so we pursue a viable identification strategy for them. Endogeneity concerns arise from both time-

invariant and time-varying omitted variables.[10] The former, such as the firm's inherent propensity to market new drugs in a particular manner, can be accounted for by firm-specific fixed effects, which we include in our model specification. These effects eliminate across-firm variance, such that our empirical identification focuses on price variation within firms, after accounting for therapeutic category fixed effects.

Time-varying omitted variables might occur at the economy or firm level. Economy-level time-varying variables influence all firms in a similar manner, such as the health of the economy or changes in health care policies and regulations. For example, a consumer welfare debate about pharmaceutical firms may reduce the marketing spending and pricing of new drugs in all therapeutic categories. To account for such changes, we include time-fixed effects in our model specification, such that we use within-year variation in the model to identify the effects. At the firm level, to address brand-specific, time-varying omitted variables, we use an instrumental variable strategy, which must satisfy relevance and exclusion restriction conditions. Because the choice and justification of this instrument varies with the marketing spending variable, we discuss them in turn.

First, for detailing to physicians, we use the number of employees of the pharmaceutical firm in a specific year as an instrument. The instrument meets the relevance condition; more employees can perform more detailing, suggesting more detailing efforts. The instrument meets the exclusion standard, because the number of employees is not likely to influence price directly. However, because our database provided information about the number of employees for only a subset of firms, we also adopted a second instrumental variable, to check for robustness. That is,

[10] We observe multiple new product introductions by firms over the 20-year study period. Because our analysis is at the new product level, it is essentially cross-sectional. However, the 20-year period prevents us from controlling for time-varying variables at the economy and firm levels.

we consider detailing spending by the same firm for the brand in an unrelated category in a successive year. This instrument is relevant; firm spending across different drug categories likely is correlated. The instrument meets the exclusion restriction too, because spending in a different category in the future is not likely to affect the launch price of the focal brand.

Second, for journal advertising, we rely on the mean number of pages dedicated to advertising pharmaceutical drugs in medical journals, interacted with firm-specific dummy variables. The mean number of pages likely correlates with advertising rates in these journals and thus with journal advertising spending by pharmaceutical firms, making it relevant. Because the number of pages in journals dedicated to pharmaceutical advertisements is unlikely to influence launch prices directly, the exclusion restriction also holds. We use this interaction of the mean number of journal advertising pages with firm-specific dummy variables to account for variation in advertising costs across firms.

Third, with regard to DTCA, we follow Narayanan, Desiraju, and Chintagunta (2004) and use the producer price index (PPI) for the advertising industry (SIC 7311) over the years of our study. The PPI reflects the prices to run advertisements in television, radio, and other public media, which likely correlate with DTCA spending in the pharmaceutical industry, making it relevant. The PPI cannot directly influence the launch prices of new drugs though, so the exclusion restriction also is satisfied. We also consider the interaction of the PPI with firm-specific dummy variables to account for variation in advertising costs across firms. We obtain 141 different instrumental variables through this interaction, for 141 different firms.

6. Results

6.1. Model-Free Evidence

With the model-free analysis, we seek initial support for the proposed determinants of pricing power in the launch of new prescription drugs. First, we examine correlations between the sources of pricing power and launch prices; these correlations should give a sense of the direction and size of the effects on launch prices. To make these correlations meaningful, we mean-centered all the pricing power variables and launch prices with respect to the 30 therapeutic categories to which each brand belongs (i.e., the correlations rely on within-category variance). As Figures 1 and 2 reveal, the pricing power variables all exhibit feeble positive correlations with launch prices, with counterintuitive directions and sizes in some cases. For example, more firms in the market (lower market concentration) indicates higher launch prices (Figure 1, Panel a), counterintuitive with our prediction that higher market concentration would lead to greater pricing power. However, patent strength (Figure 1, Panel b), the patent exclusivity period (Figure 1, Panel c), firm innovativeness (Figure 1, Panel d), and marketing spending (Figure 2) all positively correlate with the launch price, as we expected.

Second, to identify the effects within categories (i.e., category-fixed effects in the model specifications), we need to ensure sufficient variation in the distributions of prices and sources of pricing power across therapeutic categories. As is evident in Figures 3 and 4, the variation in pricing power sources and launch prices within therapeutic categories is substantial.

[Insert Figures 1–4 here]

6.2. Model-Based Results

In Table 3, we present a model-based estimate of the price function from Equation (9), including ordinary least square (OLS) estimates (column 3a) and two other estimates that we

exploit to address the potential omitted variable bias: ordinary least square with fixed effects (OLSFE) and two-stage least square (2SLS). For the OLSFE estimates, in addition to the category fixed effects included in the OLS model, we include manufacturer fixed effects that can account for omitted variations by manufacturer but not by time, as well as time fixed effects that account for variations over years but not over manufacturers or categories (column 3b). For the 2SLS estimate, we address the endogeneity of marketing spending using instrumental variables (Table 3, column 3c). For some variables, the three estimates share the same effect direction but shifting effect magnitudes. Specifically, greater market concentration, measured as the number of players, lowers launch prices (b_{OLS} = -.015, $p < .05$; b_{OLSFE} = -.013, $p < .05$; b_{2SLS} = -.032, $p < .01$), implying that earlier entry into a category enables firms to charge higher launch prices. Similarly, as number of patents associated with a new drug increase, pricing power increases as well (b_{OLS} = .088, $p < .01$; b_{OLSFE} = .056, $p < .10$; b_{2SLS} = .082, $p < .01$), and better firm reputation lead to increases in launch prices increases (b_{OLS} = .020, $p < .05$; b_{OLSFE} = .029, $p < .05$; b_{2SLS} = .106, $p < .05$). Among drug characteristics, priority review (vs. standard review) by the FDA is associated with a higher launch price (b_{OLS} = .297, $p < .01$; b_{OLSFE} = .494, $p < .01$; b_{2SLS} = 1.148, $p < .01$), and orphan drugs are priced higher (b_{OLS} = .020, $p < .05$; b_{OLSFE} = .029, $p < .05$; b_{2SLS} = .106, $p < .05$).

For marketing spending, our findings indicate that detailing (b_{OLS} = .020, $p < .05$; b_{OLSFE} = - .047, $p > .05$; b_{2SLS} = -.467, $p < .05$) and DTCA (b_{OLS} = .262, $p < .05$; b_{OLSFE} = - .030, $p < .05$; b_{2SLS} = -.067, $p < .05$) actually entail more spending for lower priced drugs—contrary to the widespread concern that marketing efforts always focus on pricey drugs (as in the OLS estimates). Journal advertising does not seem to influence launch pricing (b_{OLS} = -.011, $p > .05$; b_{OLSFE} = .006, $p > .05$; b_{2SLS} = -.027, $p > .05$), though it captures the largest share of marketing

spending by pharmaceutical firms and appears in all 30 therapeutic categories, unlike detailing or DTCA (see Figure 4).

[Insert Table 3 here]

7. Discussion

Pharmaceutical firms endure consistent media scrutiny over the prices for their prescription drugs, and consumers, policymakers, and politicians often express angst about their pricing power. Proponents of the pricing power of pharmaceutical firms instead argue that these firms would lack incentives to undertake risky R&D investments if they were not granted at least some degree of pricing power. To study the sources of this pricing power, we base our analysis on industrial economics literature (Cabral 2017; White 2012) and examine four potential sources: patent protection, marketing spending, firm reputation, and the number of players. With data from IMS Health and the FDA about 328 drugs in 30 different therapeutic categories, we estimate a new product pricing model. The results suggest that all four sources of pricing power significantly influence the launch prices of new prescription drugs.

7.1. Theoretical Contributions

Our research contributes to literature on new product pricing and prescription drugs. With regard to new product pricing, we provide insights pertaining to both new product characteristics and a comprehensive portfolio of sources of pricing power. Our research thus extends extant empirical research on pricing models that adopts the structure–conduct–performance paradigm, in which price is a function of market concentration, operationalized as the number of players, that is assumed to be the sole indicator of market structure and source of pricing power (e.g., Davis 2005; Emmons and Prager 1997). We build on this work to argue that the market structure encompasses more than the number of players (Dixit 1979), so we examine more comprehensive

sources of pricing power. Similar to Singh and Zhu (2008), we recognize the potential endogeneity of these sources of pricing power, including the number of players in a therapeutic category. However, the entry of a new drug is not entirely determined by the firm but instead depends on the length of the patent approval process, which is in the hands of FDA, so the number of players should be an exogenous variable in our study context (cf. Singh and Zhu 2008). We find statistically significant, economically meaningful effects of this comprehensive list of sources: The price of new drugs increases with patent protections and firm reputation but decreases with marketing spending and the number of players in the market.

Substantial pharmaceutical pricing research relies on hedonic price regressions, with the assumption that drug characteristics can explain price differences across drugs (e.g., Cockburn and Anis 2001; Lu and Comanor 1998). Some studies examine the influence of one or two pricing sources, mostly years after the launches, such as when Chen and Rizzo (2012) show that shorter patent exclusivity terms lead firms to increase prices, to deter the entry of generic equivalents as their patent term nears its end, or Shajarizadeh and Hollis (2014) find that in later years, the entry of new players leads firms to increase their prices. Marketing spending also constitutes a substantial part of pharmaceutical firms' budgets and cannot be ignored in terms of its significant pricing power. In 2012 alone, U.S. pharmaceutical firms spent more than $3 billion to advertise directly to consumers and around $24 billion to market to physicians (Swanson 2015). Similarly, the reputation of pharmaceutical firms, which grows as they introduce more drugs, increases their pricing power. By including variables such as marketing spending and firm reputation as sources of pricing power for new prescription drugs and empirically estimating the influence of four separate sources, we thus advance prior research on drug prices.

7.2. Implications for Policymakers and Pharmaceutical Marketers

For policymakers and pharmaceutical marketers, our research findings inform debates about barriers to entry in the industry that can act as sources of pricing power. Our empirical examination of four sources of pricing power reflects key factors that also cause anxiety among policymakers, media, and consumers. Pricing power is significantly influenced by the number of patents attached to drug, but the patent exclusivity period has a non-significant effect at the launch stage. Although we find that deeper patent protection can result in higher prices for new prescription drugs, we do not necessarily recommend that policymakers should alter patent protection terms; we did not study the impact of patent protections on new drug development decisions. The findings about marketing spending should mollify some concerns about budget allocations for marketing activities, in that we show that the sizeable marketing spending on detailing efforts and DTCA signal a penetration strategy, and not merely an attempt to push higher priced drugs. Marketing efforts, though a cause for alarm among policymakers, have been proven to be less of a devil among other sources of pricing power at the launch stage of the drug. Firms also benefit from the past reputation of the firm and it is only an indication of the quality of drugs produced by the firm. As expected, lower competition in terms of fewer players in the category allows higher pricing power; thus regulatory regimes that facilitate competition are likely to be beneficial for patients.

References

Angrist, Joshua D., and Jörn-Steffen Pischke (2010), "The Credibility Revolution in Empirical Economics: How Better Research Design Is Taking the Con out of Econometrics," *Journal of Economic Perspectives*, 24 (2), 3-30.

Bagwell, Kyle, and Michael H. Riordan (1991), "High and Declining Prices Signal Product Quality," *American Economic Review*, 81(1), 224-239.

Bajari, Patrick and C. Lanier Benkard (2005), "Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach," *Journal of Political Economy*, 113 (6), 1239–76.

Balakrishnan, Ravi, and Sam Ouliaris (2006), *US Inflation Dynamics: What Drives Them over Different Frequencies?* Publication No. 6-159. International Monetary Fund

Berndt, Ernst R (2002), "Pharmaceuticals in US Health Care: Determinants of Quantity and Price," *Journal of Economic Perspectives*, 16(4), 45-66.

Berndt, Ernst R., and Murray L. Aitken (2011), "Brand Loyalty, Generic Entry and Price Competition in Pharmaceuticals in the Quarter Century after the 1984 Waxman-Hatch Legislation," *International Journal of the Economics of Business*, 18(2), 177-201.

Berry, Steven T. (1994), "Estimating Discrete-Choice Models of Product Differentiation," *RAND Journal of Economics*, 25(2), 242-262.

Berry, Steven, James Levinsohn, and Ariel Pakes (2004), "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market," *Journal of Political Economy*, 112(1), 68-105.

Borenstein, Severin (1989), "Hubs and High Fares: Dominance and Market Power in the US Airline Industry," *RAND Journal of Economics*, 20(3), 344-365.

Brekke, Kurt R., and Michael Kuhn (2006), "Direct to Consumer Advertising in Pharmaceutical Markets," *Journal of Health Economics*, 25(1), 102-130.

Bresnahan, Timothy F. (1989), "Empirical Studies of Industries with Market Power." *In Handbook of Industrial Organization*, Vol. 2, eds. Richard Schmalensee and Robert D. Willig (pp. 1011-1057). Amsterdam: North Holland.

Cabral, Luís M. B. (2017), *Introduction to Industrial Organization*, Cambridge, MA: MIT Press.

Caves, Richard E., Michael D. Whinston, Mark A. Hurwitz, Ariel Pakes, and Peter Temin (1991), "Patent Expiration, Entry, and Competition in the U.S. Pharmaceutical Industry," *Brookings Papers on Economic Activity*, Microeconomics (1).

Chen, Jie and John A. Rizzo (2012), "Pricing Dynamics and Product Quality: The Case of Antidepressant Drugs," *Empirical Economics*, 42 (1), 279–300.

Ching, Andrew T., Robert Clark, Ignatius Horstmann, and Hyunwoo Lim (2016), "The Effects of Publicity on Demand: The Case of Anti-Cholesterol Drugs," *Marketing Science*, 35(1), 158-181.

Cockburn, Iain M., and Aslam H. Anis (2001), "Hedonic Analysis of Arthritis Drugs," in *Medical Care Output and Productivity*, (Chapter 11), eds. David Cutler and Ernst R. Berndt. Chicago: University of Chicago Press.

Cotterill, Ronald W. (1986), "Market Power in the Retail Food Industry: Evidence from Vermont," *Review of Economics and Statistics*, 68(3), 379-386.

Crown, William H., Davina Ling, and Ernst Berndt (2002), "Measuring the Costs and Benefits of Pharmaceutical Expenditures," *Expert Review of Pharmacoeconomics & Outcomes Research*, 2(5), 467-475.

Dafny, Leemore S. (2010), "Are Health Insurance Markets Competitive?" *American Economic Review*, 100 (4),1399–431.

Daughety, Andrew F., and Jennifer F. Reinganum (2008), "Imperfect Competition and Quality Signaling," *RAND Journal of Economics*, 39(1), 163-183.

Davis, Kenneth L. (2016), "Price Gougers Like Valeant Pharmaceuticals Must Be Tamed," (accessed May 11, 2017), [available at: https://www.forbes.com/sites/kennethdavis/2016/06/03/a-market-fix-for-generic-drug-price-gouging/#714df4726f21]

Davis, Peter (2005), "The Effect of Local Competition on Admission Prices in the US Motion Picture Exhibition Market," *Journal of Law and Economics*, 48(2), 677-707

Dean, Joel (1969), "Pricing Pioneering Products," *Journal of Industrial Economics*, 17 (3), 165-179.

DiMasi, Joseph A., Ronald W. Hansen, and Henry G. Grabowski (2003), "The Price of Innovation: New Estimates of Drug Development Costs," *Journal of Health Economics*, 22(2), 151-185.

Dixit, Avinash (1979), "Quality and Quantity Competition," *Review of Economic Studies*, 46(4), 587-599.

Ekelund, M and B. Persson (2003), "Pharmaceutical Pricing in a Regulated Market," *Review of Economics and Statistics*, 85(2): 298–306.

Emmons III, William M., and Robin A. Prager (1997), "The Effects of Market Structure and Ownership on Prices and Service Offerings in the US Cable Television Industry," *RAND Journal of Economics*, 28(4), 732-750.

Evans, William N., Luke M. Froeb, and Gregory J. Werden (1993), "Endogeneity in the Concentration–Price Relationship: Causes, Consequences, and Cures," *Journal of Industrial Economics*, 41(4), 431-438.

Fischer, Marc, and Sönke Albers (2010), "Patient-or Physician-Oriented Marketing: What Drives Primary Demand for Prescription Drugs?" *Journal of Marketing Research*, 47(1), 103-121.

Fleck L. M. (2006), "The Costs of Caring: Who Pays? Who Profits? Who Panders?" *Hastings Center Report*, 36(3),13–17.

Frank, Richard G. and David S. Salkever (1991), "The Supply of Charity Services by Nonprofit Hospitals: Motives and Market Structure," *RAND Journal of Economics*, 22 (3), 430.

Gettings, Jennifer, Braden O'Neil, Dave A. Chokshi, James A. Colbert, Peter Gill, Gerald Lebovic, Joel Lexchin, and Navindra Persaud (2014), "Differences in the Volume of Pharmaceutical Advertisements between Print General Medical Journals," *PLoS ONE*, 9 (2).

Hemphill, C. Scott, and Bhaven N. Sampat (2011), "When Do Generics Challenge Drug Patents?" *Journal of Empirical Legal Studies*, 8(4), 613-649.

Iizuka, Toshiaki, and Ginger Zhe Jin (2005), "The Effect of Prescription Drug Advertising on Doctor Visits," *Journal of Economics & Management Strategy*, 14(3), 701-727.

Kalyanaram, Gurumurthy, William T. Robinson, and Glen L. Urban (1995), "Order of Market Entry: Established Empirical Generalizations, Emerging Empirical Generalizations, and Future Research," *Marketing Science*, 14 (3), G212-G221.

Kannan, P. K., and Susan M. Sanchez (1994), "Competitive Market Structures: A Subset Selection Analysis. Management Science," 40 (11), 1484-1499.

Keeler, Emmett B., Glenn Melnick, and Jack Zwanziger (1999),"The Changing Effects of Competition on Non-profit and For-profit Hospital Pricing Behavior," *Journal of Health Economics*, 18(1), 69-86.

Lichtenberg, Frank R. and Tomas J. Philipson (2002), "The Dual Effects of Intellectual Property Regulations: Within- and Between-Patent Competition in the U.S. Pharmaceuticals Industry," *Journal of Law and Economics*, 45 (S2), 643–72.

Liu, Hongju (2010), "Dynamics of Pricing in the Video Game Console Market: Skimming or Penetration?," *Journal of Marketing Research*, 47(3), 428-443.

Loftsus, Peter and Ron Winslow (2015), "FDA Approves Bristol-Myers's Yervoy, Opdivo for Treatment of Melanoma," (accessed May 11, 2017), [available at https://www.wsj.com/articles/fda-approves-bristol-myers-yervoy-opdivo-for-treatment-of-melanoma-1443711746]

Lu, Z. John and William S. Comanor (1998), "Strategic Pricing of New Pharmaceuticals," *Review of Economics and Statistics*, 80 (1), 108–18.

Lucarelli, Claudio and Sean Nicholson (2009), "A Quality-Adjusted Price Index for Colorectal Cancer Drugs," NBER, Working Paper

Lyman, Stewart (2012), "Would Longer Drug Patents Really Lead to Lower Drug Prices?" (accessed May 11, 2017), [available at http://www.xconomy.com/seattle/2012/09/05/would-longer-drug-patents-really-lead-to-lower-drug-prices/?single_page=true]

Manchanda, Puneet, Peter E. Rossi, and Pradeep K. Chintagunta (2004), "Response Modeling with Nonrandom Marketing-Mix Variables," *Journal of Marketing Research*, 41(4), 467-478.

Manuszak, Mark D., and Charles C. Moul (2008), "Prices and Endogenous Market Structure in Office Supply Superstores," *Journal of Industrial Economics*, 56(1), 94-112.

Martins, Oliveira, Stefano Scarpetta, and Dirk Pilat (1996), "Mark-up Pricing. Market Structure and the Business Cycle," *OECD Economic Studies*, 27(2).

Mittal, Vikas (2016), "Conducting Experiments for Gaining Customer Insights: A Primer on Causal Research (Part 1 of 2)," https://ssrn.com/abstract=2711888 or http://dx.doi.org/10.2139/ssrn.2711888.

Nair, Harikesh (2007), "Intertemporal Price Discrimination with Forward-Looking Consumers: Application to the US Market for Console Video-Games," *Quantitative Marketing and Economics*, 5(3), 239-292.

Narayanan, Sridhar, Ramarao Desiraju, and Pradeep K. Chintagunta (2004), "Return on Investment Implications for Pharmaceutical Promotional Expenditures: The Role of Marketing-Mix Interactions," *Journal of Marketing*, 68 (4), 90–105.

PhRMA (2015), "Biopharmaceutical Research Industry Profile," *Pharmaceutical Research and Manufacturers of America*, Washington, DC, USA.

Porter, Michael (2004), *Competitive Advantage: Creating and Sustaining Superior Performance*, New York: The Free Press.

Robbins, Rebecca (2016), "Drug Makers Now Spend $5 Billion a Year on Advertising. Here's What That Buys," (accessed May 11, 2017), [available at https://www.statnews.com/2016/03/09/drug-industry-advertising/]

Schmalensee, Richard (1982), "Product Differentiation Advantages of Pioneering Brands," *American Economic Review*, 72 (3), 349–65.

Shajarizadeh, Ali, and Aidan Hollis (2015), "Price-Cap Regulation, Uncertainty and the Price Evolution of New Pharmaceuticals," *Health Economics*, 24(8), 966-977.

Shapiro, Carl (1983), "Optimal Pricing of Experience Goods," *Bell Journal of Economics*, 14 (2), 497.

Singh, Vishal, and Ting Zhu (2008), "Pricing and Market Concentration in Oligopoly Markets," *Marketing Science*, 27(6), 1020-1035.

Sorescu, Alina B., Rajesh K. Chandy, and Jaideep C. Prabhu (2003), "Sources and Financial Consequences of Radical Innovation: Insights from Pharmaceuticals," *Journal of Marketing*, 67(4), 82-102.

Steele, Henry (1964), "Patent Restrictions and Price Competition in the Ethical Drugs Industry," *Journal of Industrial Economics*, 12(3), 198-223.

Suslow, Valerie Y. (1996), "Measuring Quality Change in Pharmaceutical Markets: Hedonic Price Indexes for Anti-Ulcer Drugs," in *Competitive Strategies in the Pharmaceutical Industry* (Chapter 4), ed. Robert B. Helms, Washington, DC: The AEI Press.

Sutton, John (2007), "Handbook of Industrial Organization, Volume 3," in *Market Structure: Theory and Evidence* (Chapter 35), eds. M. Armstrong and Robert H Porter. North Holland: Elsevier.

Swanson (2015), "Big pharmaceutical companies are spending far more on marketing than research," https://www.washingtonpost.com/news/wonk/wp/2015/02/11/big-pharmaceutical-companies-are-spending-far-more-on-marketing-than-research/?utm_term=.b5002e066b35, (accessed May 11, 2017).

Thomke, Stefan and Walter Kuemmerle (2002), "Asset Accumulation, Interdependence and Technological Change: Evidence from Pharmaceutical Drug Discovery," *Strategic Management Journal*, 23 (7), 619–35.

Tirole, Jean (2015), *Theory of Industrial Organization*, Cambridge, MA: The MIT Press.

Voet M. A. (2016), *The Generic Challenge: Understanding Patents, FDA and Pharmaceutical Life-Cycle Management.* Florida, Brown Walker Press.

White L. J. (2013), "Market Power: How Does it Arise? How is it Measured?" in *The Oxford Handbook of Managerial Economics* (Chapter 3), eds. Christopher R. Thomas and William F. Shughart. New York: Oxford University Press.

Worstall, Tim (2015), "Wall Street Journal Surprised that Pharma Companies Make Out Like Bandits from Patent System," https://www.forbes.com/sites/timworstall/2015/10/06/wall-street-journal-surprised-that-pharma-cos-make-out-like-bandits-from-patent-system/#2b80120b2b80, (accessed May 11, 2017).

Walker, Joseph (2016), "Drugmakers' Pricing Power Remains Strong," https://www.wsj.com/articles/drugmakers-pricing-power-remains-strong-1468488601, (accessed May 11, 2017).

Table 1
Prescription Drug Prices Research

Study Criteria	Suslow (1996)	Lu and Comanor (1998)	Cockburn and Anis (2001)	Lucarelli and Nicholson (2009)	Chen and Rizzo (2012)	Shajarizadeh and Hollis (2014)	This Study
Categories	1	n	1	1	1	n	N = 30 (328 brands)
Quality Measures	Dosage, side effects, absorption rate, half-life, healing rate	FDA rating, dummy for chronic disease	Efficacy and toxicity measures, quality change over time	Survival months, response rate, side effects, time to progression	Physician's perception of drug quality (survey)	Pioneer/me-too/reformulation	Number of indications, priority vs. standard review, dummies for chronic, line extension, established molecule, orphan drug
Pricing Power	Promotion spending, patent length	-	-	-	Patent length	Market concentration	Patent protection, marketing spending, firm reputation, and market concentration
New Launch/ Existing	Existing	New	Existing	Existing	Existing	Existing	New

Table 2
Summary Statistics

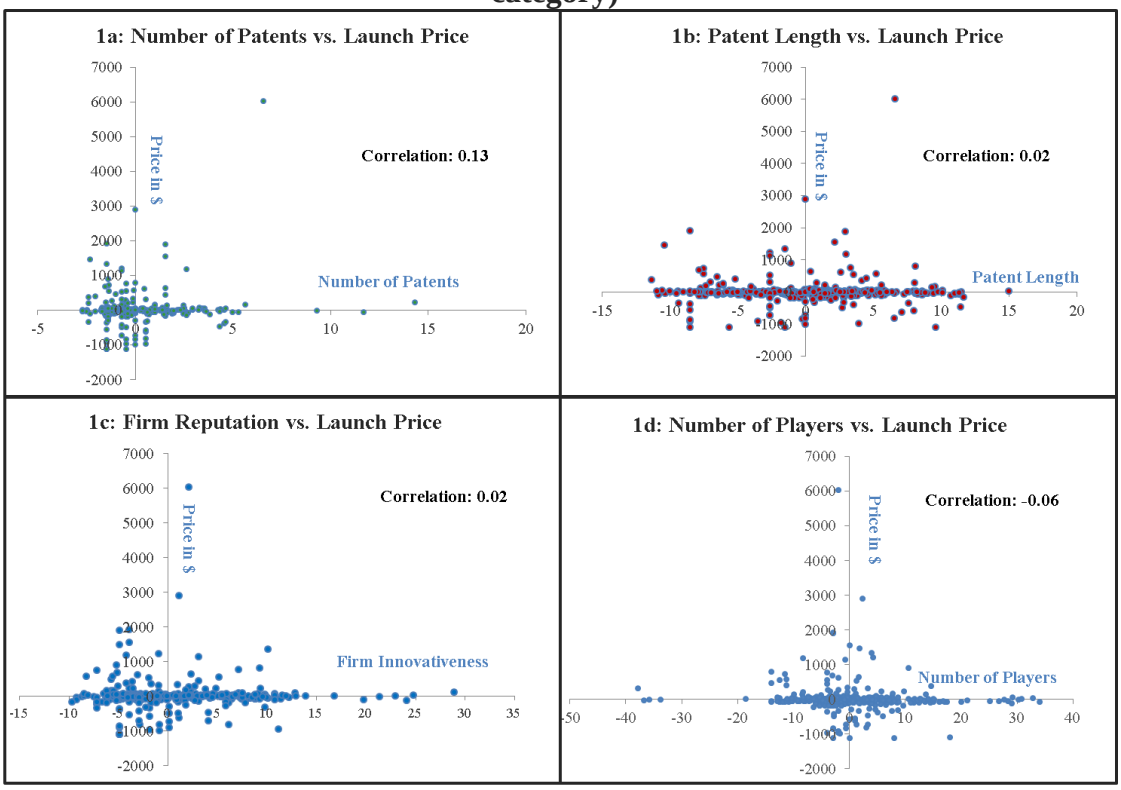
Drug Category	Number of Brands	Average Price Per Prescription	Detailing ($MM)	Journal Ad ($MM)	DTCA ($MM)	Number of Patents	Patent Length	Firm Reputation	Number of Players
Analgesics	15	78.4	15.90	3.07	1.41	1.63	10.91	5.36	11.84
Anti-Fungal Agents	6	251.4	4.32	2.70	0.00	2.43	11.02	11.57	6.29
Anti-Infectives	20	70	17.90	4.00	0.00	1.929	12.56	5.36	12.14
Anti-Obesity	3	73.4	20.70	7.23	43.80	1.67	10.80	6.00	8.00
Antiarithritics	14	191.6	38.20	6.61	8.15	1.64	9.11	10.86	15.93
Antihistamines	5	45.2	48.20	5.79	38.1	1.83	10.66	3.50	19.50
Antihyperlipidemic Agents	11	75.8	33.80	7.36	9.17	2.42	13.66	4.58	3.83
Antinauseants	4	403.4	1.31	0.98	0.04	2.50	13.09	3.83	9.33
Antineoplastic Agents	21	1162.7	0.81	0.44	0.00	1.84	10.91	5.96	5.28
Antiviral	29	407.5	4.41	1.43	2.67	2.37	14.34	7.10	9.30
Cardiac Agents	4	51.2	0.39	1.55	0.00	0.63	7.94	1.00	14.00
Contraceptives	13	44	11.40	2.38	7.88	1.82	10.15	4.64	35.09
Dermatologicals	10	88.2	6.52	3.200	12.10	1.75	11.07	4.33	12.58
Diabetes Therapy	10	79.7	22.30	4.32	3.88	2.46	12.03	8.38	4.00
Gastrointestinal	14	88.7	23.00	5.98	10.30	2.44	11.04	6.13	4.06
Genitourinary	5	77.8	19.80	3.09	3.11	2.14	12.36	6.00	4.29
Hemostatic Modifiers	4	167.3	8.68	2.96	0.00	1.44	10.32	2.67	6.44
Hormones	11	221.2	9.00	1.97	2.45	1.64	11.63	5.21	6.14
Immunological Agents	7	1034	1.76	0.52	0.00	4.00	15.85	6.00	9.00
Musculoskeletal	5	249.9	16.90	2.86	10.7	2.16	15.20	3.17	4.83
Neurological Disorders	19	152.2	10.60	3.12	0.36	2.05	12.20	5.5	12.15
Nutrients & Supplements	2	12.5	0.00	1.46	0.00	0.00	3.00	3.00	1.00
Ophthalmic Preparations	9	54.4	8.02	0.73	0.00	1.90	11.03	4.30	8.60
Psychotherapeutics	29	98.6	25.10	4.91	9.84	2.68	10.94	5.42	11.19
Respiratory Therapy	16	44	16.70	2.74	7.19	1.72	9.90	5.78	6.78
Sedatives	3	27	14.00	4.20	8.35	1.25	5.74	1.25	9.50
Sexual Function Disorder	5	92.5	44.80	4.66	57.1	2.00	12.64	8.00	4.80
Smoking Deterrents	4	65.2	5.69	7.14	9.05	1.60	15.93	4.00	4.20
Vascular Agents	30	35.6	9.48	7.30	0.00	1.61	12.16	6.14	8.30

Table 3
Model Based Evidence: Price Function Estimation

Variable	OLS	OLS with Fixed Effects	2SLS
	Coefficient (SE)		
Number of players	**-.015** (.006)	**-.013**** (.006)	**-.032***** (.012)
Number of patents	**.088***** (.026)	**.056*** (.032)	**.082**** (.012)
Patent length	-.0157 (.013)	-.008 (.014)	-.053 (.224)
Log detailing spending ($)	**.297***** (.047)	-.047 (.140)	**-.467**** (.219)
Log journal advertising spending ($)	-.011 (.012)	.006 (.014)	.027 (.023)
Log DTCA spending ($)	**.262**** (.108)	**-.030***** (.029)	**-.067**** (.029)
Firm innovativeness	**.020**** (.009)	**.029**** (.014)	**.106**** (.044)
Chronic (1/0) (1 = chronic, 0 = acute)	.075 (.363)	.135 (.162)	.475 (.661)
Total indicators	-.010 (.040)	.033 (.046)	.068 (.104)
Established molecule (1/0) (1 = established, 0 = new)	.085 (.219)	.075 (.229)	.072 (.220)
Extension (1/0) (1 = extension, 0 = new)	-.144 (.244)	-.122 (.200)	-.135 (.262)
Orphan drugs (1 = orphan, 0 = non-orphan)	.379 (.464)	**1.097**** (.515)	**1.816***** (.663)
Priority vs. standard review (1 = priority, 0 = standard)	**.297**** (.137)	**.494***** (.164)	**1.148***** (.383)
Manufacturer fixed effects	NO	YES	YES
Year fixed effects	NO	YES	YES
Category fixed effects	YES	YES	YES

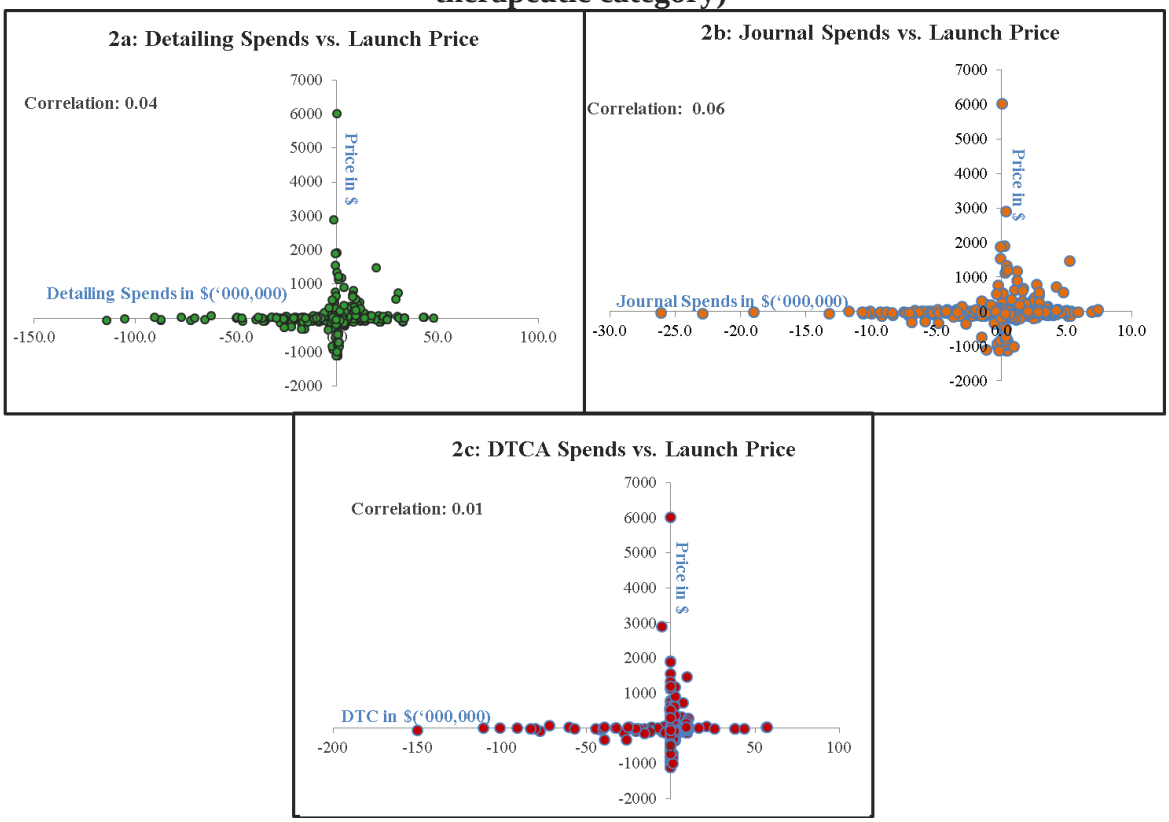
Notes: The dependent variable is ln(launch prices). We report clustered standard errors at the category level in parentheses in each cell.
*** $p < .01$, ** $p < .05$, * $p < .10$.

Figure 1
Scatter Plots of Market Power Variables vs. Launch Price (mean-centered by therapeutic category)



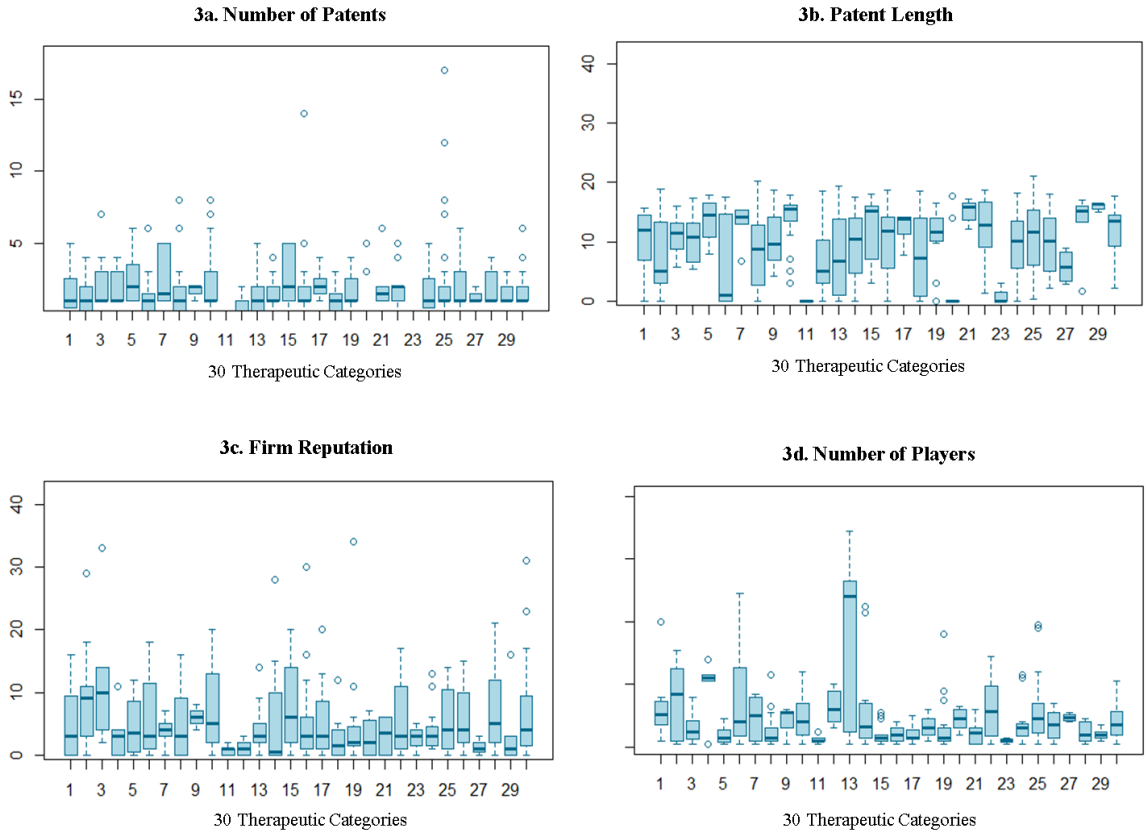
Notes: This figure presents correlations between the launch price of the drug and the source of pricing power, mean-centered by therapeutic category, where (a) number of patents, (b) patent exclusivity length, (c) firm reputation, and (d) number of players. We also provide the respective correlations.

Figure 2
Scatter Plots of Marketing Spending Variables vs. Launch Price (mean-centered by therapeutic category)



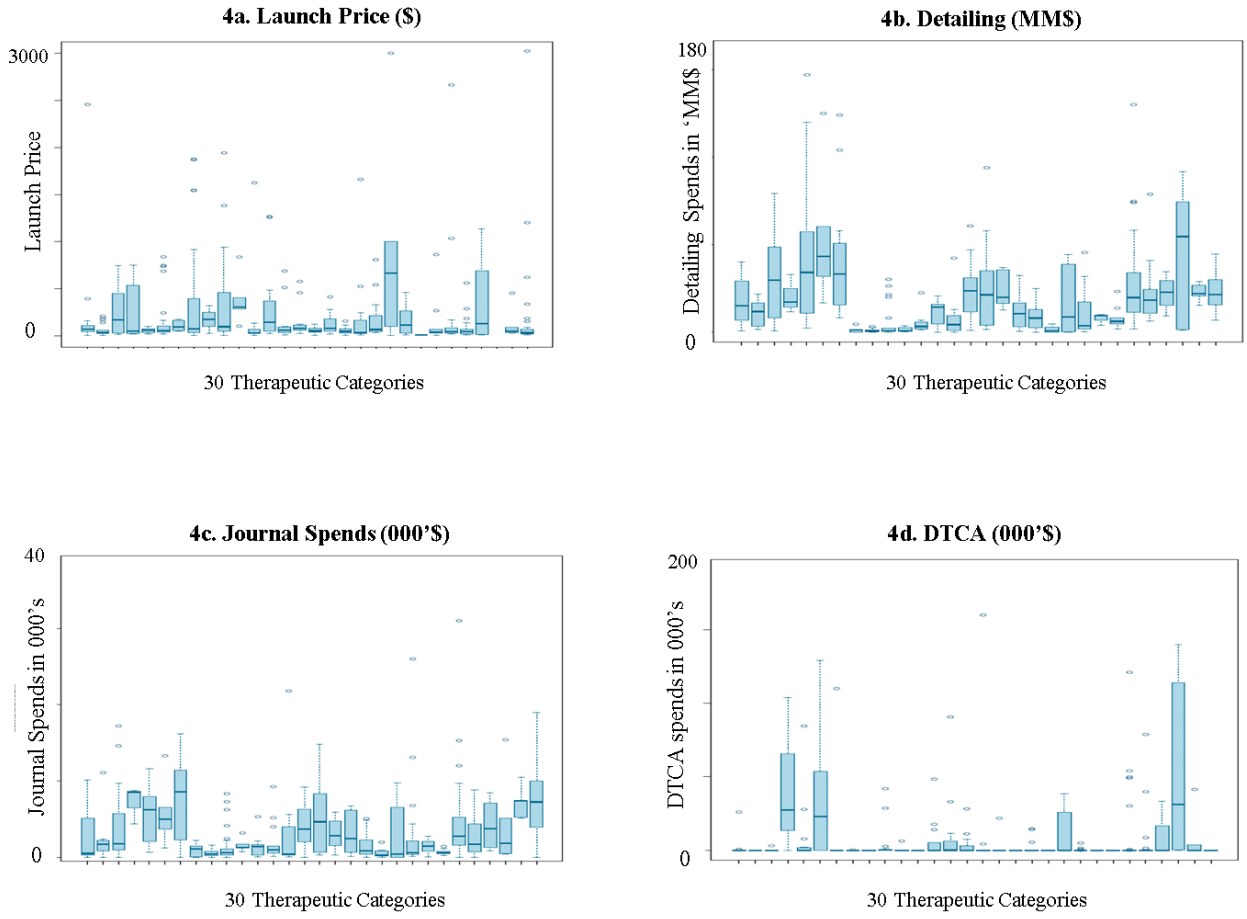
Notes: We present the correlations of the launch price of the drug and the three elements of marketing spending, (a) detailing, (b) journal advertising, and (c) DTCA. We also provide the respective correlations.

Figure 3
Box Plots of Within-Therapeutic Category Variation in Pricing Power Variables



Notes: We present the variations of the pricing power variables across the 30 therapeutic categories for (a) number of patents, (b) patent exclusivity length, (c) firm reputation, and (d) number of players.

Figure 4
Box Plots of Within-Therapeutic Category Variation in Marketing Mix Variables



Notes: We present the variations of marketing mix variables across the 30 therapeutic categories for (a) launch price, (b) detailing, (c) journal advertising, and (d) DTCA.