International Journal of

Finance

(IJF)

WHY DO PRESCRIPTION DRUG PRICES INCREASE? STATE MEDICAID EXPANSION, EXECUTIVE COMPENSATION AND CORPORATE GOVERNANCE

Mosab Hammoudeh

California State University Fullerton

mhammoudeh@fullerton.edu

Amrita Nain

the University of Iowa

Amrita-nain@uiowa.edu

Tarek Zaher

Indiana State University

Tarek.zaher@indstate.edu

ABSTRACT

We exploit a quasi-random shock, i.e., Medicaid expansion, to the demand on prescription drugs and examine its impact on drug prices conditional on manufacturing firms' financial characteristics. We use this shock to study the role of executive compensation, board independence and corporate governance, in setting drug prices. We find suggestive evidence that drug prices increased in expansion states. We also find that stock option awards are associated with lower drug prices. This provides evidence for Ross (2004)'s magnification effect that stock options may reduce the risk-taking of a CEO. Corporate governance appears to have a more complicated relationship with drug prices. This study addresses an underrepresented area in finance and provides a blueprint for researchers in finance to utilize a unique data set to answer research questions in finance and economics.

Key Words: *Product Markets, Product Prices, Executive Compensation, Corporate Governance*

www.carijournals.org

INTRODUCTION

In 2017, the US spent more than $400 billion on prescription drugs, which accounted for about 12% of total health-care spending. Berman et al., (2017) report that drug prices are the fastest growing component of total health-care costs. A few infamous cases of price hikes have led to accusations of price gouging by the pharmaceuticals industry. For example, in 2015 Turing Pharmaceuticals raised the price of Daraprim from $13.50 to $750 a pill. Mylan, another pharmaceuticals company, raised the price of its Epinephrine auto-injector by over 400% between 2007 and 2015.

An argument in defense of high prescription drug costs is that developing new drugs is time consuming and expensive. Several studies have shown that it takes on average 12 years for a drug to be introduced to the market (Grabowski et al., 1992; Hammoudeh and Garfinkel (2020)) and costs $2.5 billion to develop in 2015 (Dimasi et al., 2016). A media article examining the period from 2004 to 2010 found that only one in 10 drugs moves from early-stage Phase I clinical trials to FDA approval[1]. Allowing firms to profit from the small number of drugs that do make it to market incentivizes them to invest in the discovery of new life-saving drugs. This profit incentive, it is argued, is one of the reasons the United States is the leading innovator in biopharmaceuticals. Baily (1972) presents a model that describes pharmaceutical innovation as a function of investments in research and development and provides evidence from US pharmaceutical companies consistent with his model, however, his data only spans from 1948 to 1968; before the passing of significant laws that reshaped the industry (i.e., the Bayh–Dole Act of 1980, and the Hatch-Waxman Act of 1984). Critics, however, point out that no data are available to the public showing a link between development costs and drug prices. Several researchers express concern that prescription drug prices are determined not by costs but by what the market will bear[2] (Berman et al., 2017). Considering the rapid rise in drug prices, pharmaceutical CEOs have received increasing media attention. A recent study by Associated Press of CEO compensation at S&P 500 firms shows median salaries of pharmaceuticals and other healthcare CEOs have grown faster than in any other sector[3]. This has led to complaints that pharmaceutical manufacturers and their well-paid CEOs profit at the expense of patients in need of medicine.

High prescription drug prices and high CEO salaries are not necessarily indicators of perverse or unethical pricing practices. Even if data on drug development costs were publicly available, it would be difficult to determine whether a drug's price is fair considering the benefits the drug brings to society. Drug pricing is complicated. For generic drugs, market competition plays a role in price determination, provided there are competing generics available. However, patent protected

---

[1] Source: Berkrot, Bill. "Success Rates for Experimental Drugs Falls: Study." Reuters. Thomson Reuters, 14 Feb. 2011

[2] Source: New York Health Plan Association's 2016 memorandum in support of S.7686/A.10026 - an act to improve prescription drug cost transparency.

[3] See: Munro, Dan. "Pharma Trumps All Healthcare Sectors in Executive Compensation. Forbes, Forbes Magazine, 28 May 2015. Also see: Boodman, Eric. "Paycheck Envy? Check out How Much Pharma and Health Care CEOs Made Last Year." STAT. STAT, 26 May 2016. Web. 11 June 2018

drugs are almost monopolies for which pricing depends on a variety of factors – population of potential drug recipients, how big an improvement over existing therapy, the cost of treating the targeted condition in the absence of the new drug, and whether the drug changes the way medicine is practiced with respect to the targeted condition (Berndt, 2002). The same complexity of factors is used for pricing off-patent drugs with no generic alternatives since these drugs continue to enjoy near monopoly power after the expiration of the patent by way of litigation.

The objective of this paper is two-fold. We first examine the impact of a quasi-random shock to demand, i.e., Medicaid expansion, on drug pricing. Several papers have attempted to examine the determinants of drug prices. Berndt (2002) suggests that drug prices are determined through factors like potential recipient population, effectiveness of drug relative to peers in its class, and its patent status. These factors allow a drug to enjoy a higher monopolistic power over the market and set prices flexibly. Grabowski and Vernon (1992), Grabowski (2002), Grabowski et al., (2011), Hammoudeh and Nain (2019), and Bonaime and Wang (2019) examine the impact of patent coverage, and drug characteristics (e.g., generic and brand name drugs), and its impact on competition and prices. They find that on-patent drugs have more flexibility in setting prices. They also find, contrary to expectations, that off-patent brand name drugs will continue to increase prices at the same rate but will drop all advertising expenses for a drug. We reexamine their findings by using a semi-exogenous shock to the demand side of pharmaceuticals to examine the impact it has on prices. This shock was the Medicaid expansion that was approved by congress in 2012 and enacted by many states in 1/1/2014 allowing for a difference in differences setting between states that expanded Medicaid and states that did not.

We compile a unique dataset that includes state drug utilization data from Centers of Medicare and Medicaid Services (CMS), company financial data from Compustat, executive compensation data from Execucomp, and corporate governance data from ISS Governance. We provide an elaborate discussion on the construction of this dataset to familiarize finance researchers with a relatively uncommon dataset. We choose a sample of 16 states, 8 that have adopted the Medicaid expansion and 8 that have not, over a period of 8 years from 2010 till 2017. The CMS data is reported on a quarterly basis. To be included in our sample, we require a drug to have CMS data in all 16 states and in each of the 8 years of the sample to construct a balanced panel. Our final sample is 475 drugs of which 118 are branded and 357 are generic. Our sample of drugs cost Medicaid 12% of total spending per year. This allows us to construct a large sized dataset with almost 240,000 observations. We first examine the validity of the shock by testing whether demand on pharmaceuticals has indeed increased post expansion in states that have expanded Medicaid. We find consistent evidence with Ghosh et al., (2017), who construct a much larger database from proprietary sources and find that the expansion has significantly increased demand on prescription drugs post expansion in states that have expanded. Next, we find suggestive evidence that the price of branded drugs has increased in expansion states. These findings have implications on the drug pricing methods of manufacturers when demand increases.

The second objective of this paper is to explain price increases following Medicaid expansion from a corporate finance perspective. We explore whether accusations leveled against drug manufacturers are justified by examining the link between CEO compensation, board independence and prescription drug prices. Existing pay-for-performance literature shows that linking CEO pay to a company's equity value through employee stock options or share grants helps align CEO and shareholder interests and leads to higher firm value (Mehran, 1995; Manso, 2011). A CEO can achieve higher market value by identifying and backing development of ground-breaking drugs, cost reduction through efficiency improvements, more effective advertising etc. But higher market value can also be achieved by jacking up prices for drugs that enjoy near monopoly status. Exorbitant increases in drug prices increase revenue in the short term. However, they can also attract regulatory scrutiny and increase the risk of expensive lawsuits and reputational loss in the long term. Existing re-search shows that stock option grants increase risk-taking behavior in CEOs (Chen et al., 2006; Low, 2009). Shue and Townsend (2017) find that stock option awards induce higher risk taking in support for the convexifying effect. Whereas Ross (2004) argues that the magnification effect of stock option awards causes managers to reduce risk-taking. We hypothesize that if CEOs of drug manufacturers raise drug prices to enrich themselves, we should see larger increases in prescription drug prices when CEOs receive a greater fraction of their annual compensation in the form of stock option grants. Independent boards, however, can keep a check on excessive risk taking or unethical price gouging by CEOs (Bargeron, 2010; Pathan, 2009). Therefore, our second hypothesis is that if large price hikes are economically unjustifiable, they will be less evident in the presence of strong independent boards.

Our findings are not consistent with our ex-ante expectations. We find that stock option awards are associated with lower branded drug prices, but with slightly higher generic prices. Stock awards and cash are associated with higher branded drug prices and lower generic prices. These results provide evidence in support of the magnification effect. The magnification assumes that the stock option awards may cause the increase in delta to dominate the increase in vega and therefore cause CEOs to reduce risk taking. Our results are statistically significant at the 1% level and robust to a battery of fixed effects estimations. For this estimation we do not use the typical difference-in-differences setting due to lack of power because of sample size. Board independence is associated with an increase in drug prices and corporate governance is associated with lower drug prices. We discuss the implications and provide potential explanations to the effects.

The contributions of this paper can be seen as follows. Firstly, this paper attempts to understand pricing practices in an industry that accounts for 2% of US GDP. Despite the ubiquitous, largely negative media coverage of the prescription drug industry, there is no rigorous, large sample empirical study on the link between prescription drug prices and corporate governance and CEO compensation. With growing public controversy regarding high drug prices, a formal academic investigation is timely and relevant. Secondly, this research provides implications for policy both at the public level, and at the corporate level. The Medicaid expansion is one of the biggest components of the Affordable Care Act, also known as Obama Care, which is considered one of

President Obama's most important milestones[4]. Examining the impact of this policy on drug prices may yield implications for similar policies in the future. Furthermore, examining the impact of executive compensation structure, corporate governance and CSR policies may yield results that are useful for corporate decision makers to consider. Finally, this paper aims to provide a blueprint on matching Medicaid drug data with public corporate data, thereby facilitating the accessibility and utilization of the Medicaid drug data.

STATE MEDICAID EXPANSION

The Patient Protection and Affordable Care Act (PPACA) was passed in March 2010 and constitutionally affirmed by the Supreme Court in 2012. The original intent of PPACA was to "usher in a historic expansion of access to health care to 32 million Americans. Expanding Medicad to Americans below 138% of the federal poverty line was the primary motor for driving greater access" (Jacob and Callaghan, 2013). However, the Supreme Court also ruled that states had the option of adopting the expansion. States that failed to adopt were simply missing out on significant federal funds allocated by PPACA. The Federal Government offers to cover all expansion expenses for the first three years and, afterward, continues to pick up a large portion of the administrative and benefit costs (96% on average Young and Garfield (2018)). By refusing to accept the expansion States are leaving money on the table, for example an NPR article states that Texas is leaving up to $100 billion in federal funds as allocated by the PPACA[5]. In addition, some federal funds that were previously passed down for other medicad related purposes, were cut. This means that States that are refusing the expansion are missing out on three opportunities; first, the federal medicad expansion money as allotted by the PPACA; second, the reduction in medicad federal funding; third, the uncompensated care expenses for individuals who would be otherwise covered by the expansion. In summary, The PPACA provides more funds to the states to provide health care to a larger population, and therefore acts as a positive shock to the demand side of prescription drugs.

In this study, we include 16 states. 8 of which eventually adopt the expansion, and 8 that do not. For the 8 states that adopt the expansion, we include four states that adopted the expansion as soon as it was allowed, i.e., 1/1/2014, these states are CA, NY, NV, and VT. We include states that adopt the expansion on 1/1/2015, which include IN, NH, and PA. Finally, we include the one state that adopted in 1/1/2016, i.e., MT. The reason behind including states that have adopted the expansion during different time periods is to provide as much variation as possible for a more robust empirical set up. The states that don't adopt the expansion include FL, GA, KS, ME, NC, TN, TX, and WI. With a few exceptions, states that have adopted the expansion are primarily blue states, and states that have not are primarily red.

HOW MEDICAID SETS PRICES

---

[4] See for example: Armour, Stephanie. "Medicaid Expansion Gains Popularity in Red States." The Wall Street Journal, Dow Jones & Company, 14 June 2018.
[5] Goodwin, Wade. "Texas Politicians and Businesses Feud Over Medicaid Expansion." NPR, NPR, 29 May 2015 6.

To understand how the Medicaid expansion could impact the prices of drugs we first, must understand how pharmaceutical companies set their prices and how they get paid by Medicaid. Figure 1 below, graciously provided by the Kaiser Family Foundation (Young and Garfield, 2018), depicts this relationship. State Medicaid drug pricing can be thought of as a process of two steps. In the first step the federal Medicaid takes the minimum price a pharmaceutical company has sold the drug to other private buyers (whether health insurance or out of pocket). This minimum price becomes the highest price Medicaid is willing to pay for a drug. The federal Medicaid distributes a list containing these prices to the states, these are also known as Wholesale Acquisition Cost (WAC), and the list is known as the National Average Drug Acquisition Cost (NADAC). The second step involves additional rebate that states can negotiate with pharmaceutical companies. The rebates were estimated to be 20% of total drug spending in 2017; for perspective, in 2017 retail drug spending amounted to about $400 billion. Of the two types of rebates, states would be able to negotiate with manufacturers for the supplemental rebates. The legislative rebates are usually set in Washington for with drug manufacturers. One of the hypotheses of this paper is to test whether Medicaid expansion gave states more negotiation power with pharmaceutical companies. This increase in negotiation power comes from the increase in the demand on their drugs within that state. Intuitively, we expect State Medicaid programs of states that have adopted the expansion to ask for more statutory rebates.

DATA AND HYPOTHESES

This section provides an explanation on where and how we collect our data. The first subsection discusses the collection of Medicaid data, and the methodology used to trace it back to its manufacturer. The second subsection explains our collection and processing of executive compensation data. And the third subsection discusses the independent boards data as well as corporate governance data.

Figure 1: Drug Distribution and Medicaid Payments
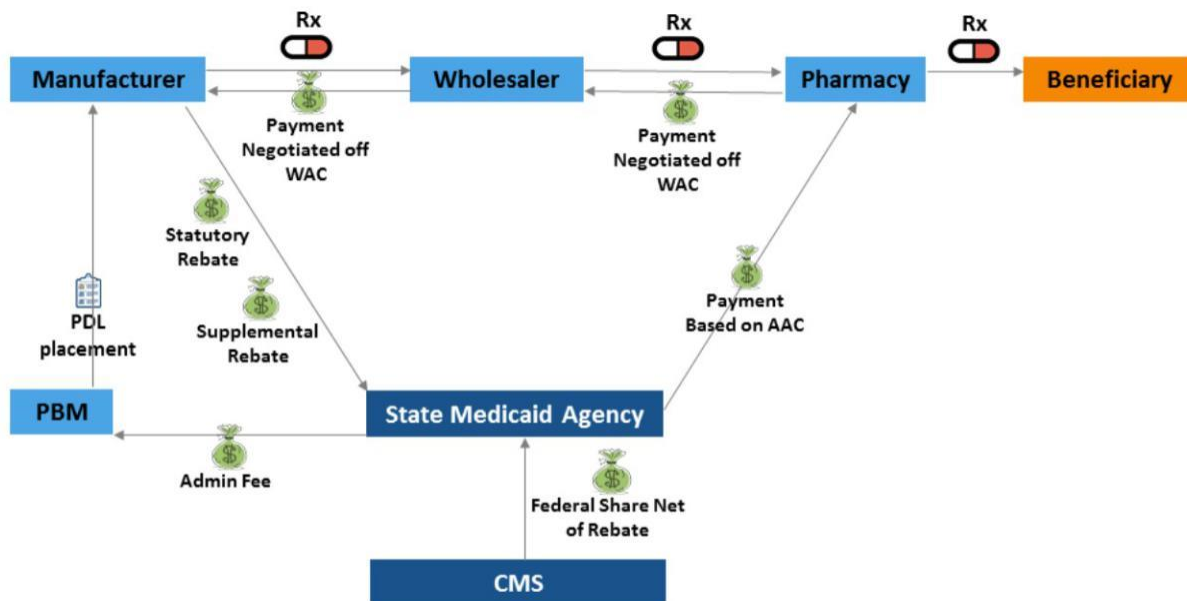
Notes: This figure is a simplified depiction of the payment and drug supply chain in the Medicaid prescription drug benefit provided through a fee-for-service setting. WAC is Wholesale Acquisition Cost. While WAC is known, the negotiated amount is not. AAC is Actual Acquisition Cost and is based on a published schedule such as NADAC or WAC.

A.   Construction of the Data

As a prequel to our main analysis, we provide elaborate description of our data. Our goal is to familiarize a researcher in finance to a relatively uncommon database. We collect our prescription drug data from the Centers for Medicare and Medicaid Services (CMS). CMS provides quarterly state drug utilization data from 1990 till current with a lag of 3 months. This data contains all prescription drugs paid for by Medicaid in that state from Federal or State funds on a pre-rebate basis. To put this in perspective, Medicaid accounts for 10% of all drug spending within the US, that's $40 billion dollars in 2017. The data contains the National Drug Code (NDC), a unique identifier for a drug comprised of three parts, the first is the manufacturer, the second is the drug type, and the third is the packaging type. The data also includes the number of units sold, the number of prescriptions sold, and the total amount in dollars spent in dollars, all reported on a quarterly basis from January 2010, till December 2017. Finally, the data covers both types of Medicaid utilization, fee-for-service and managed plan service. We perform our analysis on both types separately and combined to ensure that the results are not driven by one or the other.

Observations for a drug that was prescribed less than 10 times in one quarter are missing; the number of units and prescriptions as well as the dollar amount totals are omitted to protect the privacy of individual beneficiaries, as per federal Privacy Act and HIPAA. We drop these observations and retain only observations that contain all data points. We use a rough estimation technique to quantify the revenues generated through these omitted observations and find that the amounts are relatively negligible specifically for our drug sample.

To be included in our sample we require a drug to be available in all 16 states *and* available for every year over the period from 2010 to 2017; we don't require the drug to have all 4 quarters present in a year, however, most drugs do. This results in 475 drugs of which 118 are brand names and 357 are generic. This number of drugs is much smaller than the number of all the drugs in the drug utilization, however, our restrictions to build a balanced panel data without any missing observations in a state or year drops our sample drugs from about 20,000 drugs to 475. This results in 238,792 drug-quarter-state observations. To trace each drug back to its manufacturer, we match our data with the FDA Listed Drugs data we use the NDC code. The FDA data tells us who the manufacturer is, and whether a drug is a New Drug Application (NDA), which is a branded drug, or an Abbreviated New Drug Application (ANDA), which is a generic drug. We perform external Bloomberg searches on each of these manufacturers to find the corporation's name and ticker symbol, and in some cases the name of the parent organization, and whether the manufacturer is public or private. We use the ticker symbol to match with CRSP and Compustat data manually. We can match our data set to 28 public companies with data on both CRSP and Compustat.

Table 1 presents the distribution of Therapeutic Classes in our sample. Each therapy class is listed in the first column. The total revenue aggregated over our entire sample period for each therapy class is reported in column 2. The percentage of each drug's representation in our drug is reported in the third column. For example, our sample contains 2(0.42%) HIV drugs that have cost

State Medicaid programs a combined total $2.97 billion from 2010 till 2017. Our sample of states spent the highest on 16 (3.35%) Diabetes drugs with almost $5 billion within an 8-year period. The second highest would be the spending on 30 ADHD drugs with about $3 billion over the same period. Overall, our sample of drugs have our sample's 16 State Medicaid programs spent about $30 billion over our sample period. This accounts for on average 12.5% of Medicaid's total spending in the US per year. We assume that our sample is a valid proxy for the full Medicaid based on the size of revenues generated.

To construct our two main dependent variables, i.e., price per prescription(ppp) and price per unit(ppu), we divide the total dollar amount for a drug in a quarter by the number of prescriptions (or number of units) in that quarter. Next, we adjust for inflation and set all prices in terms of 2010 inflation adjusted dollars by $inflationppp_t = ppp_t / (1 + .0175)^n$, where n=1,2,3... for 2011,2012, 2013...etc. Finally, we attempt to smooth out the high variation in the inflation-adjusted ppp (as well as ppu) by taking the natural log of the inflation adjusted ppp (ppu). Our regressions below are reported for both the raw ppp and the LN (ppp). Table 2 reports summary statistics on these variables. our total sample ppp is $107 and ppu is $25. A Unit is the basic denomination of a manufacturer's product, e.g., 22 pills in a bottle, whereas a Prescription is a part of a treatment plan which usually contains multiple units. We assume these are similar and are highly correlated with close to 60% correlation. In our analyses below, we focus on ppp, however, we also find similar results for ppu. The average number of prescriptions in a quarter for a drug in our sample is 1,509. This number is likely driven by a smaller portion of our sample with high prescriptions since the median number of prescriptions is 480. Branded drugs are twenty multiples more expensive on average than generic drugs.

Table 3 provides summary statistics on the State Medicaid programs that we include in our sample. The table only shows 2017 numbers to give the reader an understanding of the cross section of our data. Time-series graphs describing our data can be seen in figure 2 and 3 below. In Table 4, total Medicaid is total spending on all drugs within that state over 8 years (2010 to 2017).

Table 1: Revenues and Sample Distribution by Therapeutic Class

This table reports the revenues by therapeutic class of drugs in our sample. The sample covers the years from 2010 to 2017. The third row reports the percentage of the total sample that are classified in the respective therapeutic class, calculated as the number of drugs in the class divided by the total number of drugs in the sample (e.g., HIV drugs are only 0.42% of drugs in our sample but have generated $2.97 billion dollars.) All revenue figures are thousands.

Therapy Class	Total Revenue	(%)	Therapy Class	Total Revenue	(%)
(1)	(2)	(3)	(4)	(5)	(6)
Acne	$ 21,900.00	0.21	HIV	$ 2,970,000.00	0.42
ADHD	$ 3,510,000.00	6.14	Infections	$ 1,100,000.00	12.91
Allergies	$ 330,000.00	0.42	Inflammation	$ 970,000.00	3.79
Anxiety Disorders	$ 110,000.00	4.81	Influenza	$ 97,000.00	0.19
Arthritis	$ 1,130,000.00	0.43	Insomnia	$ 42,500.00	1.27
Asthma	$ 2,810,000.00	1.92	Irregular Heartbeat	$ 6,536.18	0.63
Autoimmune	$ 549,000.00	0.21	IBS	$ 4,124.83	0.43
Bipolar	$ 294,000.00	3.99	Lice	$ 125,000.00	0.43
Birth Control	$ 359,000.00	1.9	Menopause	$ 4,059.60	0.64
Blood Cancer	$ 28,500.00	0.63	Migraine	$ 40,500.00	0.41
Blood Clots	$ 12,100.00	1.05	Motion Sickness	$ 9,155.00	0.61
Bronchospasms	$ 2,010,000.00	1.69	Muscle Spasms	$ 26,600.00	0.85
Carnitine	$ 8,863.19	0.2	Nausea	$ 171,000.00	1.26
Cavities	$ 3,149.49	0.21	Obs. Pulmonary	$ 1,980.01	0.19
Cervical Dystonia	$ 151,000.00	0.21	Osteoporosis	$ 4,339.62	0.21
Chemotherapy	$ 329,000.00	0.21	O. Active Bladder	$ 80,700.00	0.43
Cholesterol	$ 26,400.00	0.84	Pain Killer	$ 2,040,000.00	12.58
Constipation	$ 166,000.00	1.28	Pancreatitis	$ 43,900.00	0.21
Cystic Fibrosis	$ 574,000.00	0.21	Panic Disorders	$ 14,200.00	0.59

Depression	$ 170,000.00	7.79	Parkinson's	$ 4,107.16	0.21
Diabetes	$ 4,480,000.00	3.35	Progesterone	$ 76,800.00	0.42
Diarrhea	$ 6,837.12	0.42	Schizophrenia	$ 388,000.00	2.32
Estrogens	$ 65,600.00	0.63	Seizures	$ 141,000.00	2.29
Fibromyalgia	$ 25,700.00	0.21	Skin	$ 50,600.00	2.54
Fluid Retention	$ 32,300.00	0.63	Thyroid Gland	$ 54,600.00	2.13
Heartburn	$ 1,060,000.00	1.05	Ulcers	$ 522,000.00	3.4
Herpes	$ 7,132.66	0.21	White Blood Cells	$ 630,000.00	0.21
High Blood Pressure	$ 338,000.00	7.55			
Total	**$ 18,608,482.46**			**$ 9,618,702.40**	

Spending on Sample Drugs is the total spending of a State Medicaid Program on our sample of 475 drugs. mednum is the total number of individuals in that state covered by Medicaid. Uninnum is the number of people who are uninsured in that state. Insured Any is the percentage of people that are covered by any type of health insurance in that state. As expected, California had the largest Medicaid covered population with 9.3 million members and had spent the most on prescription drugs with $4.05 billion. For our sample of drugs, we notice that NY has spent the most in 2017 with $612 million, despite the population covered by Medicaid being half that of CA.

Table 2: Summary Statistics on Sample Firms and Drugs

Panel A provides the distribution of the unique counts and sample sizes for the firm and drug variables. Panel B provides summary statistics on prescription, price per prescription (ppp), and price per unit (ppu). Unit is the most basic denomination of a manufacturer's product, e.g., 22 pills in a bottle, whereas a Prescription is part of a treatment plan which usually contains multiple units.

Panel A: Unique Counts and Sample Sizes

	N	Sample	Observation Level	N
	(1)	(2)	(3)	(4)
State	16	Full Sample	Drug-Quarter-Firm-State	238,792
Drug	475	Exec. Data	D-Q-Executive-S	67,482
Quarter Year	32	Board Data	D-Q-Board-S	57,771
Public Manufacturer	28	G-Index Data	D-Q-GIndex-S	57,558
All Manufacturers	50			
Executives	23			
Board	16			
G-Index	11			

Panel B: Summary Statistics on Drug Prices, Prescriptions and Units Dispensed

	PPP	PPU	Prescript	Unit
	(1)	(2)	(3)	(4)
Mean	106.8959	25.85406	1509.271	84096.53
Median	13.59791	0.2946321	480	20384.46
Branded Avg	374.5584	102.7364	1846.528	56254.53
Generic Avg	18.58562	0.4815715	1399.976	93442.36

The high price per prescription(ppp) has low variation; all values lie within a 10% of the grand mean. All states have balanced representation in our data as can be seen in the % of Obs column. The reason why our state panel is not perfectly balanced is because some states are missing a few quarter observations. However, to be included in our sample a drug must be sold at

least for one quarter for every year-state in our sample. Texas is the state with the highest number of uninsured individuals. Our data shows that States that have adopted Medicaid have more insurance coverage for their population, and higher spending. This fact is important for our analysis below of the validity of the Medicaid expansion as a shock. Our choice of states considers 3 main points. Firstly, we attempt to find a representative sample of states with variation in political affiliation, population, economic conditions, and Medicaid coverage. Second, we match states that have adopted the Medicaid expansion with states that have a similar population but did not adopt the expansion. This will allow us to have a better basis for comparison. States that have adopted have a combined population of 81 million compared to 79 million for the states that have not adopted. Third, since we require the sample drugs to be available in all the states, we consider the following trade off: adding more states at the expense of reducing the considered sample drugs. This process results in a sample of 16 states. Table 4 provides our summary statistics on the manufacturers of our sample's drugs.

Table 3: Summary Statistics on Medicaid Drug Utilization by State

This table provides summary statistics on state Medicaid spending in 2017. Total Medicaid is the total amount of spending a State Medicaid program has spent on all drugs in 2017. Spending on Sample Drugs is the total amount of spending a State Medicaid Program has spent only on our sample of 475 drugs. mednum is the total number of individuals in that state are covered by Medicaid. uninnum is the number of people who are uninsured in that state. Insured Any is the percentage of people that are covered by any type of health insurance in that state. All dollar amounts are in thousands.

State	Adopted	Total Medicaid Spending	Spending on Sample Drugs	Average PPP	% of Obs.	mednum	uninnum	Insured (%)
CA	Yes	$ 4,050,000	$ 586,000.00	$108.44	6.35	9,313	2,980	92
FL	No	$ 1,660,000	$ 312,000.00	$103.18	6.35	3,001	2,256	88
GA	No	$ 750,000	$ 168,000.00	$102.81	6.31	1,647	1,162	88
IN	Yes	$ 956,000	$ 181,000.00	$112.88	6.34	1,300	455	93
KS	No	$ 344,000	$ 92,300.00	$106.15	5.91	399	228	92
ME	No	$ 239,000	$ 76,100.00	$ 99.82	6.28	294	98	93
MT	Yes	$ 215,000	$ 65,400.00	$103.29	6.2	220	70	93

NC	No	$ 1,860,000	$ 419,000.00	$106.29	6.35	1,728	1,056	89
NH	Yes	$ 79,100	$ 18,800.00	$105.06	6.07	174	94	93
NV	Yes	$ 284,000	$ 57,900.00	$103.60	6.23	488	244	91
NY	Yes	$ 3,980,000	$ 612,000.00	$105.49	6.35	4,651	1,163	94
PA	Yes	$ 2,030,000	$ 361,000.00	$103.60	6.35	2,413	635	95
TN	No	$ 1,020,000	$ 290,000.00	$118.64	6.14	1,280	704	89
TX	No	$ 2,070,000	$ 365,000.00	$102.51	6.35	4,024	3,773	85
VT	Yes	$ 163,000	$ 55,100.00	$123.32	6.1	126	32	95
WI	No	$ 1,110,000	$ 302,000.00	$105.48	6.32	912	399	93
Total		$20,810,100	$ 3,961,600		100%	31,970	15,349	

As can be seen more than 85% of the revenues from our drug sample are going to public corporations listed on the NYSE or NASDAQ, the remainder goes to either private firms or global firms not listed on above exchanges. Glaxo Smith Kline has the lions share pf revenues with $403 million from 11 branded drugs. Teva Pharmaceuticals generates $112 million from 105 generic drugs, and $116 million from 2 branded drugs. We infer that the number of offered drugs is not a direct factor in determining the amount of revenue generated by a corporation. Clearly a measure of a drug's competitive space is needed to determine how much pricing flexibility a firm has when pricing it. This measure should incorporate the population of the therapeutic class the drug is aimed towards, the number of drugs offered within the class, and the effectiveness of the drug relative to its competitors'. In some of our analyses that follow we use only data from public corporations. Table 4 shows that this sample is a good representative of the full sample given the amount of revenues it generates. Figure 2 illustrates our sample in time-series line plots. Figure 2A displays the average inflation-adjusted price per prescription for our full sample can be seen to monotonically increase over time. The differences between the states that adopted and the states that have not is small and starts to increase after 2014 to peak in 2017 to about $10. Since the difference in the ppp between branded and generic drugs is substantial, we break down our illustration to branded and generic. Figure 2B shows that post-2014, states that adopted the expansion are charged about $25 higher than states that have not adopted the expansion for branded drugs. This is economically significant since it accounts for 6.7% of our sample's branded avg ppp. Figure 2C Generic drugs appear to have not increased and slightly decreased over time.

Overall, these graphs suggest that states that have adopted expansion pay more for the same drugs than states that have not, especially for branded drugs.

Figure 2D shows the average number of prescriptions per year for our entire sample. This figure clearly depicts the shift in demand on our sample post-2014 in states that have adopted the expansion, while the decreasing in states that have not. This is consistent with our prediction that Medicaid expansion has caused an increase in the population covered by Medicaid which has led to a higher number of prescriptions being ordered after the adoption. The graph is also consistent with the existing evidence on reallocating federal grants to expansion programs Callaghan Jacobs (2013). This implies that states that have not accepted the expansion are losing on two fronts. The first loss is on the Medicaid expansion grants, and the second comes from the cuts to the other health-related grants. This is consistent with our results, as shown in Figure 2D, the average number of prescriptions significantly declined for non-adopting states over time. We further examine the number of prescriptions by branded vs generic and the results are reported in figures 2 E and 2 F. Both figures show a similar pattern in that the average prescription number increases significantly post-2014, and the opposite behavior is seen for states that do not adopt Medicaid expansion.

Overall, the graphs in figure 2 point out 2 interesting observations. First, the Medicaid expansion has clearly increased the demand on prescription drugs. This increase is more evident in the branded drugs relative to the generic drugs. Second, the expansion has also increased the cost of ppp, with this increase being more pronounced in branded relative to generics. On the one hand, the number of prescription results are consistent with our expectations and the notion of the expansion being a shock to the demand on pharmaceuticals. On the other hand, our results for ppp

are contrary to our expectations of the expansion giving states more negotiation power and leading to a decrease in price. We note that our data is on a pre-rebate basis, and most negotiation with the Medicaid state programs are on statutory rebates, therefore we cannot observe how much in rebates each state received. Perhaps the increase in ppp post-2014 in adopting states is due to pharmaceuticals adjusting prices in adoption states since they are now paying back more in rebates in those states.

B. Executive Compensation

We collect the executive compensation data from the Execucomp database on WRDS. We match the Execucomp data with our drug sales data set from above using the gvkey. We can match 23 CEOs and 23 CFO records over the period from 2010 till 2017 from 16 public corporations. Consistent with Mehran (1995), we construct three measures for executive compensation: (1) percentage of total compensation in grants of new stock options, with the options valued by the Black-Scholes formula, (2) percentage of total compensation that is equity-based, and (3) percentage of total compensation in salary plus bonus. The focus of our study is on the impact of the total salary structure measured as the size of each salary components proportion of the total

weight. We use CEOs for our main results, but also use CFO's data for robustness checks given that our sample of matched CEO's is rather small.

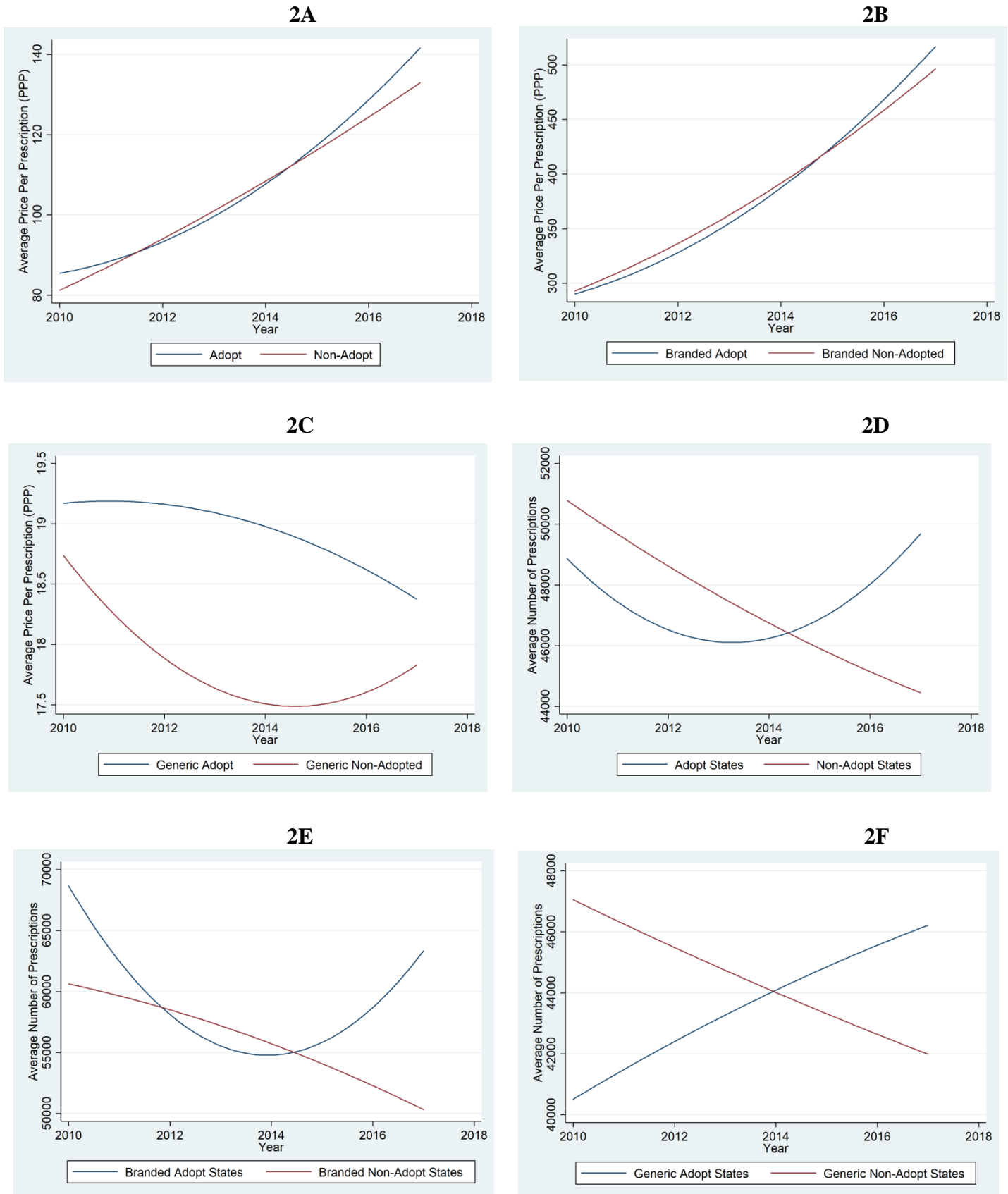**Figure 2:** Drug Price Distribution by Medicaid Adoption Over Time

Figure 3: Executive Compensation of Pharmaceutical Firms Over Time

3A

3B

3C

3D
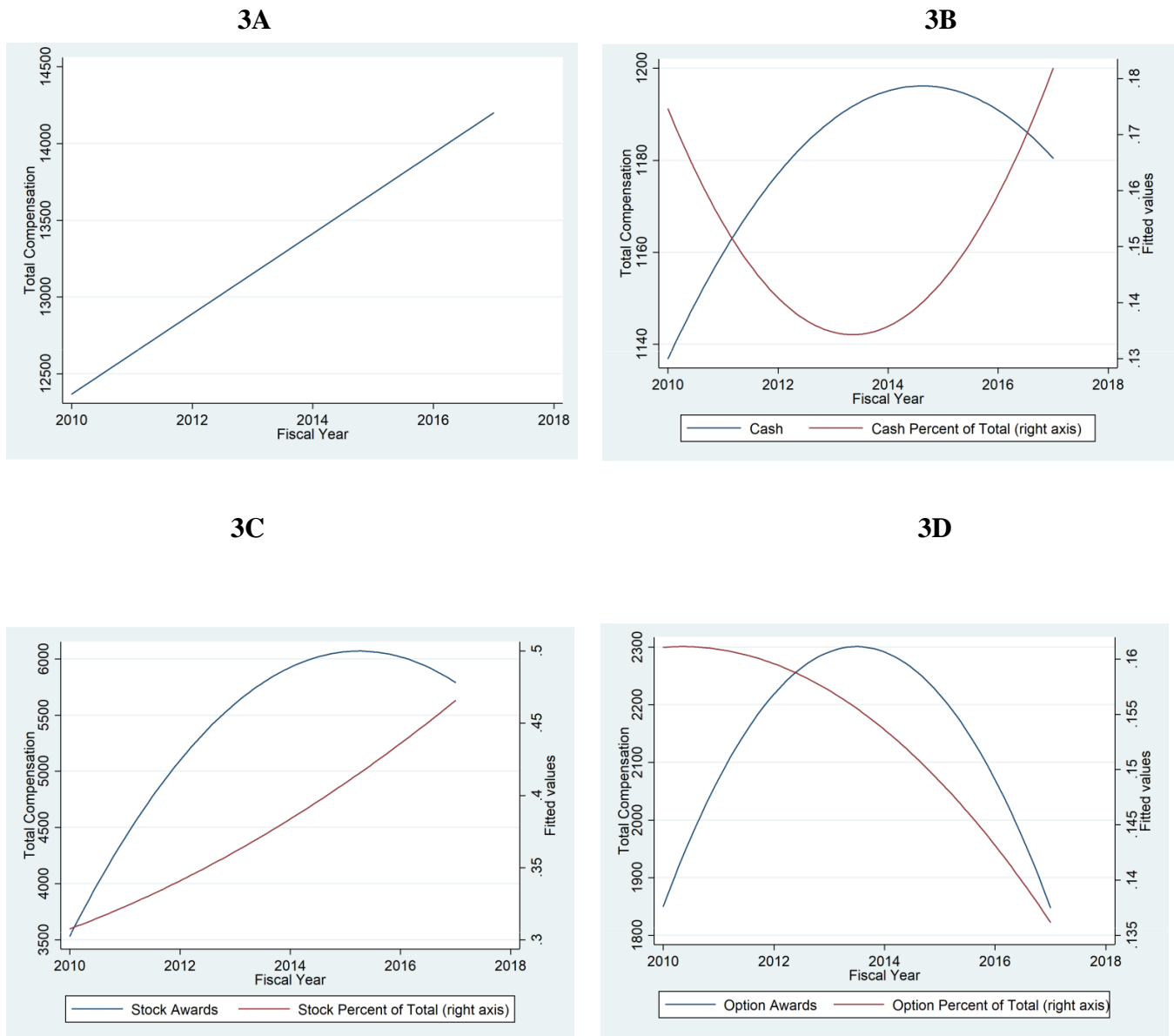
Table 4: Summary Statistics on Firm Drug Sales

This table provides summary statistics on the manufacturers of our sample's drugs. The table lists the names of the public corporations listed on either NYSE or NASDAQ in our sample. The table also lists the aggregated statistics for private and international drug manufacturers The revenues are reported for 2017 and are in thousands. # of branded/generic drugs is the number of drugs that are manufactured by the respective firm.

Name	Sample Total Revenues	# of Branded Drugs	Revenue from Branded	# of Generic Drugs	Revenue from Generics
AbbVie Inc	$ 325,000.00	3	$ 325,000.00	0	$ -
Aceto Corp	$ 865.19	0	$ -	2	$ 865.19
Adamis Pharm.	$ 725.90	0	$ -	6	$ 725.90
Allergan plc	$ 40,300.00	3	$ 39,900.00	1	$ 439.05
Akron Inc	$ 8,710.57	0	$ -	7	$ 8,710.57
Amgen	$ 189,000.00	2	$ 189,000.00	0	$ -
AstraZeneca plc	$ 190,000.00	3	$ 190,000.00	0	$ -
Bristol & Myers	$ 1,166.64	1	$ 1,166.64	0	$ -
Endo Pharm.	$ 11,300.00	1	$ 807.85	20	$ 10,400.00
Gilead Sciences	$ 215,000.00	2	$ 215,000.00	0	$ -
Glaxo Smith Kline	$ 403,000.00	11	$ 403,000.00	0	$ -
Johnson & Johnson	$ 28,000.00	1	$ 28,000.00	0	$ -
Lannett Company	$ 6,273.43	6	$ 6,273.43	0	$ -
Eli Lilly	$ 216,000.00	8	$ 216,000.00	0	$ -
Mallinckrodt PLC	$ 10,900.00	0	$ -	11	$ 10,900.00
Merck & Co	$ 204,000.00	4	$ 204,000.00	0	$ -
Mulan NV	$ 81,900.00	3	$ 37,700.00	42	$ 44,200.00
Novo Nordisk ADR	$ 255,000.00	5	$ 255,000.00	0	$ -
Novartis ADR	$ 76,500.00	6	$ 44,800.00	33	$ 31,700.00

Pfizer	$ 231,000.00	17	$ 229,000.00	2	$ 1,486.62
Perrigo Company	$ 20,400.00	0	$ -	18	$ 20,400.00
Pernix Therapeutics	$ 370.65	1	$ 370.00	0	$ -
Dr. Reddy's Lab.	$ 11,800.00	0	$ -	8	$ 11,800.00
Shire PLC ADR	$ 423,000.00	11	$ 423,000.00	0	$ -
Sanofi ADR	$ 328,000.00	2	$ 328,000.00	0	$ -
Taro Pharm.	$ 3,787.86	0	$ -	11	$ 3,787.86
Teva Pharm.	$ 116,000.00	2	$ 3,311.67	105	$ 112,000.00
Valeant Pharm.	$ 6,623.24	0	$ -	5	$ 6,623.24
Private Companies	$ 194,000.00	8	$ 159,000.00	26	$ 35,800.00
International Companies	$ 362,000.00	18	$ 297,000.00	60	$ 64,100.00
Total	**$ 3,960,623.47**	**118**	**$ 3,595,329.59**	**357**	**$ 363,938.43**

Studies that have examined the relationship between stock option awards and risk taking have introduced two conflicting hypotheses about its effect. The first hypothesis is the convexity effect, in which the salary of a CEO increases exponentially with the increase of stock price and therefore aligns the CEO's interest with the shareholders. Shue and Townsend (2017) provide causal evidence of option grants on risk taking and find a positive relationship. Shue and Townsend point out that when executives are awarded stock options their Black and Scholes value increases, as well as both the delta and vega, defined as the sensitivity of an executive portfolio of holdings

relative to the firm's stock price (volatility). Bakke et al., (2016) find causal evidence of a reduction in risk taking at oil and gas firms that reduced their stock options component of the CEO's compensations after the passing of FAS12R, their results also point to a positive relationship. On the opposite side of this hypothesis is the magnification effect posed by Ross (2004), where the relationship between option compensation and risk taking is negative. This effect is driven by the fact that options increase the sensitivity of an executive's wealth to the underlying stock price, which may lead a risk-averse executive to want to decrease risk.

In our design, we expect managers to maximize wealth of shareholders. A CEO can achieve higher market value by identifying and backing development of ground-breaking drugs, cost reduction through efficiency improvements, more effective advertising etc. But higher market value can also be achieved by jacking up prices for drugs that enjoy monopoly status. Exorbitant increases in drug prices increase revenue in the short term. However, they can also attract regulatory scrutiny and increase the risk of expensive lawsuits and reputation loss in the long term. We examine whether the compensation structure has an impact on a manufacturer's drug pricing. We hypothesize that firm's that award their CEOs with more stock options take more risks by raising drug prices to higher levels. We consider the price levels and not price growth levels because the reputation and litigation risk evidence are a focus of companies that raise prices to high levels. In other words, we examine whether stock option awards cause managers to raise prices to higher levels relative to CEOs with less stock options awards.

Table 5 provides the summary statistics of our executive compensation as well as board independence and corporate governance data. Total is the average total salary as reported to the SEC over the 8-year period. Salary and Bonus are the average cash components of the salary awarded. Options are the average stock option grants that are awarded whether vesting options or not. Stocks are the average stock awards. Ind Pct is the average percentage of independent director representation. G is the company's G-Index. The mean total salary for our sample is $13.2 million, and the median is very close at $13.7. Aceto Corp has the lowest average total salary in our sample across the 8 years at $1.7 million. Aceto has 2 generic drugs in our dataset that have generated $865 thousand. Johnson and Johnson have the highest average annual total salary in our dataset with $22.7 million. JNJ has one branded drug in our sample that generates $28 million dollars a year. All but two of the companies in our sample provide their CEOs with option compensation. The average annual stock option awards as a percentage of the total are about 18%. Our sample consists of 23 CEOs in 16 firms over 8 years, resulting in 114 executive-year observations. One pattern that is obvious: across the board, firms are on average awarding more of the stock awards component than either of both option awards and cash.

To understand better the distribution of the compensation structure of our sample we plot time-series line graphs of the compensation structure components. Figure 3A shows that the average total salary for firms in our sample has increased monotonically from 2010 to 2017, rising from

$12.5 million to about $14.5 million. We break down the total salary into its three components. Cash is shown in figure 3B left axis and is defined as the sum of basic salary and bonuses. The

Table 5: Summary Statistics on Firm Financial Characteristics

This table provides descriptive statistics on executive compensation of manufacturers of drugs within our sample. Total is the average total salary as reported to the SEC over the 8-year period. Salary and Bonus are the average cash components of the salary awarded. Options are the average stock option grants that are awarded whether vesting options or not. Stocks are the average stock awards. Ind Pct is the average percentage of independent director representation. G is the company's G-Index All dollar amounts are in thousands.

Stock Ticker	Total Salary	Salary	Bonus	Options	Stocks	Board Ind Pct	G Index
ABBV	$ 15,711.49	$ 1,294.24	$ 37.50	$ 1,953.93	$ 7,075.29	0.889	-
ACET	$ 1,726.69	$ 546.59	$ -	$ 33.44	$ 619.55	0.714	-
AGN	$ 13,588.90	$ 1,097.03	$ 417.08	$ 914.50	$ 6,254.92	0.875	11.00
AKRX	$ 4,154.55	$ 403.88	$ 158.30	$ 1,600.73	$ 1,068.69	0.712	-
AMGN	$ 16,302.53	$ 1,548.09	$ -	$ 1,767.68	$ 8,681.60	0.912	12.00
BMY	$ 16,699.10	$ 1,490.49	$ -	$ -	$ 10,134.97	0.796	8.00
ENDP	$ 12,368.47	$ 988.82	$ 500.00	$ 1,764.84	$ 4,874.86	0.891	5.00
GILD	$ 16,031.19	$ 1,517.98	$ -	$ 5,408.62	$ 5,897.66	0.844	9.00
JNJ	$ 22,723.34	$ 1,573.27	$ -	$ 3,700.69	$ 6,418.78	0.914	8.00
LCI	$ 1,798.16	$ 516.39	$ 101.44	$ 427.93	$ 357.82	0.622	-
LLY	$ 15,496.13	$ 1,487.50	$ -	$ -	$ 8,184.38	0.936	12.00
MNK	$ 9,958.43	$ 918.49	$ 25.00	$ 3,316.86	$ 4,211.31	0.905	-
MRK	$ 19,682.10	$ 1,555.70	$ -	$ 4,189.03	$ 7,056.45	0.917	8.00
MYL	$ 17,401.67	$ 1,339.29	$ 128.57	$ 3,565.70	$ 5,298.61	0.806	14.00

PFE	$ 21,839.51	$ 1,773.32	$ -	$ 5,883.60	$ 5,678.89	0.911	11.00
PRGO	$ 8,403.02	$ 926.97	$ 71.43	$ 1,071.14	$ 3,551.05	0.858	13.00
Mean	$ 13,212.36	$ 1,178.41	$ 90.33	$ 2,133.82	$ 5,282.67	0.85	11.28
Median	$ 13,713.25	$ 1,269.61	$ -	$ 1,456.64	$ 4,873.56	0.89	13.00
P25	$ 6,146.03	$ 825.00	$ -	$ -	$ 2,070.08	0.82	11.00
P75	$ 18,947.75	$ 1,513.07	$ -	$ 3,799.99	$ 7,999.91	0.89	13.00
N(exec-year)	114	114	114	114	114	93	75
Unique Firms	16	16	16	16	16	16	11

cash component increases initially, peaks in 2014, then slightly declines thereafter. The right axis shows cash as a percentage of total salary. We notice that in 2014, the year with the highest average cash compensation, the percentage of the total salary due to cash is at its lowest value at 13.5%. This counter-intuitive observation can be reconciled by the fact that there was high option and stock awards in 2014. Figure 3C left axis displays the stock awards over time. Stocks awards have increased significantly from $3.5 million in 2010 to $5.75 million in 2017. Figure 3C right axis shows that the percentage of stock awards of the total salary, is consistent with the increase of stock awards over time. Figure 3D right axis displays the change in option awards over time. Option awards peak in 2014 and drop to the same levels in 2017 as 2010. Figure 3D right axis shows that the percentage of option compensation has decreased over time from 16% to about 13.5%. These graphs demonstrate that in 2014 there was a significant increase in all components of the compensation structure. We speculate that the reason behind this increase may be related to the Medicaid expansion. We test this speculation below by regressing drug pricing on a 2-year lag of each component of the compensation drug.

C. Board Independence and Corporate Governance Data

The literature agrees about the impact of board independence on corporate decisions making. Bargeron and Zutter (2010) show that post Sarbanes Oxley Act of 2002, where most independent directors were required on the board of directors, corporate risk taking, in the form of investments and capital expenditures, decreased. Pathan (2009) finds that banks with independent boards take less risks. We expect independent managers to oppose increasing drug prices and keep a check on excessive risk taking or unethical price gouging by CEOs. We collect information about directors from the ISS Directors data base on WRDS. We use the common practice of taking the percentage of independent directors by dividing the number of independent directors by the total

number of directors. The ISS Directors data provides a classification variable that classifies directors as independent, employee or linked. We hypothesize that firms with a higher percentage of independent board members are less likely to aggressively raise prices.

Table 5 shows the average distribution of the percentage of board independence within our sample. The sample ranges from a 62.2% for Lannett Company to 93% for Eli Lily. The variation in the independence of the board is relatively small, as the percentage of independent directors in the board of directors has increased post Sarbanes and Oxley Act of 2002. Studies that usually use board independence as a main descriptive variable include sample pre and post Sarbanes and Oxley Act which provides significant variation for board independence. This issue pushes us to take the results of our analysis related to independent boards with a grain of salt. Figure 3E shows the change of the board independence over time. The variation is very small with a range from 87.4% to 84%.

We collect the corporate governance data from the ISS Governance data base on WRDS. This data provides the well-known corporate governance measure introduced by Gompers et al., (2003) known as the G-Index. This index ranges from 0 to 16, where firms with good shareholder rights having a low G-Index, and vice versa for firms with poor shareholder rights. One drawback of using this data is that it was discontinued in 2006 due to a regulatory change that made it difficult to calculate. This drawback results in a failure to account for firms that improve their shareholder rights over time, and therefore the results obtained in this section may not be accurate. We hypothesize that firms with lower G-Indexes are less likely to raise prices aggressively relative to firms with higher G-Indexes. Table 5 shows the sample is comprised of companies that have poor shareholder with relatively high G-Indexes.

METHODOLOGY AND EMPIRICAL DESIGN

In this section we define the variables that are used in the analysis. Next, we discuss the validity of the Medicaid expansion as a shock to the demand on pharmaceuticals. Finally, we describe the regression models that we test.

A.   Variable Definition

We define the following variables for the analyses that follow in section VI:

adopt: this is a dummy variable equal to one if at any point in time the state adopts Medicaid expansion, and zero for the pseudo-matched control state.

expansion: this is a time-sensitive dummy variable equal to one for both the treatment and control states *after* the treatment state adopts the expansion, and zero before the adoption. The difference between this variable and the adopt variable is that adopt is equal to one for all years of the treatment state, whereas this variable is equal to one for the treatment and the pseudo-matched control states for years only when they have adopted Medicaid. More about the matching procedure below.

interaction: this variable is the interaction between adopt and expansion. When equal to one this variable means that the observation is within a state that adopted Medicaid after or in 2014. This will be one of our main regressors. When used along with interactionbranded, this variable usually measures the impact of the generic observations since this will be the base group.

interactionbranded: this is a triple interaction between adopt, expansion, and branded variable. When this variable is equal to one, the observation is in a state that adopted the expansion, the observation is on or after 2014, and it is for a branded drug.

branded: this is a dummy variable equal to one if the drug is a brand name, and zero if the drug is a generic.

adoptedbranded: this is an interaction variable between adopted and branded. When this variable is equal to one, the observation is in a state that adopted the expansion and is for a branded drug.

expansionbranded: this is an interaction variable between expansion and branded. When this variable is equal to one, the observation is for a date on or after 2014 and is for a branded drug.

ffsuproportion: this is a variable with values between 0 and 1 and is the proportion of the observations that are fee-for-service relative to all observations for a particular drug.

percentageoptions: this is a variable with values between 0 and 1 and is the proportion of the total CEO's compensation that is due to options.

independent: this is a variable with values between 0 and 1 and is the proportion of the total board members that are independent.

GIndex: this is the G-Index of a firm.

score: Score is a measure of a state's openness and infrastructure readiness for Medicaid service. This measure is introduced by Callaghan and Jacobs (2013) and ranges from -4 (e.g., Wisconsin and Maine) to 7 (e.g., New York and Nevada).

mednum: number of people in a state covered by Medicaid.

uninnum: number of people in a state not covered by insurance.

optioncompceo: this is the percentage of options awards of the total pay. This variable ranges between zero and one and is calculated on an annual basis. We use this variable with two- and one-year lags.

cashcompceo: this is the percentage of cash awards of the total pay. This variable ranges between zero and one and is calculated on an annual basis. We use this variable with two- and one-year lags. *stockawardspctceo*: this is the percentage of stock awards of the total pay. This variable ranges between zero and one and is calculated on an annual basis. We use this variable with two- and one-year lags.

optbrandceo: this is the interaction of optioncompceo and branded. It captures the impact of option compensation on pricing of branded drugs. The base variable would be optioncomceo capturing the generic pricing impact.

cashbrandceo: this is the interaction of cashcompceo and branded. It captures the impact of cash compensation on pricing of branded drugs. The base variable would be cashcompceo capturing the generic pricing impact.

cashbrandceo: this is the interaction of stockawardspctceo and branded. It captures the impact of stock compensation on pricing of branded drugs. The base variable would be stockawardspctceo capturing the generic pricing impact.

B.   *Understanding the Shock*

In this section we conduct a regression analysis to determine the validity of the Medicaid expansion as a shock to the demand on pharmaceutical products and discuss the results. Our empirical setting will be a difference-in-differences between the average number of prescriptions in a quarter for states that adopted the expansion and states that have not. We assume our comparison is valid given that both types of states have equal populations. We expect that the number of prescriptions will increase more for expansion states than non-expansion states. Ghosh et al., (2017) Precisely examine this issue but with a different dataset. They use a proprietary database that contains all-payer pharmacy transactions to examine the effect on overall prescription utilization "as well as effects within specific drug classes." They find that "Medicaid-paid prescription utilization increased by 19% in expansion states relative to states that didn't expand." They note that the greatest increases were attributed to diabetes, contraceptives, and cardiovascular drugs. We use drugs from these 3 categories in our sample, although at smaller proportions. We employ the methodology in Ghosh et al., (2017) and model the prescription number as a raw figure as well as a natural logarithm. Our results are consistent with theirs in the increase in demand.

Table 6 shows the results of this difference-in-differences analysis. The first two columns use the interaction variable as the main regressor. Interaction is the interaction between expansion and adopted. In the first column, the raw number of prescriptions per quarter is regressed on our expansion-related variables. The prescription number in expanding states post-adoption is 159.4 prescriptions more than states that have not. This number is statistically significant at the 1% and economically significant at 10% of the grand mean, and 33% of the median, of the number of prescriptions in our sample. The population covered by Medicaid increases the average number of prescriptions 4 prescriptions every 10 thousand new members. The variable expansion is negative which implies that overall, the number of prescriptions has decreased on or after 2014. This is driven by the reduction of the number of prescriptions in the states that have not adopted. Adopted is also negative and large in magnitude implying that the states that adopted had much smaller demand on prescriptions before the expansion. Score is positive and significant implying that with each increase in the score of Medicaid openness the higher the number of prescriptions. The number of prescriptions of branded drugs is higher than the number of prescriptions for generics.

The second column uses the natural logarithm of the number of prescriptions instead. The results are like the first column in terms of statistical and economic significance. The difference is for the unemployment percentage of the total population variable becomes significant and negative. This specification yields a substantially higher R-squared relative to the first column. We suspect that this is due to the natural logarithm smoothing out the highly dispersed data. Columns 3 and 4 include both main regressors, interaction and interactionbranded. Interactionbranded is the triple interaction between expansion, adopted, and branded. This variable has a negative but insignificant coefficient. The interaction variable is now picking up the effect for the generic drug and has increased after taking branded out of it. Our fourth column demonstrates this relationship clearly with the interactionbranded variable now significant at the 1% and negative. All our regressions include year, state, and therapy fixed-effects.

The results imply that the expansion has significantly increased the demand on prescription drugs within states that have adopted the expansion, however, the increase has only affected the

Table 6: Multivariate Analyses of Drug Prescriptions Conditional on Adoption

This table provides regressions of the number of prescriptions on Medicaid expansion variables. In each column, the dependent variable is listed as the heading. All variables are defined in section V.A. Standard errors are reported in parentheses. Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	prescript # (1)	LN (prescript) (2)	prescript # (3)	LN (prescript) (4)
interaction	159.4***	0.117***	171.5***	0.149***
	(35.09)	(0.00925)	(37.11)	(0.00978)
interactionbranded			-48.70	-0.127***
			(48.35)	(0.0127)
mednum	0.000388***	3.72e-07***	0.000388***	3.72e-07***
	(9.48e-06)	(2.50e-09)	(9.48e-06)	(2.50e-09)
uninnum	8.39e-06	-2.11e-07***	8.40e-06	-2.11e-07***

	(1.98e-05)	(5.21e-09)	(1.98e-05)	(5.21e-09)
expansion	-155.4***	-0.0660***	-155.5***	-0.0661***
	(47.33)	(0.0125)	(47.33)	(0.0125)
adopted	-1,566***	-1.984***	-1,566***	-1.984***
	(70.38)	(0.0186)	(70.38)	(0.0186)
score	62.37***	0.0175***	62.37***	0.0175***
	(7.890)	(0.00208)	(7.890)	(0.00208)
branded	369.6***	0.0397***	379.9***	0.0666***
	(25.12)	(0.00662)	(27.13)	(0.00715)
Constant	1,209***	6.830***	1,207***	6.824***
	(189.7)	(0.0513)	(189.7)	(0.0512)
Observations	238,792	238,792	238,792	238,792
R^2	0.123	0.489	0.123	0.489
Year FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Therapy FE	YES	YES	YES	YES

generic drug prescription numbers: at most, the branded drug prescription numbers didn't increase. This result suggests that Medicaid expansion increased accessibility to generic drugs. Our results are consistent with Ghosh et al., (2017); they find a 0.103 coefficient on their "Post X Expansion" variable, we find a 0.117 on our interaction variable. These results provide evidence for the Medicaid expansion as a shock to the demand on pharmaceuticals.

C. *Empirical Design*

We use a difference-in-differences for the identification of our hypotheses. The adoption of expansion states did not happen for all at the same time, instead in different years (2014, 2015 and 2016). Therefore, we don't have a fixed before and after period. We fix this issue by using a pseudo matching of states. This is the expansion variable. If we designate a control state C1 to a treated

state T1 then, the Expansion dummy variable will take a value of 0 for both state T1 and state C1 before the expansion date (which will be 2014 or 2015 or 2016 depending on the treated state) and value of 1 after expansion date for both T1 and C1. The same applies to the other 7 treated states. This is not true matching procedure because we don't directly calculate any difference in prices between control and adoptive states. All we do is create a sample in which each adopting state's before and after period is mirrored by one control state's pseudo before and after period. Then we define an interaction term which is Adopt x Expansion. The regression coefficient on this interaction term will effectively be our differences in differences test. We use this as our main regressor variable in our analyses below.

We hypothesize that states that expand will have more leverage in their negotiations with the manufacturers and thus get a lower price (or better statutory rebates). To find this we use the following regression model:

$$log(ppp)_{i,\,t} = \alpha + \beta_1 interaction_{it} + \beta_j controls + it \qquad (1)$$

Controls are adopted, expansion, adoptedbranded, branded, proportion ffsu, expansionbranded, score, mednum, uninnum, year FE, state FE, and therapy FE. Our main coefficient of interest here is the β_1 which is the difference in difference variable, i.e., the difference in the log(ppp) between states that adopt before and after adoption subtracted by the difference in the log(ppp) for the states that do not adopt. To understand better the impact of the expansion on drug price setting we add a variable to distinguish the prices of generic from branded drugs. We use equation 1 above with the generic drugs as the base group and add a triple interaction between expansion, adopted, and branded. This is displayed in the following regression equation:

$$log(ppp)_{i,\,t} = \alpha + \beta_1 interaction_{it} + \beta_2 interactionbranded_{it} + \beta_j controls + it \,_{(2)}$$

We follow the literature in constructing equation 2 above. Berndt 2002 and Grabowski et al., 2013 discuss pricing in pharmaceuticals drugs and find that brand names that are significantly better than the alternatives and are on patent have the highest flexibility in setting prices. Our data does not provide patent dates, and drug effectiveness relative to the alternatives. We use whether a drug is a branded or generic to make this distinction. We use the control variables used by Ghosh et al., (2017).

To construct our executive compensation regressions, we follow the literature in examining the impact of lagged compensation structure on corporate decisions (Shue and Townsend (2017), Mehran (1995), Bakke et al., (2016). We add all three components of compensation in our regressions, namely, cash, stocks, and options. These variables are in percentage form because we are interested in the structure of compensation and not in the levels of compensation. We include these three compensation components interacted with branded. This is to distinguish the impact of a compensation structure on brand versus generic drug pricing of manufacturers.

$$log(ppp)_t = \alpha + \beta_1 \%option_{it-n} + \beta_2 \%cash_{it-n} + \beta_3 \%stocks_{it-n} + \beta_k INTERACTIONS_{it-n} + \beta_j controls_t + it \qquad (3)$$

Where INTERACTIONS is a vector of interaction variables between each of the three compensation components and branded: optionbranded, cashbranded, and stockbranded. Controls are the same controls from Ghosh et al., (2017). N is alternated between 1 and 2 in our regressions.

For our board independence and corporate governance analyses, we use equation 3 above and add Indpct and GIndex variables. These variables are current and not lagged. Indpct is the percentage of independent directors on the board, and GIndex is Gompers et al., (2003)'s corporate governance measure based on the rights of shareholders of a firm.

RESULTS

In this section we preview and discuss our main results. In the first part we examine the impact of our expansion variables on drug pricing. Next, we investigate whether the compensation structure of a CEO can impact the manufacturer's drug pricing. Finally, we determine whether board independence and corporate governance have an impact on drug prices in our sample.

A. Medicaid Expansion and Drug Pricing

Table 7 shows our results for the difference-in-differences regression analysis. We report both OLS and double-clustered results. The double clustering is at the quarter (32 clusters) and state (16 cluster). All OLS results include Year FE, State FE, and Therapy FE. For our dependent variables we use ppp (columns 1 and 2) and the natural logarithm (columns 3 and 4). Our first column shows that branded drugs were priced on average $15.49 higher in expansion states. This difference is statistically significant at the 5% level and economically significant at 5% value of the mean of branded drugs. Branded drugs were priced $294.5 higher than generic drugs on average. Branded ppp have increased $86.1 more on years post expansion relative to pre-expansion. On the other generic drug prices are not different from zero in statistical significance. The coefficient is positive which is what we would expect but the change is not significant. The second column includes our FE variables to control for the unobservable factors in our panel. This model can explain more of the variation of ppp with an R-squared of 61.4%. This provides stronger evidence that the price of branded drugs in our sample has significantly increased in states that have adopted expansion relative to states that have not. Score is now significant at the 1% level and suggests that states that score higher on a measure of how open and equipped is a state to Medicaid services pay $2 more for each unit of the measure. Generic ppp are also positive but insignificant in this specification.

We rerun these regressions using the natural logarithm of ppp as the dependent variable since ppp is a highly volatile variable, we attempt to smooth out our data and examine the results. Column 3 shows our double-clustered regressions. Using Petersen (2009)'s code on Stata we run a double clustered regression using quarter-year and state as our clusters. Three of our variables are now omitted due to high multi-collinearity. These results suggest that ppp has not significantly

increased in expansion states relative to states that have not expanded. Both coefficient for generic and branded ppp are positive. Our fourth column includes our FE variables and provides similar evidence. In column 4 some of the variables become significant at the 1% level. States that have adopted have higher generic ppp than states that have not before the expansion. This could explain why the variable interaction, which captures the impact of the expansion on generic ppp, is statistically insignificant. This could be because generic drugs were already relatively higher before the expansion for expansion states and there was no possibility for further increase. Expansion variable is suggesting that for the post expansion period generic ppp's have decreased between all states on average. Proportionffsu is a percentage of the fee for service relative to the combined provided service for both fee for service and managed care plan. The negative coefficient on proportionffsu suggests that Medicaid pays more for prescription drugs through managed care plans than for fee for service transactions. expansionbranded variable suggests that branded ppp's have increased post-expansion for all states. The signs on the coefficients on mednum and uninnum are consistent with the literature. uninnum suggests that states with more uninsured individuals have slightly higher ppp.

Table 7: Multivariate Analyses of Drug Prices Conditional on Adoption

This table provides the regressions of the PPP and natural logarithm of PPP on our expansion-related variables. All variables are defined in section V.A. Standard errors are reported in parentheses. Statistical significance is indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

	PPP	PPP	LN(PPP)	LN(PPP)
	(1)	(2)	(3)	(4)
interaction	0.205	0.918	0.0133	0.00924
	(3.441)	(2.333)	(0.0836)	(0.00837)
interactionbranded	15.49**	15.77***	0.0210	0.0159
	(6.879)	(4.611)	(0.0699)	(0.0165)
adopted	-0.998	-8.762**	0.0283	0.595***
	(2.629)	(4.142)	(0.111)	(0.0149)
expansion	-1.000	-28.48***	-0.0331	-0.171***
	(2.461)	(2.848)	(0.0521)	(0.0102)
adoptedbranded	-2.937	-3.067		-0.0160

	(4.480)	(3.003)		(0.0108)
branded	294.5***	162.5***	2.249***	1.781***
	(3.174)	(2.309)	(0.0582)	(0.00829)
proportionffsu	1.204	2.157		-0.0517***
	(3.062)	(4.265)		(0.0153)
expansionbranded	86.10***	86.33***		0.310***
	(4.867)	(3.262)		(0.0117)
score	0.240	2.167***	0.00890	-0.0411***
	(0.244)	(0.463)	(0.00959)	(0.00166)
mednum	3.11e-08	-6.17e-07	-4.17e-09	-3.57e-08***
	(6.31e-07)	(5.58e-07)	(2.44e-08)	(2.00e-09)
uninnum	-1.69e-06	-5.32e-07	4.90e-08	3.50e-08***
	(1.38e-06)	(1.18e-06)	(5.08e-08)	(4.22e-09)
Constant	18.78***	-180.4***	2.255***	1.199***
	(3.235)	(12.24)	(0.160)	(0.0439)
Observations	238,792	238,792	238,792	238,792
R^2	0.141	0.614	0.461	0.677
Year FE	NO	YES	NO	YES
State FE	NO	YES	NO	YES
Therapy FE	NO	YES	NO	YES
Double-Clustered SE	NO	NO	YES	NO

Overall, our results are not unequivocal. On the one hand, the level of ppp provides significant evidence that branded drugs have increased their ppp's in expansion states relative to states that have not adopted. On the other hand, using logged data, we find no evidence of a significant increase in the ppp of branded or generic drugs. Our results are suggestive and do not imply causality.

B.   *Compensation Structure and Drug Pricing*

Table 8 provides the results of our regression of ppp (and LN (ppp)) on one and two lags of the compensation structure variables. We include the three variables of compensation structure, namely optioncom-pceo, cashcompceo, and stockawardspctceo. We also include these three variables each interacted with branded. This allows us to examine the impact of compensation structure on generic ppp and branded ppp separately. Columns 1 and 2 show these results for ppp. Both one and two lags in years yield similar results. The percentage of stock awards has a statistically and economically significant coefficient. A 1% increase in stock compensation is associated with a $0.609 decrease in the price of generic ppp. For branded drugs, stock awards have the opposite impact in that they are associated with price increases. A 1% increase in stock awards is associated with a $1 increase in brandname ppp. Option awards don't have an impact on ppp for generic drugs, however, for branded drugs, a 1% increase in option awards decreases the branded ppp by about $3. Cash compensation show results with weak significance with negative coefficients. Both one lag and two lags of the ppp provide similar results. Two lags seem to be doing a better job of describing the variation because of the higher R-squared.

Columns 3 and 4 report the results from reruns of the same regressions in columns 1 and 2 only using the natural logarithm of ppp as the dependent variable. The results are similar to the results from the raw ppp regressions; however, the compensation structure variables are now statistically significant at the 1% level. On the one hand, option awards are associated with higher generic LN (ppp), but lower branded LN (ppp). On the other hand, cash and stock awards exhibit the opposite association with LN (ppp); they are associated with lower generic ppp, and higher branded ppp.

Overall, our evidence suggests that the compensation structure for a CEO may influence their decision when setting the price of drugs. Generic drug prices are relatively low and room to increase prices is usually limited because of the high competition Grabowski and Vernon (1992). Our results for the impact of option awards on the ppp of branded drugs is contrary to our expectations. Option awards cause managers to reduce their drug prices. This could be induced by the high costs and reputation damage of the potential litigation risk pursuant to drug price increases. We point out that each firm awards all three components simultaneously. Studies in this literature calculate vega and delta of a firm to measure the impact of the combined compensation on risk taking of a CEO (Shue and Townsend 2017, Bakke et al., 2016). We don't use the typical difference in differences setting here due to the small sample size; we lose significant sample size when we only use observations around the expansion.

C.   *Board Independence and Corporate Governance*

Table 9 displays our regressions that include the board independence and GIndex variables. We include the twice-lagged compensation structure variables since they had stronger results relative to the single lag. Using ppp as the dependent variable our model yields the highest R-square for all specifications describing the variation in ppp. In the raw ppp, the independence variable is not significant. The GIndex is significant and positive. This suggests that companies with weaker shareholder rights tend to increase prices more than companies that have better shareholder rights. This suggests that corporate governance can help with the excessive drug pricing of manufacturers. The second column uses LN (ppp) as the dependent variable. In this setting indpct variable is significant and positive. This suggests that more independent boards raise prices on average more than other companies.

Table 8: Multivariate Analysis of Drug Prices Conditional on Executive Compensation

This table provides the regressions of the PPP and natural logarithm of PPP on the compensation structure variables. All variables are defined in section V.A. L2 indicates a two-year lag, and L indicates a one-year lag. Standard errors are reported in parentheses. Statistical significance is indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	PPP	PPP	LN(PPP)	LN(PPP)
	(1)	(2)	(3)	(4)
L2. optioncompceo	19.89		0.202***	
	(15.23)		(0.0503)	
L2. cashcompceo	-18.58		-0.274***	
	(29.21)		(0.0964)	
L2. stock_awardspct_ceo	-60.91***		-0.306***	
	(14.86)		(0.0491)	
L2. cash_brand_ceo	-82.31*		0.158	
	(43.12)		(0.142)	
L2.opt_brand_ceo	-294.7***		-1.321***	
	(40.08)		(0.132)	

L2. stock_brand_ceo	108.3***		0.661***	
	(28.30)		(0.0934)	
L.optioncompceo		18.97		0.174***
		(17.00)		(0.0409)
L.cashcompceo		-31.63		-0.270***
		(32.57)		(0.0783)
L.stock_awardspct_ceo		-67.15***		-0.296***
		(16.57)		(0.0399)
L.cash_brand_ceo		-84.44*		0.187
		(48.12)		(0.116)
L.opt_brand_ceo		-328.2***		-1.231***
		(44.74)		(0.108)
L.stock_brand_ceo		114.9***		0.667***
		(31.58)		(0.0759)
Constant	14.84	16.54	2.839***	2.838***
	(19.00)	(21.15)	(0.0627)	(0.0509)
Observations	33,384	50,147	33,384	50,147
R^2	0.692	0.551	0.683	0.684
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 9: Multivariate Analysis of Drug Prices Conditional on Executive Compensation and Corporate Governance

This table provides the regressions of the PPP and natural logarithm of PPP on the compensation structure variables, board independence percentage, and GIndex. All variables are defined in section V.A. L2 indicates a two-year lag, and L indicates a one-year lag. Standard errors are reported in parentheses. Statistical significance is indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

	PPP	LN(PPP)
	(1)	(2)
L2. optioncompceo	19.65	0.432***
	(18.72)	(0.0763)
L2. cashcompceo	-53.97	-0.994***
	(45.13)	(0.184)
L2. stock_awardspct_ceo	-58.38***	-0.136*
	(18.85)	(0.0768)
L2. cash_brand_ceo	450.9***	3.405***
	(82.08)	(0.334)
L2.opt_brand_ceo	-367.3***	-2.220***
	(39.61)	(0.161)
L2. stock_brand_ceo	204.6***	0.223*
	(30.72)	(0.125)
ind_pct	26.80	0.703***
	(65.60)	(0.267)
gindex	398.1***	0.636***
	(2.362)	(0.00962)

Constant	-2,004***	-1.527***
	(69.52)	(0.283)
Observations	25,357	25,357
R^2	0.778	0.680
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes

We take caution when interpreting the results in this section for two reasons. First, the variation in the independent board percentage variable is very small and belongs to 16 unique companies. This small variation is problematic when identifying an effect and may lead to spurious findings given the high autocorrelation of the dependent variable. Second, the G-Index data dates to 2006 and has not been updated and is only comprised of 12 unique firm. There is very little power in the G-Index tests.

CONCLUSION

This paper addresses an under-represented area in finance; the role of firm financial characteristics on real outcomes in the health sector, and more specifically in the pharmaceutical and biological technology industry. We examine the impact of the Medicaid expansion program, as well as the impact of executive compensation and corporate governance, on drug pricing. Consistent with previous findings, we find an increase in the demand on pharmaceutical products in states that adopted the expansion relative to states that have did not adopt. Furthermore, the prices of branded drugs in the expansion adopting states are higher, on average, than in states that have not adopted the expansion. Finally, we find that option awards are associated with lower branded drug prices and higher generic drug prices. Which provides evidence for the magnification effect presented by Ross (2004). In addition, board independence has no statistically significant impact on drug prices, and weaker shareholder rights is associated with higher drug pricing. We caution readers that our results are suggestive and should be interpreted cautiously.

The findings of this paper provide several insights that can help guide policy for lawmakers and executives. First, the variation in prices of the same drug across adopting and non-adopting states may be of particular interest to policy makers who wish to optimize public spending efficiency. Second, the evidence for the magnification effect of stock options may help inform corporate boards – that want to strike a healthy balance between competitive pricing and maximizing shareholder wealth - in setting executive compensation plans that achieve optimal product pricing. Finally, the relationship between shareholder rights and drug prices may inform

the relevant authorities on the factors contributing to rising drug prices that are related to firm characteristics.

Future studies can exploit the presence of the NDC-to-ATC crosswalk to granularly define the product market of each drug and include competition and portfolio similarity between pharmaceutical companies to answer corporate finance research questions at granular depth. Furthermore, the FDA provides several data files that identify the patent status, and the regulatory approval status (e.g., breakthrough therapies, priority review program…etc.) of a drug which would help characterize product's competition, quality and innovativeness.

REFERENCES

Baily. Martin Neil. (1972). *Research and Development Costs and Returns: The U.S. Pharmaceutical Industry.* Journal of Political Economy.

Bakke. Mahmudi. Fernando, and Salas. (2016). *The Causal Effect of Option Pay on Corporate Risk Management.* Journal of Financial Economics.

Bargeron, Lehn, and Zutter. (2010). *Sarbanes-Oxley and Corporate Risk-taking.* Journal of Accounting and Economics.

Berman, Aaron, Theodore Lee. Adam Pan, Zain Rizvi, and Arielle Thomas. (2017). *Curbing Unfair Drug Prices: A Primer for States.* Yale Law School.

Berndt, Ernst R. (2019). *Pharmaceuticals in U.S. Health Care: Determinants of Quantity and Price.* Journal of Economic Perspectives.

Bonaime, Alice A. and Wang, Ye. (2019) *Mergers, Product Prices, and Innovation: Evidence from the Pharmaceutical Industry.* SSRN.

Chen, Steiner, and Whyte. (2006). *Does Stock Option-based Executive Compensation Induce Risk-taking? An Analysis of the Banking Industry.* Journal of Banking and Finance.

Dimasi, Grabowski, and Hansen. (2016). *Innovation in the Pharmaceutical Industry: New Estimates of R&D Costs.* Journal of Health Economics.

Ghosh, A., Simon, K., & Sommers, B. D. (2017). *The effect of state Medicaid expansions on prescription drug use: evidence from the Affordable Care Act (No. w23044).* National Bureau of Economic Research.

Gompers, Paul, Ishi, Joy, and Metrick, Andrew. (2003). *Corporate Governance and Equity Prices.* The Quarterly Journal of Economics.

Grabowski, Henry. (2002). *Patents, Innovation and Access to New Pharmaceuticals.* Journal of International Economic Law.

Grabowski, Henry G. Margaret Kyle, Richard Mortimer, Genia Long, and Noam Kirson. (2011). *Evolving Brand-name and Generic Drug Competition May Warrant a Revision of the Hatch-Waxman Act.* Health Affairs.

Grabowski, Henry, and John Vernon. (1992). *Brand Loyalty, Entry, and Price Competition in Pharmaceuticals after the 1984 Drug Act.* Journal of Law and Economics.

Hammoudeh, Mosab and Nain, Amrita. (2019). *Seeking Efficiency or Price Gouging? Evidence from Pharmaceutical Mergers*. SSRN.

Garfinkel, Jon A. and Hammoudeh, Mosab. (2020). *Competition and Innovation Revisited: A Product-Level View*. SSRN.

Jacobs, Lawrence R., and Timothy Callaghan. (2013). *Why states expand Medicaid: Party, resources, and history.* Journal of Health Politics, Policy and Law.

Manso, Gustavo. (2011). *Motivating innovation.* Journal of Finance.

Mehran, Hamid. (1995). *Executive Compensation Structure, Ownership, and Firm Performance.* Journal of Financial Economics.

Pathan. Shams. (2009). *Strong Boards, CEO Power and Bank Risk-taking*. Journal of Banking and Finance.

Ross, Stephen A. (2004). *Compensation, Incentives, and the Duality of Risk Aversion and Riskiness.* Journal of Finance.

Shue, Kelly. and Townsend, Richard. (2017). *How Do Quasi-Random Option Grants Affect CEO Risk-Taking?* The Journal of Finance.

Mitchell A. Petersen. (2009*). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches.* The Review of Financial Studies.

Young, Katherine, and Rachel Garfield. (2018). *Snapshots of Recent State Initiatives in Medicaid Prescription Drug Cost Control*. The Henry J. Kaiser Family Foundation