DOES MEDICARE REIMBURSEMENT DRIVE UP DRUG LAUNCH PRICES?

David B. Ridley and Chung-Ying Lee*

Abstract—Medicare reimburses health care providers for the drugs they administer. Since 2005, it has reimbursed based on the past price of the drug. Reimbursement on past prices could motivate manufacturers to set higher launch prices because providers become less sensitive to price and because provider reimbursement is higher if past prices were higher. Using data on drug launch prices between 1999 and 2010, we estimate that reimbursement based on past prices caused launch prices to rise dramatically. The evidence is consistent with the 2018 claim from Medicare's administrator that it "creates a perverse incentive for manufacturers to set higher prices."

I. Introduction

In the past decade, launch prices for some drugs, especially cancer drugs, have been much higher than earlier generations of the drugs (Howard et al., 2015). One cause for high drug prices in the United States could be the way Medicare pays health care providers. According to a 2018 speech by the head of the Centers for Medicare and Medicaid Services, "Medicare pays Part B providers for drugs at an amount equal to the average price the drug sells for plus a six percent add-on fee. This payment structure creates a perverse incentive for manufacturers to set higher prices" (Verma, 2018). Private insurers often mimic Medicare (Clemens & Gottlieb, 2017), so the policy affects Medicare and private insurers.

We investigate whether the 2005 change to reimbursement based on past prices caused an increase in launch prices. We compare drug launch prices before and after the reimbursement change. We use launch-price variation within a molecule for drugs launching different dosage forms of the same molecule in different years. We also use launch-price variation across molecules for drugs in the same class. Finally, we compare launch prices for drugs reimbursed under different payment mechanisms. For some drugs, including retail drugs and some provider-administered drugs, Medicare reimbursement did not change to a markup on the average sales price, and these drugs function as a control group.

Medicare and other insurers do not directly pay drug manufacturers. Instead, Medicare reimburses health care providers that administer the drugs. The way in which an insurer like Medicare reimburses a health care provider influences the price that the drug manufacturer charges the provider (see figure 1).

Received for publication June 18, 2018. Revision accepted for publication April 15, 2019. Editor: Amitabh Chandra.

*Ridley: Duke University; Lee: National Taiwan University.

We are grateful for helpful comments from Peter Arcidiacono, Ernst Berndt, Colleen Carey, David Howard, Eli Liebman, Ryan McDevitt, and Su Zhang, and seminar participants at Duke University, Emory University, and Yale University. We also thank participants at the Congressional Budget Office annual meeting, the International Health Economics Association Congress, the International Industrial Organization Conference, the Life Sciences Symposium, and the Shanghai University of Finance and Economics Industrial Organization Conference.

A supplemental appendix is available online at http://www.mitpressjournals.org/doi/suppl/10.1162/rest_a_00849.

Before 2005, Medicare paid health care providers an amount largely unrelated to the actual price. Medicare-reimbursed providers based on AWP, which officially stood for average wholesale price but was widely known as "ain't what's paid." Beginning in 2005, Medicare reimbursed providers based on average sales price (ASP) (Jacobson et al., 2010; Yurukoglu, Liebman, & Ridley, 2017). ASP is the average price of purchases made by providers in the previous six months. Hence, in 2005, reimbursement changed from an amount unrelated to the actual price to an average of lagged prices.

Because some of the effects of the reimbursement mechanism are subtle, we use a model to provide intuition. In the model, we show that when insurers reimburse providers based on lagged prices, manufacturers choose a high launch price for two reasons. The first reason is straightforward: providers are less sensitive to the price when reimbursement covers a portion of the price. The second reason is subtle: a provider's current reimbursement depends on past prices. Hence, while a provider prefers low current prices, the provider prefers high past prices because the insurer pays the provider more when past prices are higher. Hence, firms "invest" in a high launch price, higher than the profit-maximizing current price, in order to secure higher reimbursement for the provider in the future. By setting a higher launch price, the future reimbursement is higher, so future demand is higher, and the firm can charge a higher price in the future. We illustrate these effects using a model of reimbursement in a market with rising willingness to pay.

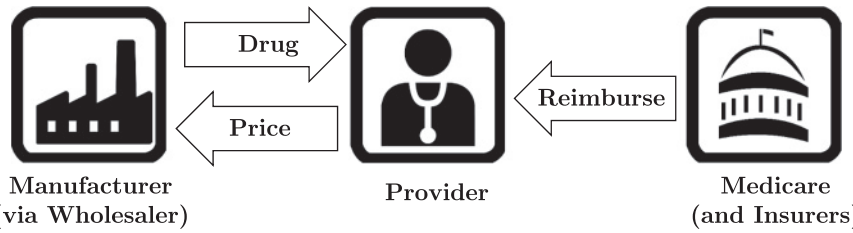
We estimate that a 2005 change in reimbursement policy caused launch prices for outpatient drugs to double. This is the first study to show that the 2005 policy increased launch prices for branded drugs administered by providers. Previous studies examined the effect of the 2005 policy change on product mix (Jacobson et al., 2010), shortages (Yurukoglu et al., 2017), and vertical integration (Alpert, Hsi, & Jacobson, 2017).

Previous research also examined how other government reimbursement policies affect drug manufacturer strategy. Competition among drug manufacturers is weaker when the government regulates prices (Ekelund & Persson, 2003) or requires that a manufacturer give the government its lowest price among its customers (Scott Morton, 1997). Government-provided insurance can offset the deadweight loss of monopoly unless the manufacturer fully captures the increase in willingness to pay through a higher price (Lakdawalla & Sood, 2009). Government policy can also induce manufacturers to launch new versions of products in order to reset prices (Ikegami, Ikeda, & Kawai, 1998; Duggan & Scott Morton, 2006). We examine launch prices for new branded drugs, rather than generic drugs, because competition tends to suppress generic drug prices (Scott Morton, 1999;

The Review of Economics and Statistics, December 2020, 102(5): 980–993

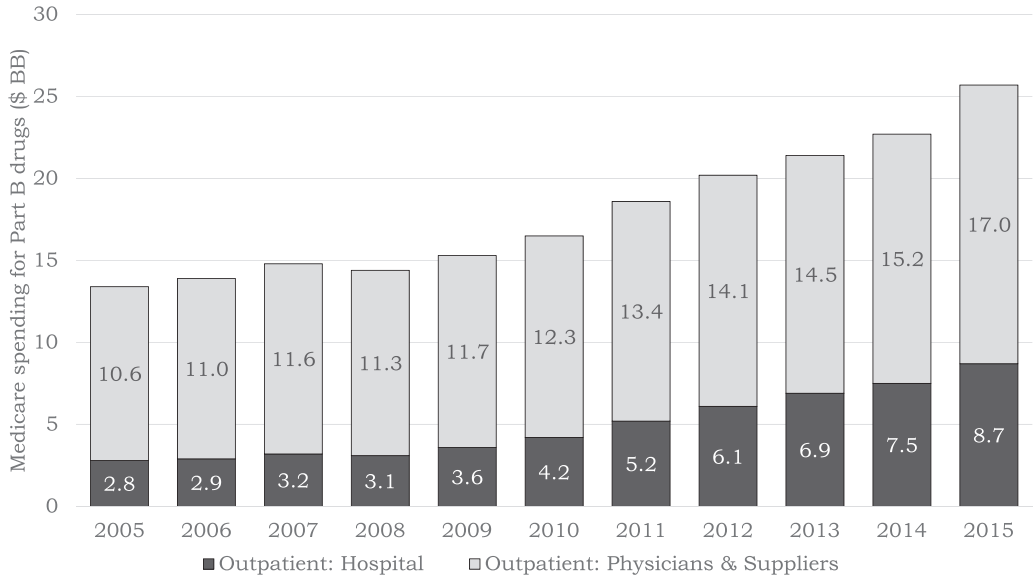
https://doi.org/10.1162/rest_a_00849

FIGURE 1.—FLOW OF FUNDS FOR PROVIDER-ADMINISTERED DRUGS



A manufacturer (through a wholesaler or a specialty pharmacy) sells a drug to a provider (a physician clinic or hospital), and the provider is then reimbursed by Medicare or a private insurer. The way in which Medicare reimburses the provider influences the price charged by the manufacturer.

FIGURE 2.—MEDICARE SPENDING FOR OUTPATIENT PROVIDER-ADMINISTERED DRUGS



Medicare outpatient provider-administered (Part B) drug spending has accelerated in recent years, perhaps because drugs launched since the 2005 policy have had higher prices and constitute a growing share of drugs in use.
Source: Authors' analysis using data from the Medicare Payment Advisory Commission (2017).

Reiffen & Ward, 2005; Grabowski, Ridley, & Schulman, 2007; Ching, 2010).

The study contributes to the literature on dynamic pricing. Previous research showed that a firm will launch at a price above the current profit-maximizing price if regulations prohibit price increases (Abbott, 1995), especially if consumers are shortsighted (Ridley & Zhang, 2017) and if the firm is uncertain about demand (Shajarizadeh & Hollis, 2015). We identify a new reason for high launch prices: reimbursement based on lagged prices.

A. *Background on Drugs Administered by Providers in Medicare*

In the United States, Medicare provides health insurance for people over age 65 and the disabled. Medicare Part A covers inpatient hospital stays, Part B covers care in physician clinics and hospital outpatient departments, and Part D covers prescription drugs purchased through a retail pharmacy or mail order. Medicare patients receive drugs in all of these settings.

We are interested in the effect of a change in provider reimbursement under Medicare Part B. Part B drug spending was $25.7 billion in 2015, with $17 billion for drugs administered in physician clinics and $8.7 billion for drugs administered in hospital outpatient departments (see figure 2). Under Medicare Part B, health care providers buy drugs from manufacturers (through a wholesaler). For example, a provider in a cancer clinic would administer pegfilgrastim to a patient to stimulate her level of white blood cells. In 2014, Medicare spent more than $1 billion on pegfilgrastim to treat cancer patients (U.S. Government Accountability Office, 2016).

Before 2005, Medicare paid providers an amount largely unrelated to the actual price. Medicare reimbursed providers based on AWP, which officially stood for average wholesale price but was widely known as "ain't what's paid." Some manufacturers inflated the list price while holding down the actual price in order to increase the spread received by the provider (Berndt & Newhouse, 2010; Alpert et al., 2013). Inflating the list price did not directly increase profit, but it increased the surplus of the health care providers purchasing the drug, possibly increasing demand and thus profit. Knowing

TABLE 1.—TWO EXAMPLES OF PRICE VARIATION WITHIN A MOLECULE

				Launch		Earliest ASP	
Class Abbreviation	Generic Name	Dosage Form	Strength	Year	WAC	Year	ASP
Steroids	budesonide	ampul	0.25 mg/2 ml	2000	$1.75	2005	$2.02
Steroids	budesonide	ampul	0.5 mg/2 ml	2000	$1.75	2005	$2.02
Steroids	budesonide	ampul	1 mg/2 ml	2007	$5.34	2008	$5.09
Hormones	somatropin	cartridge	10 mg/2 ml	2002	$191.84	2005	$211.90
Hormones	somatropin	cartridge	20 mg/2 ml	2008	$526.47	2008	$495.30

Manufacturers launched new strengths of budesonide and somatropin at higher prices after the 2005 policy change.

TABLE 2.—TWO EXAMPLES OF PRICE VARIATION WITHIN A CLASS

				Launch		Earliest ASP	
Class Abbreviation	Generic Name	Dosage Form	Strength	Year	WAC	Year	ASP
Hematinics	iron sucrose	vial	100 mg iron/5 ml	2000	$11.00	2005	$7.24
Hematinics	ferumoxytol	vial	510 mg/17 ml	2009	$23.34	2010	$24.75
Heparins	enoxaparin	syringe	150 mg/ml	2002	$73.50	2005	$77.33
Heparins	enoxaparin	syringe	120 mg/0.8 ml	2002	$73.50	2005	$77.33
Heparins	dalteparin	syringe	18,000 unit/0.72 ml	2007	$129.60	2008	$111.71
Heparins	dalteparin	syringe	15,000 unit/0.6 ml	2007	$129.60	2008	$111.71
Heparins	dalteparin	syringe	12,500 unit/0.5 ml	2007	$129.60	2008	$111.71

Products launched after the 2005 policy change have higher prices than those launched before despite comparable efficacy.

that AWP was not an actual price, insurers paid 80% to 85% of the AWP (Berndt & Newhouse, 2010).

Beginning in 2005, Medicare reimbursed providers based on average sales price (ASP) as part of the Medicare Modernization Act of 2003 (Jacobson et al., 2010; Yurukoglu et al., 2017). ASP is the average price of purchases made by providers in the previous six months. It is net of discounts and rebates as described in a 2010 report from the Office of the Inspector General: "The ASP is net of any price concessions, such as volume discounts, prompt pay discounts, cash discounts, free goods contingent on purchase requirements, chargebacks, and rebates other than those obtained through the Medicaid drug rebate program" (U.S. Department of Health and Human Services, 2010). Congress initially set reimbursement at 106% of the previous two quarters' ASP. Payments fell from 106% to 104.3% of ASP under the sequestration order in the Balanced Budget and Emergency Deficit Control Act beginning in 2013. For a new drug, there is no past price on which to base average price so reimbursement is a markup of the wholesale acquisition cost (WAC) (Centers for Medicare and Medicaid Services, 2016).

The manufacturer sells to a wholesaler or specialty pharmacy, which sells to a provider. The wholesaler purchases at the WAC with a discount of, say, 1% for prompt payment. There are only small differences between the WAC and ASP at launch for provider-administered drugs after the policy change (see tables 1 and 2).

Medicare reimburses a provider 104% to 106% of the ASP, but providers still complain about being undercompensated. First, ASP is an average, and some providers pay prices above the average. Second, the provider bears administrative costs, including the cost of interacting with insurers, denied or delayed payments, and breakage. Third, if providers are perfect agents for their patients, then they will feel the pain of the patient paying 20% coinsurance. Hence, the provider is more sensitive to price than 100% compensation implies.

Medicare undercompensates some providers but overcompensates other providers. Hospitals that serve a substantial portion of low-income people are eligible to purchase drugs at steeply discounted prices under the 340B program. We provide summary statistics showing that the new reimbursement policy is associated with care shifting to hospitals, many of which are eligible to purchase at discounted prices under the 340B program (figure 2).

The policy change directly affects Medicare fee-for-service and indirectly affects privately administered plans. Private insurers typically mimic Medicare reimbursement (Clemens & Gottlieb, 2017). In 2012, private insurers reimbursed based on ASP for more than half of patients (Magellan Rx Management, 2013). Private insurers were more generous than Medicare, with a mean reimbursement of 118% of ASP in 2012 (Academy of Managed Care Pharmacy, 2013). Hence, both Medicare and many private insurers reimburse providers based on lagged prices following the policy change.

While we find large increases in launch prices for outpatient drugs, we find little change in prices for retail drugs, even though Medicare coverage of retail drugs also expanded during the time. Congress created a retail drug benefit for seniors, but the effect on retail prices was small for two reasons. First, while demand increased, prices did not, because insurers used their bargaining power to hold down prices (Duggan & Scott Morton, 2010). So prices did not rise, although the quantity demanded did. With rising quantity demanded, there was higher revenue and more incentive for innovation (Blume-Kohout & Sood, 2013). Second, the change in Medicare did not spill over to the private retail market because Medicare was mimicking the private retail market. Congress

made private insurers responsible for administering the Medicare retail drug benefit, so Congress took the private retail drug model and applied it to Medicare. In contrast, in the outpatient drug market, Congress changed Medicare, and the private insurance market emulated it in the adoption of ASP.

A large increase in launch prices does not immediately have a large effect on spending if the newly launched drugs are a small share of the total spending. Over time, a larger share of the market consists of drugs launched since the policy change at higher prices. Hence, we expect spending to accelerate. Between 2005 and 2010, Medicare Part B (outpatient provider-administered) drug spending increased from \$13.3 billion to \$16.5 billion, a compound annual growth rate of 4%. However, between 2010 and 2015, spending increased from \$16.5 to \$25.7 billion, a 9% growth rate (figure 2).

Provider demand not only depends on reimbursement, but also on the provider's experience with the drug (Coscelli & Shum, 2004; Crawford & Shum, 2005). According to one provider, "You sort out whether it works or not by experience." According to another provider, "It doesn't really matter one bit what happens with other people, it matters what happens with your patients, if your patients are feeling better on a drug and not having side effects of a drug, it really doesn't matter what the journals say" (Prosser, Almond, & Walley, 2003). For a new drug, not only are providers inexperienced with the benefits and side effects, but they are also inexperienced with reimbursement for the drug. Hence, in our model, we include adoption costs for the provider. Adoption costs work in the opposite direction of reimbursement: they drive down the launch price. With adoption costs, a firm will choose a price below the current profit-maximizing price, so-called penetration pricing (Dean, 1969; Schmalensee, 1982; Lu & Comanor, 1998; Bergemann & Välimäki, 2006). Adoption costs drive down the launch price because the firm wants to attract more buyers who will later have a higher willingness to pay (Ridley & Zhang, 2017).

II. Theory

We construct a model of drug demand by health care providers who buy drugs for injection or infusion, such as an oncologist buying drugs to use in chemotherapy. The government (e.g., Medicare) reimburses providers for the drugs. The way the government reimburses providers affects the demand for the drug.

The model has two key elements. First, the government reimburses providers based on price or in a fixed amount unrelated to price. Reimbursement based on price desensitizes providers to price. If the government reimburses based on current price, then price will rise proportionately to reimbursement, quantity will be unchanged, and deadweight loss will be unchanged. However, if the government reimburses providers based on lagged price, the firm will raise the launch price even more in order to raise future reimbursement and willingness-to-pay. The firm will set the launch price above the current profit-maximizing price, quantity demanded will fall, and deadweight loss will rise.

The second key element is that willingness-to-pay is rising over time due to an adoption cost. The justification for this cost is that drugs are experience goods for providers. A provider might be reluctant to prescribe a new drug, especially for a patient with good outcomes on an old drug, because of uncertainty about benefits, side effects, and reimbursement. We will show that an adoption cost causes the firm to set a lower launch price to increase launch quantity, so that more buyers have higher willingness-to-pay in the future. In this way, the adoption cost pushes the launch price in the opposite direction of reimbursement based on price.

In the model, each provider purchases 1 or 0 units. A provider has a reservation price x from administering a drug even if she is not reimbursed for the cost of the drug. We can think of the value x coming from the procedure payment (a payment that is often separate from reimbursement for the drug) and from the satisfaction of helping a patient. The reservation price x is uniformly distributed on $[0, \bar{x}]$. The first time a provider purchases, she bears an adoption cost κ, where $x > \kappa > 0$. Providers pay a price p_t and are reimbursed r_t. A provider's utility is:

$$u_t = \begin{cases} x - p_t + r_t - \kappa & \text{if purchasing for the first time} \\ x - p_t + r_t & \text{if purchasing again} \\ 0 & \text{if not purchasing} \end{cases}.$$

A provider purchases or not to maximize utility in that period. The indifferent provider who has not previously purchased has utility $u(\hat{x}) = \hat{x} - p_t + r_t - \kappa = 0$. Providers purchase if they have a reservation price higher than $\hat{x}$, so quantity demanded in the first period is $q_1 = \bar{x} - \hat{x}$, which can be rewritten as

$$q_1 = \bar{x} - p_t + r_t - \kappa. \tag{1}$$

After the first period, κ drops out for the portion of the demand curve with repeat purchasers.

The firm is a monopolist that chooses prices to maximize a discounted stream of profit $\pi_t = \sum_{t=1}^{T} \delta^t p_t q_t$, where δ is the discount rate and q_t is quantity demanded. We assume that the firm produces at zero cost.

We solve a two-period model—a simple way to characterize markets in which there is a known, final period, such as the pharmaceutical industry in which patents expire. Because the second-period price is a function of the first-period price, the firm can solve the profit maximization problem by solving for the profit-maximizing first-period price:

$$\max_{p_1} \pi(p_1) = \max_{p_1} (\pi_1(p_1, p_2(p_1)) + \delta(\pi_2(p_1, p_2(p_1))). \tag{2}$$

The firm chooses prices such that quantity demanded will be the same in both periods (for a proof, see Ridley & Zhang,

2017). The logic is as follows. The second-period profit-maximizing price will not be so low as to attract providers who chose not to purchase in the first period, because those producers are willing to pay just as much in the first period as the second. Furthermore, the second-period profit-maximizing markup will not be so high as to exceed the adoption cost and drive away quantity, because the firm invested in those producers and would not then stop selling to them after they incurred the adoption cost. We can solve for the second-period price at which quantity demanded is the same in both periods: $p_2 = \kappa + p_1 - r_1 + r_2$.

A. Reimbursement

The government reimburses the provider a multiple (σ) of lagged price and/or a fixed amount per unit (ϕ), so $r_t = \sigma p_{t-1} + \phi$ where $1 > \sigma \geq 0$ and $\phi \geq 0$. For reimbursement in the initial period, let $p_0 = p_1$, so $r_1 = \sigma p_1 + \phi$.

Prior to 2005, Medicare reimbursed providers an amount unrelated to the actual price so $\sigma = 0$. Since 2005, Medicare has reimbursed providers based on lagged price so $1 > \sigma > 0$. The reimbursement σ is net of administrative costs and net of the patient copayment so is less than 100% of the price.

Under lagged-price reimbursement, the second-period price at which quantity demanded is the same in the second period as in the first period is $p_2 = p_1 + \kappa$. In other words, the firm marks the second-period price up by the adoption cost. Substituting p_2 into the profit-maximization problem in equation (2), and assuming no discounting ($\delta = 1$) gives the profit-maximizing prices and quantities when reimbursement is a function of lagged prices (σp_{t-1}) or fixed amounts (ϕ):

$$
\begin{aligned}
p_1^*(\sigma, \phi) &= \frac{1}{4}(2\bar{x} + 2\phi - 3\kappa + \sigma\kappa)/(1 - \sigma),\\
p_2^*(\sigma, \phi) &= p_1 + \kappa,\\
q_t^*(\sigma, \phi) &= \frac{1}{4}(2\bar{x} + 2\phi - \kappa - \kappa\sigma). \qquad (3)
\end{aligned}
$$

Recall that $\sigma < 1$. We can see that the profit-maximizing launch price is rising with the share of the price that the insurer reimburses. This leads to our first hypothesis:

Hypothesis 1. The launch price rises if the government reimburses a higher share of the price.

Equation (3) also shows that quantity demanded at the profit-maximizing price is decreasing in σ. Reimbursement based on lagged price exacerbates the monopoly pricing problem because the firm "invests" in a launch price above the single-period, profit-maximizing price for the sake of higher future prices. We will show that with lower quantity demanded, there is greater deadweight loss and lower social welfare.

Equation (3) also shows that quantity demanded at the profit-maximizing price is increasing in ϕ. Reimbursement per unit causes quantity demanded to rise. Increases in per unit reimbursement reduce the deadweight loss from monopoly pricing and increase welfare, up to a point. Quantity could rise so much as to be inefficient. If the subsidy ϕ is especially large, then quantity could rise above the quantity demanded associated with zero price, which would reduce social welfare.

B. Contemporaneous-Price Reimbursement

If reimbursement is based not on lagged prices but on contemporaneous prices, then $r_2 = \sigma p_2 + \phi$. The second-period price at which quantity demanded will be the same in both periods is $p_2^c = p_1 + \kappa/(1 - \sigma)$. Substituting p_2^c into the profit-maximization problem in equation (2) gives the profit-maximizing prices and quantities when reimbursement is a function of contemporaneous prices (σp_t) only ($\phi = 0$):

$$
\begin{aligned}
p_1^c(\sigma, 0) &= \frac{1}{4}(2\bar{x} - 3\kappa)/(1 - \sigma),\\
p_2^c(\sigma, 0) &= p_1^c + \kappa/(1 - \sigma),\\
q_t^c(\sigma, 0) &= \frac{1}{4}(2\bar{x} - \kappa). \qquad (4)
\end{aligned}
$$

Comparing equation (4) to (3), we can see that under contemporaneous price reimbursement (rather than under lagged-price reimbursement), the price is $\kappa\sigma/(4 - 4\sigma)$ lower and the quantity demanded is $\kappa\sigma/4$ higher. Recall that $\sigma < 1$ and $\kappa > 0$.

The intuition for a higher launch price under lagged-price reimbursement is as follows. A firm reimbursed on lagged price will "invest" in a first-period price that is above the static profit-maximizing price in order to increase the provider's reimbursement in the second period and allow for a higher price in the second period. Under contemporaneous reimbursement, the firm will make no such "investment."

The launch price is higher when reimbursement is based on lagged price ($p_1^*(\sigma p_{t-1}, 0)$) rather than contemporaneous price ($p_1^c(\sigma p_t, 0)$). With no reimbursement, first-period price is low, ($p_1^*(0)$). Given adoption costs, the firm sets the price low to attract a higher quantity demanded, knowing it can raise the price in the next period. With adoption costs, the profit-maximizing price is below the single-period, profit-maximizing price. (See the appendix for illustrations of launch price and demand.)

C. Welfare

Policymakers might assume that increasing subsidies for health care providers will benefit providers, but we show the opposite: provider surplus falls if subsidies depend on lagged prices because prices rise. Provider surplus (not to be confused with producer surplus, which we denote as π_t) is $s(p_1, p_2) = (1/2)(\bar{x} - \kappa - p_1 + r_1)q_1 + \delta(1/2)(\bar{x} - p_2 + r_2)q_2$. Substituting for p_1, p_2, q_t, r_1, and r_2 and differentiating

provider surplus with respect to σ and ϕ yields

$$\begin{aligned}\text{Lagged price:}\quad & \frac{\partial s(\sigma p_{t-1})}{\partial \sigma} = \frac{\kappa}{8}(\kappa + \kappa\sigma - 2\bar{x}) < 0,\\ \text{Contemporaneous price:}\quad & \frac{\partial s(\sigma p_t)}{\partial \sigma} = 0,\\ \text{Per unit:}\quad & \frac{\partial s(\phi)}{\partial \phi} = \frac{1}{4}(2\bar{x} + 2\phi - \kappa) > 0.\end{aligned} \tag{5}$$

Provider surplus is falling with increases in reimbursement on lagged prices (recall that $\bar{x} > \kappa$ and $\sigma < 1$). This result leads to a hypothesis concerning surplus for the provider:

Hypothesis 2. Under reimbursement based on lagged prices, provider welfare is decreasing with the share of the price that the government reimburses.

We provide evidence consistent with hypothesis 2 in the appendix. We compare incomes for specialists who are most affected by the reimbursement change (because they are high users of outpatient drugs) to those who are not, before and after the policy change.

Finally, we compare social welfare across the three reimbursement schemes. Adding provider surplus plus profit less government spending g gives social welfare: $w = \sum_{t=1}^{T} \delta^t(s_t + \pi_t - g_t)$. Assuming two periods and no discounting, welfare is $w = (1/2)(\bar{x} - \kappa - p_1 + r_1)q_1 + \delta(1/2)(\bar{x} - p_2 + r_2)q_1 + (p_1 + \delta p_2)q_1 - (r_1 + \delta r_2)q_1$.

Substituting for p_1, p_2, q_t, r_1, and r_2 and then differentiating provider welfare with respect to σ and ϕ yields

$$\begin{aligned}\text{Lagged price:}\quad & \frac{\partial w(\sigma p_{t-1})}{\partial \sigma} = \frac{\kappa}{8}((1+\sigma)\kappa - 2\bar{x})\\ & \qquad < 0,\\ \text{Contemporaneous price:}\quad & \frac{\partial w(\sigma p_t)}{\partial \sigma} = 0,\\ \text{Per unit:}\quad & \frac{\partial w(\phi)}{\partial \phi} = \frac{1}{4}(2\bar{x} - 2\phi - \kappa) > 0\\ & \qquad \text{if } \phi < \bar{x} - \frac{\kappa}{2}.\end{aligned} \tag{6}$$

From equation (6), welfare is decreasing in σ and increasing in ϕ up to $\bar{x} - \frac{\kappa}{2}$. Hence, the reimbursement that maximizes social welfare is $\sigma^w = 0$ and $\phi^w = \bar{x} - \frac{\kappa}{2}$.

Given that welfare is decreasing in σ, equation (6), and price is increasing in σ, equation (3), we can write our final hypothesis:

Hypothesis 3. Changing from reimbursement on price to fixed reimbursement would reduce the launch price and increase welfare if the fixed reimbursement is not too high.

Changing from reimbursement on price to a fixed amount would reduce the deadweight loss from monopoly prices and increase welfare for small values of the fixed amount ϕ. However, large values of ϕ induce excess consumption and welfare loss. See the appendix for illustrations of demand and welfare effects.

III. Data

We use five data sources: drug prices from AnalySource, quality-adjusted prices from Howard et al. (2015), drug classifications from the Food and Drug Administration (FDA), drug reimbursement codes from the Centers for Medicare and Medicaid Services (CMS), and drug classifications from IMS Health.

First, we use drug price data from AnalySource. Our sample includes monthly prices for every form of every drug sold in the United States between January 1999 and December 2010. We observe the launch prices of drugs for six years before and after 2005 when the U.S. government implemented the policy. The AnalySource data include a National Drug Code (NDC), a unique ten-digit, three-segment number, with the three segments identifying the labeler, the product, and the commercial package size. We also observe the form of the drug. Drugs in liquid dosage forms are usually injectable or infused and measured in milliliters. The data also include the drug's Uniform System of Classification (USC) number, a hierarchical classification system developed by IMS Health. The USC provides groupings of drugs considered to compete in the same or similar markets.

We measure price using WAC data, which are available for all brand-name drugs before and after the 2005 policy change. In contrast, ASP data are available only after the policy change, because Congress introduced ASP with the policy change. WAC is close to the price paid by providers and received by manufacturers for most brand-name drugs at launch (tables 1 and 2). Exceptions include health care providers who serve poor patients and are eligible to purchase at lower prices through the 340B program.

Second, we use price per life year gained for anticancer drugs from Howard et al. (2015). The anticancer drugs included in the analysis were approved in the United States between 1995 and 2013 and are intended to extend life rather than alleviate pain or side effects. The price is the cost to Medicare of an episode of treatment. The benefit is measured as additional survival or progression-free survival for the first FDA-approved indication of the drug compared to the previous standard of care.

Third, we use data on drug characteristics from the FDA, including whether the drug was a new molecular entity and whether the FDA gave the drug priority review. FDA gives priority review to drugs that represent significant improvements over existing treatments for serious conditions. We merge FDA and AnalySource data using FDA application numbers.

Fourth, we use Healthcare Common Procedure Coding System (HCPCS) codes from CMS to identify outpatient drugs. Medicare uses these codes to identify drugs

administered by a physician and reimbursed under Part B. We matched HCPCS to NDC codes in the AnalySource data using a crosswalk file provided by CMS.

Fifth, we use IMS Health data to identify drug classes that are primarily retail to serve as one of the control groups. We calculate retail market share at the four-digit Anatomical Therapeutic Chemical (ATC) classification level. We then merge with AnalySource data using a drug's USC.

IV. Empirical Model

The dependent variable is the launch price $Price_i$ of drug i. We measure price as the wholesale acquisition cost.

We are interested in the effect of reimbursement on launch prices. The reimbursement policy changed on January 1, 2005, so we define the preperiod as 1999 to 2004 and the postperiod as 2005 to 2010. The variable $Post_i$ equals 1 in the year 2005 and later.

An observation in our analysis is a drug. We define a drug by its National Drug Code (NDC), meaning a molecule-manufacturer-dose-form-package. We do not aggregate to the molecule-manufacturer level because different doses and forms have different prices. We cluster standard errors by drug class to account for intertemporal correlation in the error term. We define a class using the USC.

We removed from the analysis an outlier, a drug reimbursed based on ASP in the postperiod, so it would have caused our estimated policy effect to be larger. The drug is ranibizumab (marketed as Lucentis), launched in 2006. Ranibizumab has a high price per milliliter in part because providers use only small quantities in the eye.

Three types of variation help us identify the effect of the policy on drug launch prices. We look before and after the policy change at multiple launches of a molecule, multiple launches in a class (section IVA), and multiple launches for a reimbursement mechanism (section IVB).

First, there is launch-price variation for a given molecule. Manufacturers launched some molecules in different dosage forms or strengths in different years. Launching a new dosage form is costly because the manufacturer must provide to the FDA clinical-trial evidence demonstrating safety and efficacy. We illustrate the variation using examples in which the same molecule was launched both before and after the policy change.

A. *Identifying Policy Effects Using Changes over Time*

There is also variation in launch prices in the same class before and after the policy change. In one specification, we use interrupted time series regression analysis.

We control for drug quality using indicator variables for $NewMolecule_i$, $PriorityReview_i$, and therapeutic class. The variable $NewMolecule_i$ equals 1 for new molecular entities. We expect the launch price for a new molecule to be higher than for a new dosage form of an existing molecule. $PriorityReview_i$ indicates that FDA staff regarded the drug as important and worthy of faster review. We include class fixed effects ($\zeta_{c(i)}$) but not molecule fixed effects because many of the molecules have only one launch.

We report results with and without controlling for competition. We control for competition using counts of branded and generic competitors (the vector h_i). We omit competition in some specifications due to concerns about reverse causality. However, reverse causality is a small concern in the pharmaceutical market due to scientific and regulatory delays. Each of the three phases of clinical testing takes about two years, and the time between regulatory submission and drug launch is around a year (DiMasi, Grabowski, & Hansen, 2016). Hence, the branded drugs that we study cannot quickly enter the market when prices are high. The error term (ε_i) captures unobserved factors that affect launch prices.

We begin with the following interrupted time series regression analysis:

$$\begin{aligned} Price_i = {} & \beta_0 + \beta_1 T_i + \beta_2 Post_i + \beta_3 (T_i - T_{2005m1}) \times Post_i \\ & + \delta NewMolecule_i + \gamma PriorityReview_i \\ & + \zeta_{c(i)} + h_i'\eta + \varepsilon_i, \end{aligned} \tag{7}$$

where T_i is the time in years between January 1999 and the launch date of drug i. To account for a change in the underlying trend of the series, we include a scaled interaction term between $Post_i$ and T_i, $(T_i - T_{2005m1}) \times Post_i$. β_2 is the price-level break following the reimbursement change, and β_3 indicates the slope change of the time trend following the reimbursement change. We expect the estimated β_2 or β_3 to be positive and significant for drugs reimbursed based on ASP beginning in January 2005. In some specifications, we omit the post-intervention trend ($(T_i - T_{2005m1}) \times Post_i$) and test if $\beta_2 > 0$.

To allow policy effects to change over time, we estimate the following interrupted time series model:

$$\begin{aligned} Price_i = {} & \beta_0 + \beta_1 T_i + \beta_2 Post_i + \beta_3 Year2006_i \\ & + \beta_4 Year2007_i + \beta_5 Year2008_i + \beta_6 Year2009_i \\ & + \beta_7 Year2010_i + \delta NewMolecule_i \\ & + \gamma PriorityReview_i + \zeta_{c(i)} + h_i'\eta + \varepsilon_i, \end{aligned} \tag{8}$$

where $YearX_i = 1$ if drug i was launched in year X. We expect a positive β_2, the average effect of the policy. $\beta_3, \beta_4, \ldots, \beta_7$ represent deviations from the average effect.

Recall that we control for variation in product quality using a drug's therapeutic class and whether it is a new molecule and has priority review. We also use data on survival benefits for anticancer drugs (Howard et al., 2015). We use prices per life-year gained relative to the previous standard of care. We only have data for initial launches of anticancer drugs, so we have few observations and must estimate a parsimonious model. We include only *Post* in one specification and add *NewMolecule* and *PriorityReview* in the other.

B. *Identifying Policy Effects Using Differences in Reimbursement*

In addition to using variation across dosage forms of the same molecule and across time for drugs in the same class, there is variation in the launch price across different reimbursement schemes. We exploit this variation in a difference-in-differences framework. We compare drug launch prices before and after the 2005 policy change, and we compare launch prices for the treatment and control groups.

The treatment group consists of outpatient provider-administered drugs in a liquid form. We identify drugs as administered by a provider in an outpatient setting if they have an HCPCS code. Medicare and private insurers began reimbursing providers for such drugs based on ASP beginning in 2005.

The control group varies. In one specification, the control group is prescription drugs with 70% or more sales in the retail market. We check whether the result is robust to replacing 70% with 80%. In another specification, the control group is prescription drugs administered by providers in an outpatient setting but not reimbursed based on ASP. These drugs include vaccines, blood products, and infusion drugs furnished through a covered item of durable medical equipment.[1]

The drugs included in the analysis are branded drugs with dosage measured in milliliters. Providers tend to administer drugs in liquid form. Using only liquid forms of drugs in both the treatment and control groups provides more consistency in manufacturing costs because liquids are costlier to manufacture than solids due to a high standard for sterility. Also, drugs in solid dosage forms do not have standardized units, making comparisons difficult.

In the difference-in-differences analysis, we estimate the following relationship:

$$Price_i = \beta_0 + \beta_1 TreatedDrug_i \times Post_i + \delta NewMolecule_i + \gamma PriorityReview_i + \zeta_{c(i)} + \lambda_{t(i)} + h_i'\eta + \varepsilon_i, \quad (9)$$

where $TreatedDrug_i$ equals 1 for drugs in the treatment group, meaning provider-administered drugs subject to the reimbursement change. Of particular interest is the interaction between $TreatedDrug_i$ and $Post_i$; a positive coefficient indicates that drug launch prices rose more for drugs reimbursed based on ASP. In an alternative specification, we add the interaction between $TreatedDrug_i$, $Post_i$, and $NewMolecule_i$ to allow for the heterogeneous policy effect based on the degree of novelty. We control for $NewMolecule_i$ and $PriorityReview_i$ and include fixed effects for the drug's therapeutic class ($\zeta_{c(i)}$) and for the launch year ($\lambda_{t(i)}$). Again, we report results with and without controlling for competition (h_i).

We test whether the results are robust to other specifications and report the results in the appendix. First, we drop the years 2004 and 2005 because manufacturers might have delayed launch for a few weeks or even a few months in expectation of higher reimbursement in the postperiod. Second, we change the control group to consist of drugs with more than 80% (rather than 70%) of sales in the retail market. Third, we add Medicare market share. We expect to find a positive effect of Medicare market share on drug launch prices, because Medicare initiated the change. However, the effect will be mitigated because private insurers emulate Medicare's reimbursement mechanisms (Clemens & Gottlieb, 2017). This consistency of reimbursement mechanisms across payers helps us see a large effect because it affects so many payers, but it limits our ability to use this source of variation for identification.

We also conduct placebo tests to examine whether we see effects when we should not. We expect to find no significant results when we use a specification with the wrong postperiod. In the first placebo test, we use the sample between 1999 and 2004, the period before the policy implementation, with a false policy enacted in 2002. In the second placebo test, we use the sample between 2005 and 2010, the period after the policy implementation, with a false policy enacted in 2008.

In all specifications, the treatment group consists of outpatient drugs in a liquid form that Medicare reimburses based on ASP. All of the control groups consist of outpatient drugs in a liquid form that Medicare does not reimburse based on ASP, either because they are exceptions to the rule (such as vaccines) or sold at retail.

V. Results

We use three approaches to find evidence of increases in drug launch price. We look within molecule over time, within class over time, and across reimbursement schemes affected and unaffected by the policy change.

First, we look for changes in the launch price of the same molecule before and after the policy change. Manufacturers launched some of the molecules in different dosage forms in different years. Consider budesonide, which increased in price (WAC per milliliter) from \$1.75 to \$5.34 following the policy change. Likewise, somatropin increased in price from \$192 to \$526 after the policy change (table 1).

Second, we look for changes in launch prices across different drugs in the same class over time. Consider the "hematinics, iron alone" class. The launch price of iron sucrose was \$11 before the policy change, while the launch price of ferumoxytol was \$23 after the policy change, despite their equivalent quality (table 2). According to Macdougall et al. (2014). "In this randomized, controlled trial, ferumoxytol and iron sucrose showed comparable efficacy and adverse events rates."

Likewise, consider the "anticoagulants, fractionated heparins" class. The launch price of enoxaparin was \$74 before the policy change, and the price of dalteparin was \$130 after the policy change, despite their equivalent quality. According to Miano et al. (2018), "Our results suggest that dalteparin has

[1] For a list of exclusions, see the appendix or 42 CFR §414.904.

TABLE 3.—SUMMARY STATISTICS FOR DRUGS LAUNCHED BETWEEN 1999 AND 2004

Variable	Observations	Mean	SD	Minimum	Maximum
Treated drug					
Price per ml	85	94.97	430.60	0.09	3,933.33
Price per ml in 2010 dollars	85	139.47	634.13	0.13	5,787.40
log (Price per ml)	85	2.01	2.32	−2.44	8.28
Priority review	85	0.26	0.44	0.00	1.00
New molecule	85	0.54	0.50	0.00	1.00
Retail					
Price per ml	29	4.84	5.06	0.09	16.04
Price per ml in 2010 dollars	29	7.08	7.46	0.14	23.97
log (Price per ml)	29	0.88	1.40	−2.44	2.78
Priority review	29	0.55	0.51	0.00	1.00
New molecule	29	0.41	0.50	0.00	1.00
Treated drug exceptions to ASP					
Price per ml	8	5.98	2.28	3.98	11.24
Price per ml in 2010 dollars	8	8.60	2.85	5.97	15.25
log (Price per ml)	8	1.74	0.32	1.38	2.42
Priority review	8	0.25	0.46	0.00	1.00
New molecule	8	0.38	0.52	0.00	1.00

The level of observation is a national drug code (NDC), which identifies the labeler, product, and commercial package size. Price is the wholesale acquisition cost (WAC). Classes are defined according to the Uniform System of Classification (USC). Retail is defined as drugs in classes with more than 70% of sales in the retail sector in 2009 and without an outpatient provider drug.

TABLE 4.—SUMMARY STATISTICS FOR DRUGS LAUNCHED BETWEEN 2005 AND 2010

Variable	Observations	Mean	SD	Minimum	Maximum
Treated drug					
Price per ml	148	747.40	1,772.02	0.21	9,326.00
Price per ml in 2010 dollars	148	834.92	1,926.29	0.27	10,162.51
log (Price per ml)	148	4.89	2.13	−1.54	9.14
Priority review	148	0.20	0.40	0.00	1.00
New molecule	148	0.53	0.50	0.00	1.00
Retail					
Price per ml	45	30.41	69.15	0.01	361.20
Price per ml in 2010 dollars	45	33.93	74.58	0.01	367.07
log (Price per ml)	45	1.78	2.09	−4.42	5.89
Priority review	45	0.18	0.39	0.00	1.00
New molecule	45	0.29	0.46	0.00	1.00
Treated drug exceptions to ASP					
Price per ml	7	20.07	29.98	0.80	80.00
Price per ml in 2010 dollars	7	20.43	29.77	1.04	80.00
log (Price per ml)	7	1.75	1.85	−0.22	4.38
Priority review	7	0.00	0.00	0.00	0.00
New molecule	7	0.14	0.38	0.00	1.00

The level of observation is a national drug code (NDC), which identifies the labeler, product, and commercial package size. Price is the wholesale acquisition cost (WAC). Classes are defined according to the Uniform System of Classification (USC). Retail is defined as drugs in classes with more than 70% of sales in the retail sector in 2009 and without an outpatient provider drug.

an effectiveness similar to that of enoxaparin in real-world trauma patients."

We can also look at average launch prices over time (see figure 4). In the six years before the policy change, the average launch price for outpatient provider drugs was about $100 (see table 3). In the six years after the policy change, the average launch price for outpatient provider drugs was about $700 (see table 4). However, outliers might be driving the difference in means, so we looked for outliers and eliminated ranibizumab, which launched at an especially high price after the reimbursement change. Even after omitting the outlier, average launch prices are much higher after the price change (see figure 3). Nevertheless, other factors might drive up launch prices, so we control for novelty, class, and year in our regression analysis. In some analyses, we also control for competition.

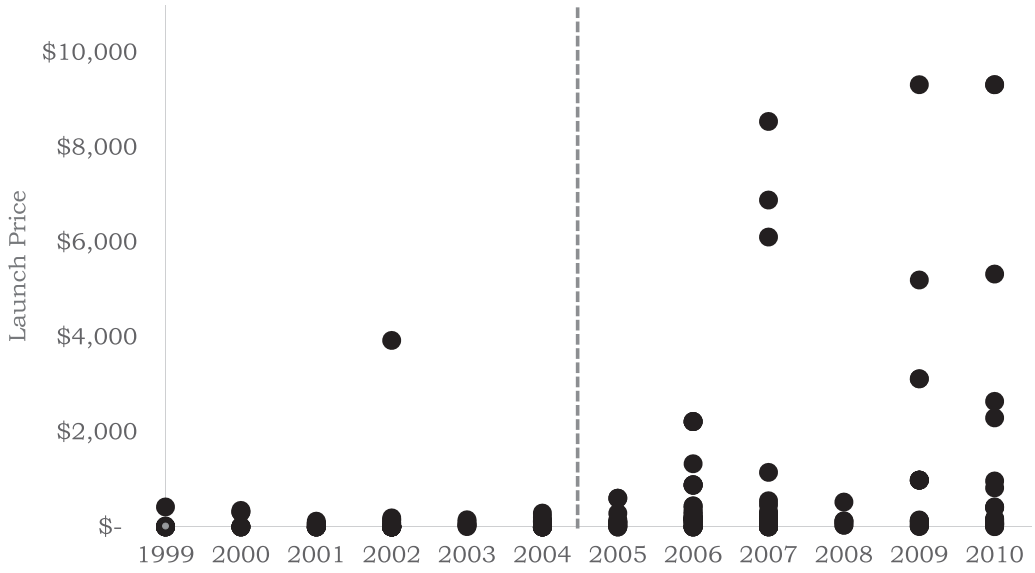
A. *Results for Interrupted Time Series Analysis*

We can see the policy effect in interrupted time series regression results (see table 5). The coefficients on $Post_i$ are positive and economically large for the drugs affected by the policy change. A coefficient of 2 indicates that launch prices rose 640%.[2] When we allow for time-varying policy effects in models 5 and 6, the estimated coefficient on $Post_t$ remains positive and economically large.

We also adjust for quality using data on price per life year gained. We compare quality-adjusted prices before and after the policy change in a figure (see figure 5) and regression analysis (see table 6). Without controlling for quality the coefficient on *Post* is 0.79 (model 2). When controlling for

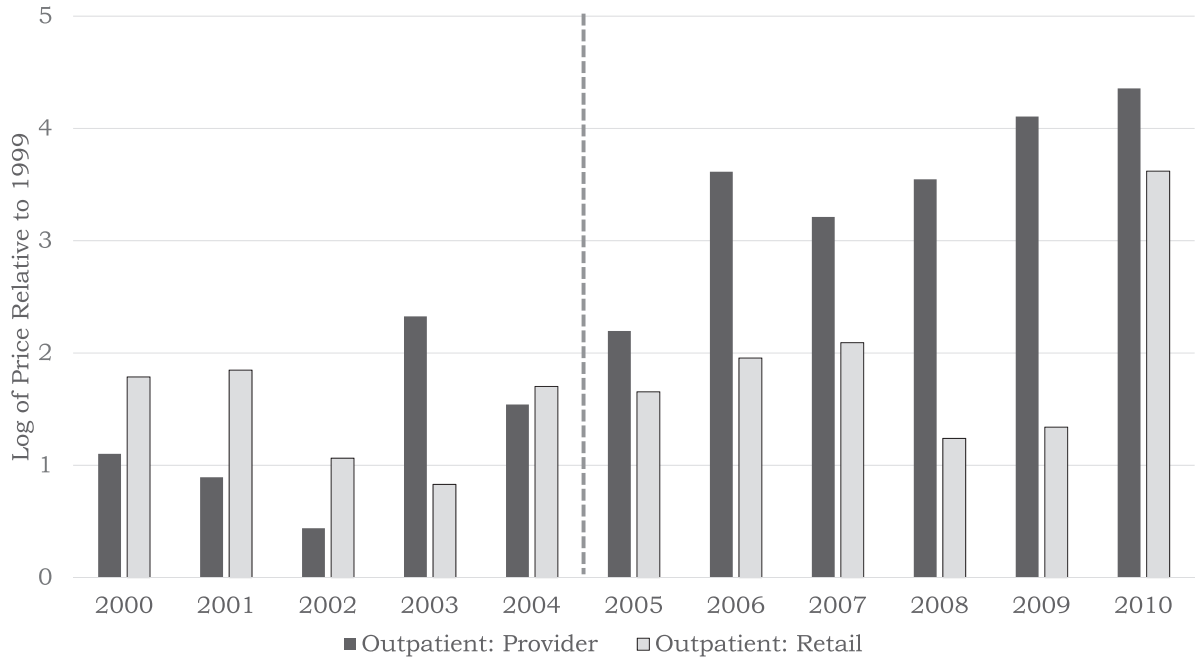
[2]For a coefficient of 2, an increase from 0 to 1 means prices rise exp(2) − 1 = 6.4.

FIGURE 3.—LAUNCH PRICES FOR DRUGS ADMINISTERED BY PROVIDERS IN AN OUTPATIENT SETTING BEFORE AND AFTER THE 2005 POLICY CHANGE



Prices are wholesale acquisition costs. We omit from the analysis an outlier with an especially high price: ranibizumab launched in 2006.
Source: Authors' analysis using data from AnalySource.

FIGURE 4.—LAUNCH PRICES FOR DRUGS ADMINISTERED BY PROVIDERS (DARK BARS) AND FOR RETAIL DRUGS (LIGHT BARS) BEFORE AND AFTER THE 2005 POLICY CHANGE



Launch prices for drugs administered by providers (dark bars) appear to have risen after the 2005 policy change compared to launch prices for retail drugs (light bars) when controlling for drug characteristics and competition. Prices are wholesale acquisition costs in logs and relative to 1999.
Source: Authors' analysis using data from AnalySource.

quality, the coefficient on *Post* is 0.61 (model 4). The difference between the coefficients on price with and without quality is small. Assuming the difference is significant means that adding more quality controls would reduce the magnitude of the launch price effect by about a third.[3] Even when controlling for quality, there is a large effect of the policy on launch price.

B. *Results for Difference-in-Differences Analysis*

We can also see the policy effect using difference-in-differences regression analysis. We compare drug launch prices before and after the 2005 policy change, and we

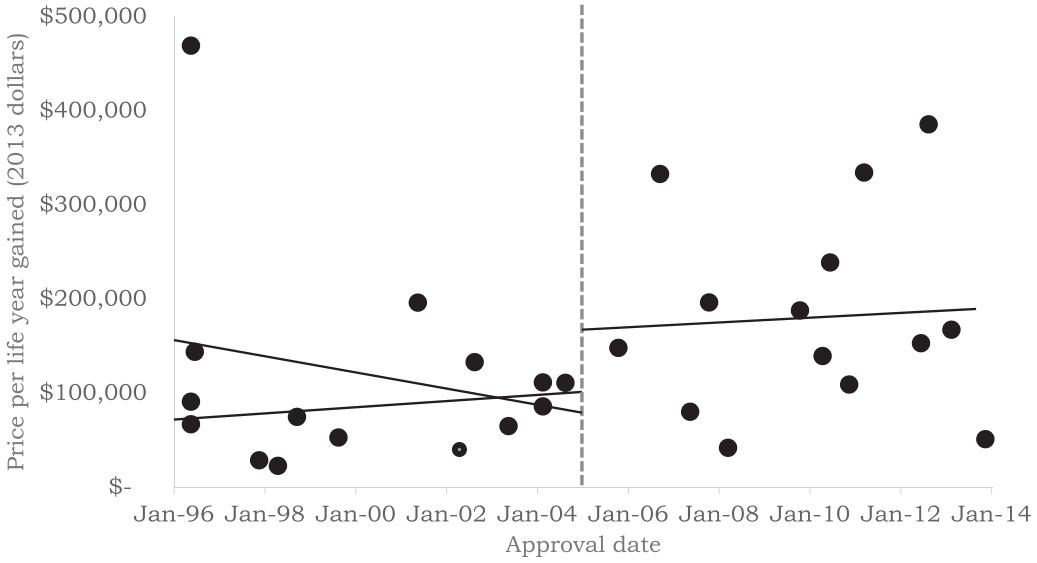
[3]Without controlling for quality, the coefficient on *Post* is 0.79, implying a 120% price increase. When controlling for quality, the coefficient on *Post* is 0.61, implying an 84% price increase.

TABLE 5.—ESTIMATES OF THE EFFECT OF A REIMBURSEMENT CHANGE ON DRUG LAUNCH PRICES USING INTERRUPTED TIME SERIES REGRESSION

	log (price per ml in 2010 dollars)					
Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
Post	1.902*	2.115**	1.803	1.937**	1.941*	1.983*
	(1.114)	(1.021)	(1.096)	(0.958)	(1.129)	(1.105)
Year 2006					0.0459	0.0398
					(0.858)	(0.861)
Year 2007					−0.243	−0.278
				(1.149)	(1.083)	
Year 2008					−0.438	−0.648
				(1.205)	(1.241)	
Year 2009					−0.414	−0.724
					(1.461)	(1.280)
Year 2010					−0.0610	−0.437
					(1.704)	(1.612)
Years since 1999	0.0747	−0.144	0.154	−0.00179	0.0949	−0.0685
	(0.104)	(0.191)	(0.234)	(0.228)	(0.243)	(0.231)
Years since 2005 × Post			−0.120	−0.231		
			(0.304)	(0.281)		
New molecule	1.186*	0.982	1.175*	0.967	1.186*	0.990
	(0.621)	(0.687)	(0.634)	(0.711)	(0.629)	(0.732)
Priority review	−0.772	−0.804	−0.778	−0.838	−0.797	−0.854
	(1.056)	(1.016)	(1.059)	(1.008)	(1.046)	(1.045)
Constant	1.896***	−1.124	1.647**	−1.719	1.825**	−1.344
	(0.429)	(2.499)	(0.819)	(3.067)	(0.801)	(3.140)
Competition controls	No	Yes	No	Yes	No	Yes
Class fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	233	233	233	233	233	233
R^2	0.82	0.84	0.82	0.84	0.82	0.84
Adjusted R^2	0.76	0.78	0.76	0.78	0.75	0.77

Price is wholesale acquisition cost. *Post* = 1 if the drug launch was 2005 or later. Standard errors (clustered by therapeutic class) are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

FIGURE 5.—QUALITY-ADJUSTED PRICES FOR ANTICANCER DRUGS BEFORE AND AFTER THE 2005 POLICY CHANGE



Lines indicate trends with and without the outlier before and after the policy change.
Source: Authors' analysis using data from Howard et al. (2015).

compare launch prices for the treatment and control groups. In one specification, the control group consists of retail, and we can see the change in the launch price in both a plot of the case (figure 4) and regression analysis (see table 7). In another specification, the control group consists of outpatient provider-administered drugs that are not reimbursed based on ASP but instead continue to be reimbursed based on AWP (see table 8). For both control groups, the results are economically and statistically significant. Coefficients vary from 1.7 to 1.8 for new molecules (tables 7 and 8), indicating that launch prices are 450% to 500% higher.[4]

[4]For a coefficient of 1.7, an increase from 0 to 1 causes price to rise by $\exp(1.7) - 1 = 450\%$.

TABLE 6.—ESTIMATES OF THE EFFECT OF A REIMBURSEMENT CHANGE ON LAUNCH PRICES FOR ANTICANCER DRUGS APPROVED BETWEEN 1995 AND 2013 AND REIMBURSED UNDER MEDICARE PART B

	ln (episode treatment price)		ln (price per life year gained)	
Dependent Variable:	(1)	(2)	(3)	(4)
Post	0.834**	0.785**	0.595*	0.607*
	(0.276)	(0.266)	(0.332)	(0.298)
New molecule		−0.635*		−0.433**
		(0.302)		(0.168)
Priority review		0.170		0.680*
		(0.235)		(0.366)
Constant	3.014***	3.248***	4.432***	4.103***
	(0.271)	(0.219)	(0.251)	(0.311)
Observations	29	29	29	29
R^2	0.30	0.46	0.16	0.29
Adjusted R^2	0.27	0.39	0.12	0.20

Prices are adjusted for inflation. *Post* = 1 if the drug launch was 2005 or later. Standard errors (clustered by disease) are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

TABLE 7.—ESTIMATES OF THE EFFECT OF A REIMBURSEMENT CHANGE ON DRUG LAUNCH PRICES USING DIFFERENCE-IN-DIFFERENCES REGRESSION IN WHICH THE CONTROL GROUP CONSISTS OF RETAIL DRUGS

Dependent Variable:	log (price per ml)			
Control Group:	Drugs with >70% Retail Sales			
	(1)	(2)	(3)	(4)
Treated drug × Post × New molecule		1.720**		1.795**
		(0.766)		(0.806)
Treated drug × Post	1.418***	0.449	1.689***	0.843
	(0.533)	(0.396)	(0.624)	(0.544)
New molecule	0.885***	0.625**	0.842***	0.609**
	(0.302)	(0.290)	(0.281)	(0.262)
Priority review	−0.259	−0.249	−0.393	−0.430
	(0.594)	(0.730)	(0.617)	(0.771)
Constant	3.092***	3.183***	−0.377	0.139
	(0.462)	(0.426)	(2.878)	(2.414)
Competition controls	No	No	Yes	Yes
Class fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	307	307	307	307
R^2	0.87	0.88	0.88	0.89
Adjusted R^2	0.82	0.83	0.83	0.84

The treatment group consists of provider-administered drugs affected by the reimbursement change in the postperiod, while the control group consists of retail drugs reimbursed in other ways. Price is wholesale acquisition cost. *Post* = 1 if the drug launch was 2005 or later. Standard errors (clustered by therapeutic class) are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

We find that the effect of the policy is strongest for new molecules. Manufacturers of new molecules have more freedom to launch at higher prices, because they are less constrained by public expectations of what the price should be. In contrast, people perceive that a new version of an old drug should have a price similar to the price of the old version. A price considerably higher than the old version would seem unfair. Perceived fairness is a key consideration for many manufacturers. According to the *Washington Post*, one manufacturer "considered a range of prices ... and weighed the value to its shareholders against the 'reputational risks,' meaning the potential outrage from patients, physicians and payers."[5]

[5]https://www.washingtonpost.com/news/wonk/wp/2015/12/01/how-an-84000-drug-got-its-price-lets-hold-our-position-whatever-the-headlines/.

TABLE 8.—ESTIMATES OF THE EFFECT OF A REIMBURSEMENT CHANGE ON DRUG LAUNCH PRICES USING DIFFERENCE-IN-DIFFERENCES REGRESSION IN WHICH THE CONTROL GROUP CONSISTS OF PROVIDER-ADMINISTERED DRUGS UNAFFECTED BY THE REIMBURSEMENT CHANGE

Dependent Variable:	log (price per ml)			
Control Group:	Other Provider-Administered Drugs			
	(1)	(2)	(3)	(4)
Treated drug × Post × New molecule		1.707**		1.687**
		(0.761)		(0.780)
Treated drug × Post	1.808	1.085	1.803	1.063
	(1.279)	(1.147)	(1.297)	(1.222)
New molecule	0.879***	0.387	0.736*	0.360
	(0.328)	(0.305)	(0.388)	(0.309)
Priority review	−0.692	−0.797	−0.717	−0.802
	(0.817)	(1.007)	(0.844)	(1.020)
Constant	3.148*	3.142*	2.212	2.908
	(1.289)	(1.269)	(2.737)	(2.357)
Competition controls	No	No	Yes	Yes
Class fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	248	248	248	248
R^2	0.83	0.84	0.83	0.84
Adjusted R^2	0.77	0.78	0.76	0.78

Both the treatment and control groups are provider-administered drugs, but the drugs in the treatment group changed reimbursement in the postperiod. Price is wholesale acquisition cost. *Post* = 1 if the drug launch was 2005 or later. Standard errors (clustered by therapeutic class) are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

If reimbursement is "cost plus," then there are fewer constraints on price, and perceived fairness plays a bigger role in determining price.

Controlling for competition has a small effect on the policy change in the postperiod. While generic competition tends to drive down the sales of the brand-name drug, it often has little effect on the price of the brand-name drug. Faced with generic competition, brand-name manufacturers segment the market and sell to consumers with less elastic demand. The dearth of an effect of generic competition on branded price is called the "generic paradox" (Grabowski & Vernon, 1992; Scherer, 1993; Bhattacharya & Vogt, 2003).

In the appendix, we report results for other specifications. We also report results from placebo tests. Furthermore, we list the molecules included in the analysis.

The large effect of the policy on launch prices indicates that switching costs are large for pharmaceuticals. Recall that the model predicts that if drugs have large switching costs, then reimbursement based on lagged prices will cause high launch prices. Launch price (p_1) depends on the interaction between switching costs (κ) and reimbursement (σ) (equation [3]).

VI. Limitations

The study has several limitations. First, we use list prices rather than prices net of discounts and rebates. However, the treatment effect we estimate is so large that it is unlikely that an increase in rebates drove the effect. Furthermore, rebates probably fell in the postperiod, because reimbursement on average price creates an incentive to reduce price dispersion. We expect the policy to decrease price dispersion because reimbursement on average price would mean potential losses

for customers paying high prices. If rebates fell in the post-period, then we will underestimate the effect.

Second, we focus only on drug launch prices, ignoring changes in the prices of existing drugs. Preliminary analyses on price changes of existing drugs indicated a null effect. This is not surprising. On one hand, reimbursement based on price makes demand less sensitive to price, so prices could rise. On the other hand, prices of existing drugs could fall, or at least rise slowly, because reimbursement is based on lagged prices. Also, we do not estimate changes in price dispersion because we do not have data on prices to individual buyers.

Third, in the difference-in-differences analysis, the control groups might be flawed. One control group is outpatient provider drugs exempt from ASP-based reimbursement. Another control group is retail drugs. The retail drug environment changed during the sample period with the creation of Medicare Part D, which might have driven up the prices of some drugs sold at retail because of the moral hazard problem (Besanko, Dranove, & Garthwaite, 2016). Alternatively, Medicare Part D might have driven down prices if insurers used their buying power to drive down prices. The 2006 policy change caused an average drop in prices of 10% for retail drugs used heavily by seniors, while prices rose an average of 12% for other retail drugs (Duggan & Scott Morton, 2010). Drugs used by seniors constitute one-fifth of the market, so the average retail price increased about 8%.[6] Hence, we would ideally increase the control by 4% (from 8% to 12%). Inflating the control variable by 4% would decrease our treatment effect a bit, though not dramatically, because we estimate a treatment effect that is 100 times greater.

Fourth, if payers accommodate higher prices for provider-administered drugs, then drug makers might shift their focus to making provider-administered drugs. Whether a drug is provider-administered rather than patient-administered depends on the characteristics of the disease. A drug is more likely to be provider-administered for acute conditions affecting sicker patients and having more side effects. A drug is more likely to be patient-administered for chronic conditions affecting healthier patients and having fewer side effects. The drug maker can choose its disease focus, but it takes years to change strategies, because drug development from patent to launch typically takes more than a decade (DiMasi et al., 2016) and thus would fall outside the study period. At the margin, a manufacturer might choose to continue phase III development for a drug that the manufacturer would have discontinued prior to the reimbursement change. If the marginal drug is of lower-than-average value and if low value is associated with low price, introduction of the drug would bias our prices downward, causing us to underestimate the effect of the policy.

[6]The average price change is $(1/5)(1 - .10) + (4/5)(1 + .12) = 1.08$.

VII. Conclusion

We introduce a model of reimbursement in a market with rising willingness-to-pay. The model shows that when insurers such as Medicare reimburse providers based on lagged prices, launch prices are high and efficiency is low. Launch prices are high for two reasons. First, reimbursement based on price makes buyers less sensitive to price. Second, reimbursement on lagged prices induces firms to "invest" in a high launch—higher than the current profit-maximizing price—in order to secure a higher reimbursement and a higher willingness-to-pay in the future. The firm then captures the high willingness-to-pay with high prices.

We find that a 2005 change in outpatient provider drug reimbursement caused a large increase in drug launch prices. We do not intend to persuade readers about the precise increase, but to provide theory and evidence that reimbursement based on lagged prices encourages manufacturers to set high launch prices. To our knowledge, this is the first study to show that the policy drove up launch prices.

Changing to reimbursement based on a fixed, per unit amount could reduce prices because providers would be more sensitive to the price and manufacturers would have less incentive to choose a high launch price to drive up future prices. Lower prices would benefit providers, as well as patients who pay a share of the price. One option for a fixed reimbursement would be to cap reimbursement based on the cost effectiveness of the product, as estimated by the Institute for Clinical and Economic Review in the United States or the National Institute for Health and Care Excellence in the United Kingdom.[7]

[7]For more on reimbursement based on cost-effectiveness analysis, see the appendix.

REFERENCES

Abbott, Thomas A., "Price Regulation in the Pharmaceutical Industry: Prescription or Placebo," *Journal of Health Economics* 14 (1995), 551–565.

Academy of Managed Care Pharmacy, "AMCP Guide to Pharmaceutical Payment Methods, 2013 Update," technical report (2013).

Alpert, Abby, Helen Hsi, and Mireille Jacobson, "Evaluating the Role of Payment Policy in Driving Vertical Integration in the Oncology Market," *Health Affairs* 36 (2017), 680–688.

Alpert, Abby, Mark Duggan, and Judith K. Hellerstein, "Perverse Reverse Price Competition: Average Wholesale Prices and Medicaid Pharmaceutical Spending," *Journal of Public Economics* 108 (2013), 44–62.

Bergemann, Dirk, and Juuso Välimäki, "Dynamic Pricing of New Experience Goods," *Journal of Political Economy* 114 (2006), 713–743.

Berndt, Ernst R., and Joseph P. Newhouse, "Pricing and Reimbursement in U.S. Pharmaceutical Markets," NBER working paper 16297 (2010).

Besanko, David, David Dranove, and Craig Garthwaite, "Insurance and the High Prices of Pharmaceuticals," NBER working paper 22353 (2016).

Bhattacharya, Jayanta, and William B. Vogt, "A Simple Model of Pharmaceutical Price Dynamics," *Journal of Law and Economics* 46 (2003), 599–626.

Blume-Kohout, Margaret E., and Neeraj Sood, "Market Size and Innovation: Effects of Medicare Part D on Pharmaceutical Research and Development," *Journal of Public Economics* 97 (2013), 327–336.

Centers for Medicare and Medicaid Services, *Medicare Claims Processing Manual* (2016).

Ching, Andrew T., "A Dynamic Oligopoly Structural Model for the Prescription Drug Market after Patent Expiration," *International Economic Review* 51 (2010), 1175–1207.
Clemens, Jeffrey, and Joshua D. Gottlieb, "In the Shadow of a Giant: Medicare's Influence on Private Physician Payments," *Journal of Political Economy* 125 (2017), 1–39.
Coscelli, Andrea, and Matthew Shum, "An Empirical Model of Learning and Patient Spillovers in New Drug Entry," *Journal of Econometrics* 122 (2004), 213–246.
Crawford, Gregory S., and Matthew Shum, "Uncertainty and Learning in Pharmaceutical Demand," *Econometrica* 73 (2005), 1137–1173.
Dean, Joel, "Pricing Pioneering Products," *Journal of Industrial Economics* 17 (1969), 165–179.
DiMasi, Joseph A., Henry G. Grabowski, and Ronald W. Hansen, "Innovation in the Pharmaceutical Industry: New Estimates of R&D Costs," *Journal of Health Economics* 47 (2016), 20–33.
Duggan, Mark, and Fiona Scott Morton, "The Distortionary Effects of Government Procurement: Evidence from Medicaid Prescription Drug Purchasing," *Quarterly Journal of Economics* 121:1 (2006), 1–30.
——— "The Effect of Medicare Part D on Pharmaceutical Prices and Utilization," *American Economic Review* 100:1 (2010), 590–607.
Ekelund, Mats, and Bjorn Persson, "Pharmaceutical Pricing in a Regulated Market," this REVIEW 85 (2003), 298–306.
Grabowski, Henry G., David B. Ridley, and Kevin A. Schulman, "Entry and Competition in Generic Biologics," *Managerial and Decision Economics* 28 (2007), 439–451.
Grabowski, Henry G., and John M. Vernon, "Brand Loyalty, Entry and Price Competition in Pharmaceuticals after the 1984 Drug Law Act," *Journal of Law and Economics* 35 (1992), 331–350.
Howard, David H., Peter B. Bach, Ernst R. Berndt, and Rena M. Conti, "Pricing in the Market for Anticancer Drugs," *Journal of Economic Perspectives*, 1:29 (2015), 139–162.
Ikegami, Naoki, Shunya Ikeda, and Hiroki Kawai, "Why Medical Care Costs in Japan Have Increased Despite Declining Prices for Pharmaceuticals," *PharmacoEconomics* 14 (1998), 97–105.
Jacobson, Mireille, Craig C. Earle, Mary Price, and Joseph P. Newhouse, "How Medicare's Payment Cuts for Cancer Chemotherapy Drugs Changed Patterns of Treatment," *Health Affairs* 29 (2010), 1391–1399.
Lakdawalla, Darius, and Neeraj Sood, "Innovation and the Welfare Effects of Public Drug Insurance," *Journal of Public Economics* 93 (2009), 541–548.
Lu, Z. John, and William S. Comanor, "Strategic Pricing of New Pharmaceuticals," this REVIEW 80 (1998), 108–118.
Macdougall, Iain C., William E. Strauss, Justin McLaughlin, Zhu Li, Frank Dellanna, and Joachim Hertel, "A Randomized Comparison of Ferumoxytol and Iron Sucrose for Treating Iron Deficiency Anemia in Patients with CKD," *Clinical Journal of the American Society of Nephrology* 9 (2014), 705–712.
Magellan Rx Management, "Medical Pharmacy Trend Report" (2013).
Medicare Payment Advisory Commission, "A Data Book: Health Care Spending and the Medicare Program," technical report (2017).
Miano, Todd A., Adam Cuker, Jason D. Christie, Niels Martin, Brian Smith, Amy T. Makley, Wensheng Guo, and Sean Hennessy, "Comparative Effectiveness of Enoxaparin vs Dalteparin for Thromboprophylaxis after Traumatic Injury," *Chest* 153 (2018), 133–142.
Prosser, Helen, Solomon Almond, and Tom Walley, "Influences on GPs' Decision to Prescribe New Drugs: The Importance of Who Says What," *Family Practice* 29 (2003), 61–68.
Reiffen, David, and Michael R. Ward, "Generic Drug Industry Dynamics," this REVIEW 87 (2005), 37–49.
Ridley, David B., and Su Zhang, "Regulation of Price Increases," *International Journal of Industrial Organization* 50 (2017), 186–213.
Scherer, Frederic M., "Pricing, Profits, and Technological Progress in the Pharmaceutical Industry," *Journal of Economic Perspectives* 7 (1993), 97–115.
Schmalensee, Richard, "Product Differentiation Advantages of Pioneering Brands," *American Economic Review* 72 (1982), 349–365.
Scott Morton, Fiona, "The Strategic Response by Pharmaceutical Firms to the Medicaid Most-Favored-Customer Rules," *RAND Journal of Economics* 28 (1997), 269–290.
——— "Entry Decisions in the Generic Pharmaceutical Industry," *RAND Journal of Economics* 30 (1999), 421–440.
Shajarizadeh, Ali, and Aidan Hollis, "Price-Cap Regulation, Uncertainty and the Price Evolution of New Pharmaceuticals," *Health Economics* 24 (2015), 966–977.
U.S. Department of Health and Human Services, Office of the Inspector General, "Average Sales Prices: Manufacturer Reporting and CMS Oversight," technical report (February 2010).
U.S. Government Accountability Office, "Medicare Part B: CMS Should Take Additional Steps to Verify Accuracy of Data Used to Set Payment Rates for Drugs," technical report (July 2016).
Verma, Seema, "Remarks by the Administrator for the Centers for Medicare and Medicaid Services at the American Hospital Association Annual Membership Meeting" (2018).
Yurukoglu, Ali, Eli Liebman, and David B. Ridley, "The Role of Government Reimbursement in Drug Shortages," *American Economic Journal: Economic Policy* 9 (2017), 348–382.