Lagged-Price Reimbursement Contracts: The Impact of Medicare Part B on Pharmaceutical Price Growth

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Abstract

We examine cost-plus lagged-price reimbursement contracts, focusing on Medicare Part B's payment for physician-administered drugs. While previous research showed Part B increased launch prices, we estimate its effect on later prices and find that lagged-price reimbursement *lowers* prices in later periods. Drugs more exposed to Medicare reimbursement have lower price growth (net of rebates): a drug with above median Part B exposure has a 10% lower price after 3 years than a below median exposure drug that launched at the same price, with a larger effect for newly approved molecules.

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1 Introduction

Governments purchase goods and services from private firms ranging from defense contractors to healthcare providers. When contracting with the government, prices are rarely determined by a market mechanism, which can lead to distortions. In an efficient market, prices signal firm production costs and consumers' willingness to pay. Absent such an information aggregating mechanism, governments frequently use cost-plus contracts. Absent good information on costs, the government may use proxies, including past prices. The combination of cost-plus contracting and dynamic incentives can amplify or dampen distortions, especially when firms price strategically: the input price set by the firm today will affect the future reimbursement that contractors buying these inputs will receive from the payer.

This paper empirically characterizes the effects of lagged-price cost-plus reimbursement on dynamic incentives for price setting. We focus on physician-administered drugs covered by Medicare Part B, which includes anti-cancer/chemotherapy drugs and immunosuppressives. However, lagged-price cost-plus procurement contracts show up in other markets as well. For instance, in construction contracting, a producer sets a price for a construction-related input (e.g. asphalt), a construction contractor purchases that input, and the government makes additional payments to contractors if they have an economic price adjustment clause if an index of prices is higher than forecasted.[1]

Payment for prescription drugs is particularly controversial, as the government (via Medicare) is a major purchaser from pharmaceutical firms who often hold a monopoly on the drug. In Medicare Part B, which covers physician-administered drugs, the government pays physicians using cost-plus reimbursement based on lagged-prices. However, widespread concern about rising drug prices has driven proposals to change how drugs are paid for and recent policy reforms in which government will directly negotiate drug prices.[2] Moreover, in addition to affecting drug spending, Part B policy could have important consequences for enrollee health. Medicare is a major payer for cancer care in the US, and Part B drugs are a major source of revenue for oncology practices.

Part B has a buy-and-bill policy, in which physicians purchase drugs (either on their own, or as part of a group purchasing organization). Medicare pays physicians when they deliver these drugs based on lagged average cost (from two quarters ago) plus a percentage

[1] See economic price adjustment clauses in construction and defense contracts discussed in Crocker and Reynolds (1993) and Kosmopoulou and Zhou (2014).

[2] In addition to the 2022 Inflation Reduction Act, e.g. as discussed in Cutler (2022), potential policy reforms are discussed in Ridley and Zhang (2017); Dubois et al. (2022); Ginsburg and Lieberman (2021). Lakdawalla (2018) provides a review of the literature on the economics of pharmaceuticals. By contrast, in Medicare Part D, which covers most self-administered drugs, the government has largely devolved price negotiation to private firms that offer insurance plans.

markup. The policy has different incentives than either a simple fixed price or cost-plus contract (see Bajari and Tadelis (2001)). In particular, since physician margin is increasing in lagged-price, higher prices may ultimately lead physicians to prescribe *more*. While the introduction of the current Part B payment policy has been linked to higher drug prices at launch (Howard et al. 2015; Ridley and Lee 2020), it is unknown how Part B affects changes in prices over time.

We first examine empirically how Part B's payment policy affects prices changes over time during the period 2006-2019. Our identifying variation comes from drugs that are more or less exposed to Part B: the share of expenditures for a drug that comes via Medicare Part B, as opposed to private insurers. A similar research design is used by Yurukoglu et al. (2017) to show that exposure to Part B led to shortages in the generic market.[3] We observe average prices net of rebates. Our identification strategy includes a drug fixed effect, so it does not rely on Medicare market share not being correlated with drug value or demand.

For a drug whose Medicare market share at launch is above the median, we estimate that prices 3 years after launch are at least 10% lower than a drug with below median exposure that launched at the same price, with a larger effect for newly approved molecules. Previous literature shows that physician-administered drug prices at launch have been increasing over time ((Howard et al. 2015) on anti-cancer drugs), and changes to Part B reimbursement in 2006 led to higher launch prices (Ridley and Lee 2020). We show that, following launch, more exposure to Part B payment led to slower price growth. We further document that the dynamic impact dampens but likely does not erase the overall upward pressure on prices generated by the Medicare program.

We then develop a conceptual framework to understand the economic forces that could generate the observed pricing patterns, which contrast common "invest-then-harvest" pricing that is typically observed in this market (e.g. Farrell and Shapiro (1988); Ericson (2014)). We model the key features of Medicare payment for physician-administered drugs: pharmaceutical firms set prices, physicians buy the drug on behalf of patients and choose how much to consume, and Medicare reimburses physicians based on lagged market average prices. In our theoretical model, pharmaceutical firms account for changes in future reimbursement when setting prices. Physician demand is affected by both current price and reimbursement, the difference between which is their margin. But because reimbursement levels affect not only physician reimbursement but patients' level of cost-sharing, the model allows price and reimbursement to have different impacts on demand. We show that lagged-price cost-plus

[3]Duggan and Scott Morton (2010) also use this strategy to show that the introduction of Medicare Part D *lowered* the cost of covered drugs, as plan formularies made the demand of newly insured individuals more elastic. Ippolito and Levy (2023) also show that drugs more exposed to Medicare Part D have larger differences between net and list prices of drugs.

reimbursement, as implemented in Part B, can lead to both higher initial prices but *and* lower prices relative to launch in later periods.

Our paper is related to a large literature that explores the impact of contracting and procurement rules in healthcare (e.g. Gaynor et al. (2023); Decarolis (2015)), construction(e.g. Bosio et al. (2022); Krasnokutskaya and Seim (2011)), and telecommunications (e.g. Kang and Miller (2022)). However, many of these papers do not examine the effects on how prices evolve over time (for an exception, see Ji and Rogers (2023)). Our paper examines these dynamic forces theoretically and empirically.

2 Institutional Setting

The Medicare program provides health insurance to elderly and disabled individuals in the United States. Part B covers outpatient care, including drugs administered by physicians. The majority of Part B drug payments are for services rendered in physician office settings; Part D covers outpatient drugs.Spending on Medicare Part B drugs totaled $37.1 billion in 2019, which is about one-fifth the size of spending on Part D drugs. (MedPAC 2022). The top ten drugs ranked by Medicare Part B expenditures constitute about 40% of Part B drug spending. Since 2005, Medicare has reimbursed providers based on average sales price (ASP) (Jacobson et al. 2010; Yurukoglu et al. 2017; Ridley and Lee 2020).

The provider pays a price to the manufacturer that is averaged to construct an average sales price (ASP). The provider is then typically reimbursed at lagged ASP times a multiplier, here 106% the ASP from two quarters ago.[4] The out-of-pocket costs for the patient are 20% of the reimbursed amount in the form of coinsurance; the Medicare program covers the remaining 80%.[5] Initial period reimbursement cannot rely on lagged-prices, and is set at a markup over the "list" price, either Wholesale Average Cost (WAC)+6% or Average Wholesale Price (AWP) -5%. WAC is a list price reported by hospitals for drugs acquired through drug wholesalers. AWP is also a list price, reported by drug wholesalers. As noted by Ridley and Lee (2020), list prices at launch may be artificially high in these markets.

The Part B reimbursement system is controversial for several reasons. First, it is difficult for any administered price system to capture marginal costs. While some worry about overpayment, particularly for biologics (Morton and Boller 2017), others note that government policy can put a financial strain on providers (Polite et al. 2015). Lagged-price reimbursement will additionally create dynamic pricing incentives that may affect provider treatment

[4]The controversial 340B program allows some providers treating low-income patients to buy at a discount and (in some time periods) receive lower reimbursement. See Desai and McWilliams (2018).

[5]Patient cost-sharing is substantially reduced if they purchase additional Medigap insurance or are dual-eligible for Medicaid.

decisions and the lifetime profitability of drugs. For some physicians, reimbursements for these drugs constitute a substantial share of revenue. Financial incentives for physicians may be particularly strong in oncology because average drug margins for chemotherapy can range anywhere from a few cents to $2,000 for a single dose. Physicians might have a preference for drugs with higher price levels, in so far as these yield a higher margin.

To build intuition, consider how the Part B reimbursement rules may affect a monopolist's pricing incentives (62% of drugs covered under Part B have a monopoly manufacturer). A pharmaceutical firm introducing a new drug into the market may want to enter at a low price to encourage physicians to adopt the new treatment, but Part B reimbursement rules imply that physicians will get reimbursed at low rates in subsequent periods, which may cause them to stop prescribing the drug future periods. If physicians who prescribe the drug are sensitive to both the acquisition price and the reimbursement rate of a particular drug, then lagged-price reimbursement affects the pharmaceutical firm's trade-off between current and future profits. Because the pharmaceutical monopolist can control future reimbursement through its choice of current prices, the firm has an incentive to raise prices in the current in order to ensure that Medicare reimburses physicians at a high rate in the future period. These pricing incentives are exactly the opposite of "invest-then-harvest" pricing: if physicians are reluctant to adopt new drugs, then setting high prices with high future reimbursement rates may be unprofitable. Thus, the effect of lagged-price reimbursement rules on price growth is theoretically ambiguous, ex-ante.

3 Data and Descriptive Statistics

3.1 Data

We construct a sample of prices and Medicare market shares for physician-administered drugs spanning 2006 through 2019. Our unit of analysis is the drug-quarter, where drugs are uniquely identified by Health Care Procedure Coding System (HCPCS) codes. We combine data from three sources: pricing files, aggregate Medicare claims, and Truven Marketscan spending aggregates.

To measure the price and reimbursement of a drug, we use the Average Sales Price (ASP) of Part B drugs from 2005 through 2019, which are publicly available from the Center for Medicare Services (CMS). ASP data are reported at the HCPCS level. We include only HCPCS introduced later than 2005 and exclude drugs in the ASP files that are reimbursed under alternative methodologies (vaccines and blood/clotting products), limiting to "J Code" HCPCS.

We measure price by inverting the reimbursement rate. The ASP pricing files contain quarterly data on the reimbursement rate, which is a function of the lagged sale price of the drug. We construct our price variable for each drug j in quarter t by taking the reimbursement rate from quarter $t+2$ and dividing it by 1.06.

To measure exposure to the Medicare Part B program, we construct Medicare market share (MMS) for each HCPCS, following a similar approach to Yurukoglu et al. (2017). We aggregate drug payments both from private insurers and from Medicare, and define MMS for each drug-year as Medicare over Medicare plus private drug payments in that year.

We obtain Medicare's aggregate drug payments from the CMS Part B National Summary Data File, which contains yearly data on aggregate payments for each HCPCS code in by Part B. We obtain aggregate private drug payments at the HCPCS-year level using Truven MarketScan data for each year. We follow Yurukoglu et al. (2017) and scale these payments up by the ratio all commercial insurance enrollees to the number of Marketscan enrolees in that particular year, assuming that Marketscan provides an approximately nationally representative sample of the commercial insurance market, which allows us to construct a national private drug payments figure.

Our key treatment variable is a drug j's Medicare market share at launch, which we term MMS_j. We focus at MMS at launch to measure a persistent characteristic of a drug– its exposure to the pricing incentives created by Medicare Part B. Finally, drugs are launched in different years, so we use τ to describe time in quarters relative to a drug's launch. The first period that HCPCS is observed is normalized to $\tau = 1$.

3.2 Descriptive Statistics

Prices evolve quite heterogeneously across drugs. We give some examples in Figure 1 Panel A, which displays the price paths (relative to launch price) of the top 10 Medicare Part B expenditure drugs across the 2015-2019 period. We plot prices relative to prices in 2015, though note that these drugs were introduced are a variety of different times. While many of these drugs show a steady increase across time, there are exceptions, such as Ranibizumab (a drug used for macular degeneration), that show declining prices over time. Various drugs experience a drop in prices after prior increases; these drop-offs are sometimes but not always related to billing-code entry.

Medicare quantity sold, measured as revenue divided by price, varies over time (See Appendix Figure A0). While highly heterogeneous across drugs, on average quantity sold doubles in the first two years post-launch. As a result, prices in later periods contribute more to the volume-weighted lifetime cost of a drug than the launch price, motivating our

analysis of the dynamic pricing impact of Part B reimbursement.

Table 1 gives descriptive statistics on our cohort of drugs, and Appendix Figure A1 shows the distribution of MMS at launch. We identify 215 unique HCPCS, and split them into above and below median MMS at launch, which is 0.193. Relative prices 2 years after launch are about 3% higher for above median MMS and 8% higher for below median MMS drugs. However, above Median MMS drugs are about 1.3 years "newer."

Prices grow at a slow enough rate to leave positive profit margins for the average provider. Constructing the average annual and quarterly growth rate for each drug provides insight into the profits that prescribing providers make. A provider who acquires the drug at a price equal to ASP every quarter will make zero profit margin on a drug whose price grows at 6% over two quarters. (The reimbursement rate will equal acquisition costs in this case.) Note that for prices to grow by 6% over two quarters, the compound quarterly growth rate has to be 2.96%, since $(1.0296)^2 = 1.06$. Here, the mean compound quarterly growth rate is 0.92%.

Figure 1 Panel B shows the price evolution of drugs over time, split by exposure to Part B. We split the sample by whether the drug was above or below median MMS at launch to allow us to compare prices between drugs that are more or less exposed to the Medicare market. This figure normalizes the price at launch ($\tau = 1$) and plots price in later quarters, weighting by total market size. Weighted by market size, prices are 10-20% more expensive 2 years after launch, with greater price growth for drugs more exposed to Part B.

4 Empirical Strategy and Results

4.1 Estimation

Our empirical strategy uses cross-sectional variation in individual drug exposure to the Medicare market to identify the effects of Part B's lagged ASP reimbursement rule on drug price growth. We estimate:

$$ln(p_{jt}) = \beta_{\tau_{jt}} MMS_j \times \tau_{jt} + \tau_{jt} + X_{jt} + \epsilon_{jt} \quad (1)$$

where p_{jt} is the price (ASP) of drug j in year t, τ_{jt} is a set of indicator variables for the quarter relative to when drug j was introduced, MMS_j is the Part B share of drug j's claims in its first quarter. We include drug and year fixed effects in X_{jt}. Note that MMS_j does not vary over time– it is constant within a drug– and we include drug fixed effects. (MMS is highly correlated within a drug over time, above 0.9.)

The key coefficients of interest are the $\beta_{\tau_{jt}}$, the coefficients on the interactions between time since launch τ_{jt} and MMS_j. The estimates describe how prices in later periods com-

pare to the launch price for HCPCS with relatively high Medicare market share at launch. The identifying assumption is that drugs with different MMS_j would have had the same percentage change in price in later periods in the absence of incentives created by the Medicare reimbursement program. Conditional on drug fixed effects, the regression coefficients can be interpreted as percentage price changes relative to launch. While we cannot identify the effect of Medicare market share on launch prices, this strategy has a number of advantages. For example, we do not need that the price per standardized dosage of one drug is comparable to the price per dosage of another.

We weight our regressions by a drug's average total market size over the time of our sample. This allows us to identify the average causal effect of Medicare market share per dollar spent, rather the average per drug, as there are many small drugs that are relatively unimportant for overall drug spending. (See Solon et al. (2015) on weights).

4.2 Main Results

Panel A of Figure 2 shows that drugs that are more exposed to Medicare Part B have slower price growth. The confidence intervals on each individual interaction coefficient are wide, but we can test the hypothesis that the interactions between MMS and time since launch are all zero ($F(23, 214) = 3.52, p < 0.001$). We thus reject the hypothesis that high Medicare market share drugs have the same price path as low Medicare market share drugs.

To interpret the results, note that the interaction coefficient on $\tau \times MMS_j$ tells us how higher versus Medicare market share drugs will be priced in period τ, relative to their launch price. The interaction coefficient of -0.18 on $\tau = 24 \times MMS_j$ tells us that high Medicare market share drugs will have increased their prices less than low Medicare market share drugs. For a drug sold only to Medicare (MMS=1), the estimates predict that after 6 years, its price would be about 18% below a drug with no Medicare market share that launched at the same price. (They may, however, launch at different prices.)

We summarize our results succinctly in Table 2, which presents results for both the full analysis sample and a balanced panel of drugs. In Column 1, we impose a linear time trend in prices post launch, and interact that with MMS. These specifications indicate that drugs with zero MMS grow at about 0.7% per quarter, while drugs with 100% MMS grow about -0.8 percentage points less per quarter than zero MMS drugs. Results in Column 3 for a balanced panel show a similar pattern, but with a stronger interaction where $MMS = 1$ drugs grow about -1.5 percentage points per quarter less than $MMS = 0$ drugs.

However, a linear specification in time and MMS may not be appropriate. Table 2 also presents a specification in which time period is split into early ($\tau <= 12$) and late, and drugs

are split into above and below median MMS. Holding launch price constant, prices of above median MMS drugs are 11% below those of below median MMS drugs after 3 years in our Analysis Sample, with a smaller estimate for the balanced panel.

Our main analysis examines price and reimbursement for all newly introduced J-codes, regardless of whether the underlying molecule was newly approved. However, the pricing dynamics of older drugs might be different, due to greater generic competition (or the threat thereof), as well as potential anchoring on prices that pre-dated the introduction of the new HCPCS code. Indeed, Appendix Figure A2 shows that competitor entry can happen quickly for new J-codes for existing molecules. To address these concerns, we created a narrow sample of drugs whose molecule FDA approval date was concurrent (within 1 year) with the introduction of the HCPCS code.[6] The resulting estimates displayed in Panel B of Figure 2 show that the MMS interaction effects are larger in magnitude and more precisely estimated in this sample, with coefficients approximately -0.13 after 12 quarters and -0.29 after 24 quarters, compared to about -.09 and -0.18 in our main results. This suggests our main specification is conservative.[7]

4.3 Robustness

Appendix Figure A4 shows that our results are robust to using a variety of alternative two-way fixed effects estimators that remove these concerns. Point estimates in each case are quite similar. (To test robustness to alternative estimators, we need to discretize our treatment. We do this by splitting our sample into above versus below median MMS, as in Table 2.)

We also consider a series of additional robustness checks in Appendix Figure A5. Each panel presents an analogue of Figure 2 Panel A run on a different sample. In Panel A, we show that excluding outliers does not meaningfully affect our results. In Panel B, we weight all drugs equally, rather than by drug market size. The results are noisier, thought the point estimates are larger in magnitude. To address any concerns that our results are driven by an unbalanced panel, we construct a sample with a balanced panel. We first shorten our estimation window to the first 4 years since launch in order to maximize sample size, and show the regression results on an unbalanced panel in Panel C. Panel D then shows the balanced panel results. The results are quite similar, and in fact more precisely estimated than our main results.

[6] This required merging the HCPCS to NDC using string matching on drug names. The narrow sample is smaller– 88 unique HCPCS, rather than 215 in our main analysis sample. Appendix Figure A3 shows that this sample has a longer time until competitor entry in the billing code.

[7] A linear specification in time gives a coefficient on $\tau \times MMS$ of -0.013, about twice that in Table 2 column 1.

In Appendix Figure A6, we consider a set of additional robustness checks related to sample composition. Panel A reproduces our main Figure 2 on a common axis for reference. The negative trend becomes, if anything, stronger in three robustness checks: excluding the initial (and largest) cohort of observations in Panel B, excluding small cohorts of two or fewer drugs in Panel C, and excluding drugs that ever have a period of missing price data in Panel D. We also examine whether the effect of MMS is different in cohorts of drugs introduced sooner versus later after Part B's lagged-price reimbursement system was introduced. Appendix Table A1 shows no clear evidence that the effect is different for these cohorts.

Finally, to address concerns that MMS might be endogenous to firm pricing strategy, we create another independent measure of exposure to Medicare's pricing incentives. We examine individuals with commercial insurance not on Medicare, and compare drugs with higher market share among older versus younger commercially insured individuals. The correlation at launch between MMS and this alternative measure is 0.46. Appendix Tables A2 and A3 give details and show that we find similar and perhaps more negative estimated impacts of this alternative measure of exposure on price growth.

4.4 Medicare Market Share and Launch Price

To place in context our estimates of the dynamic effects of lagged-price reimbursement, we also provide estimates of the impact of Medicare Part B on initial launch price. We view these estimates with skepticism. Our main results include drug fixed effects and simply require that counterfactual percentage changes in prices be the same across groups. However, to identify whether drugs with higher Part B exposure have higher launch prices, we must remove drug fixed effects from our regression. The identification assumption required is now much stronger: in the absence of Part B's reimbursement formula, the types of drugs with greater exposure to Medicare Part B would have had initial prices that were the same on average as drugs with less exposure to Part B. Moreover, in the absence of a clearly comparable unit of measure for drug pricing, we anticipate greater variation in measured HCPCS prices.

Nonetheless, Table A4 shows the results of regressions that parallel those in our Table 2, but now drops drug fixed effects and displays the effect of MMS_j on launch prices. We estimate that drugs with above median MMS have launch prices that are 64 log points (90%) higher, but this is imprecisely estimated and we cannot reject declines of 26 log points or increases of 154 log points. Despite the imprecision, these results plus those of Ridley and Lee (2020), suggest that the effects of Part B on initial price are larger than the declines in

later periods.[8]

4.5 Implications

What is the overall impact of high (above-median) exposure to Medicare on the lifecycle price of drugs? We compare our estimates to the estimates we would get if we ignored the dynamic price effect and simply extrapolated the estimated Part B effect on launch price to all future periods. We focus on the first 6 years (24 quarters), and assume no difference after that time, as this is the window for which we are able to estimate results. The lifecycle price of a drug is $\frac{\sum_{\tau=1}^{24} p_\tau Q_\tau}{\sum_{\tau=1}^{24} Q_\tau}$, ignoring discounting over this short horizon. Each period's price is weighted by the quantity sold Q_τ in that period using the estimates from Figure A0.

Our estimate of the effect of being above median MMS in years 3-6 comes from Table 2 Column 2. The estimate of the effect of being above median MMS on launch is taken from Table A4 Column 2. We transform these log point changes into percentage changes. Naively extrapolating the launch price effect implies that being above median MMS raises lifecycle price by 89%. However, the lifecycle price is actually only 79% higher accounting for the decline in years 3-6. Ignoring the dynamic price changes would lead to an overestimate of the lifecycle price.

The estimated net effect is that more exposure to Part B leads to higher lifecycle prices. This result is robust to a range of possible launch price effects– it holds even if the actual increase in launch price was only about one-tenth our observed estimate.

5 Conceptual Framework

We develop a stylized model of monopolist pricing under lagged-price reimbursement to interpret our empirical findings. In the model, some drug purchases are reimbursed by the government with lagged-price reimbursement, and the remainder are reimbursed by private insurers at an independently determined rate. The model shows the conditions under which Medicare's lagged-price reimbursement will lead to slower price growth or declining prices over time.

[8] Ridley and Lee (2020) estimates that the average effect of being exposed to Part B's lagged-price reimbursement payment system, compared to Medicare's previous reimbursement system, was a 0.61 log point price increase at launch. That estimate is not directly comparable to ours, as our estimate comes from variation in exposure to Medicare versus private payment.

5.1 Demand

Consider a two period ($t = 1, 2$) model of pharmaceutical pricing.[9] Physicians acquire drugs directly from a pharmaceutical firm each period, and pharmaceutical firms set prices. (We abstract away from intermediaries, such as pharmacy benefit managers.) Physicians then receive payment for the drug purchases from the government using lagged-price reimbursement. Private firms use their own independent payment methodology, which is determined outside the model. The fraction of patients with Medicare insurance is μ, with the remainder in private insurance.

Drug demand depends on physician utility, which consists of both profits and (potentially) patient well-being. A physician makes a binary decision of whether to prescribe a drug to each patient, and the utility of administering a drug to patient i in time period t is:

$$V_{it} = \underbrace{(r_{it} - p_{it})}_{\text{physician profits}} + \widetilde{\lambda} \underbrace{(h_{it} - oop(r_{it}))}_{\text{patient utility}}$$

where r_{it} is the reimbursement received by the physician, p_{it} is the price the physician pays to acquire the drug, $\widetilde{\lambda}$ is the physician's weight on patient utility, h_{it} the health benefit from administering the drug to patient i, and $oop(r_{it})$ is the patient out-of-pocket cost, which can depend on reimbursement levels. [10] Reimbursement and acquisition prices will differ between patients. Reimbursement depends on the patient's source of insurance. Acquisition prices will depend on a variety of supply-side factors and, indirectly, the mix of patients a physician serves. For simplicity, we assume that the provider faces different acquisition prices depending on whether they have a Medicare patient (p_t^M) or a privately insured patient (p_t^P). While this assumption is stylized, evidence suggests there is substantial heterogeneity in acquisition price across providers (Medicare Payment Advisory Commission 2016).

Whether a physician prescribes the drug depends on the physician's margin– the difference between reimbursement and acquisition price–which can vary across patients. It also depends on the utility of the patient, which is comprised both of a stochastic health component and out-of-pocket spending. To simply expressions, define the physician's *effective* margin in period t as the difference between the weighted reimbursement and the price: $m_{it} \equiv \lambda r_{it} - p_{it}$, where the weight on reimbursement $\lambda \equiv (1 - \widetilde{\lambda}\frac{oop(r_{it})}{r_{it}})$ accounts for both the effect of reimbursement on physician profits and patient cost-sharing.

Quantity demanded is thus a function of the physician's *effective margin*, where λ is a

[9] This can be generalized to multiple periods but two periods suffices to show the dynamics.

[10] Cost-sharing depends on insurer reimbursement, *not* physician acquisition price. This cost-sharing can vary across patients depending on whether they have supplemental coverage, but we abstract away from that in the theory.

weight that discounts the reimbursement based on disutility of patient cost-sharing. The probability a physician prescribes the drug to a Medicare patient is thus $Q(m_{it}) = \mathbb{P}(m_{it} + \tilde{\lambda} h_{it}) > 0$. A parallel expression defines the probability Q^P that a private patient is prescribed the drug. Demand is increasing in the effective margin ($Q'(m_{it}) \geq 0$). The effective margin is increasing in reimbursement so long as $\lambda > 0$, which requires the weight placed on physicians' own reimbursement to outweigh any disutility from higher patient cost-sharing.

5.2 Lagged-Price Reimbursement and Private Insurance

The reimbursement received by the physician will depend on the insurance status of the patient. The private reimbursement rate, r_t^P, is independent of the Medicare rate and determined outside the model. In order to focus on the pricing dynamics created by lagged-price reimbursement in isolation, we assume private reimbursement stays constant over time, $r_t^P = \rho$.

The Medicare reimbursement rate, r_t^M, is a function of the average sale price in the previous period times a multiplier $(1 + A)$. That is, $r_t^M = (1 + A)\overline{p_{t-1}}$ with $A > 0$, for $t > 1$. When $t = 1$ and there is no data available on lagged prices, the Medicare reimbursement is based off of the manufacturer list price or wholesale price. We define the average price to be $\bar{p}_t \equiv \mu p_t^M + (1 - \mu) p_t^P$, weighting Medicare by its share of potential patients. In practice, Medicare uses the transacted quantity-weighted price, which is endogenous to price. We simplify the expressions by using the share of Medicare patients μ. Our approach is, as a result, closely tied to the empirical exercise. In the appendix, we show this assumption does not change the key economic intuition.

5.3 Price Setting

We now consider a pharmaceutical monopolist with constant marginal cost c choosing prices for its drug to maximize profits. Given $\mathbf{r} = \{r_1^M, r_2^M(p_1^M), \rho\}$, the pharmaceutical firm chooses a vector of prices $\mathbf{p} = \{p_1^M, p_2^M, p_1^P, p_2^P\}$ to maximize:

$$\Pi(\mathbf{p}; \mathbf{r}) = \mu \underbrace{\left(\pi(p_1^M; r_1^M) + \delta\pi(p_2^M; r_2^M(p_1^M))\right)}_{\text{Medicare market profits}} + (1-\mu) \underbrace{\left(\pi(p_1^P; \rho) + \delta\pi(p_2^P; \rho)\right)}_{\text{private market profits}} + \delta^2 \underbrace{EV(p_2^M)}_{\text{cont. value}}$$

where $\pi(p_t; r_t) \equiv Q(\lambda r_t - p_t)(p_t - c)$ are flow profits in period t, and the term $EV(p_2^M)$ captures total discounted continuation profits. To the extent that firms can affect future reimbursement via their second period Medicare price, continuation profits are a function of the period two Medicare price. For intuition, assume the continuation value is near zero

(e.g. the firm faces generic entry), but the theory allows for positive continuation profits.

Optimal prices will depend on the elasticity of demand with respect to the effective margin, since the payment a physician receives is the difference between list price and reimbursement. Define the semi-elasticity of demand with respect to the effective margin as $\eta(m) \equiv \frac{Q'(m)}{Q(m)}$.

In a single-period static model, the firm would set prices equal to marginal costs plus a markup term based on the inverse semi-elasticity. In the private insurance market, the pharmaceutical firm indeed chooses the same price in both periods, $p_t^P = p^P$ given that reimbursement rates are independent across periods and constant. Private demand will thus be constant over time.

However, Medicare's lagged-price reimbursement links the prices set between periods. The first order conditions for the the optimal Medicare prices are then:

$$p_1^M = c + \frac{1}{\eta(m_1)} + \delta(p_2^M - c)\underbrace{\frac{Q'(m_2)}{Q'(m_1)}(1+A)\lambda\mu}_{\substack{\text{effect of } \uparrow p_1 \\ \text{on } Q_2 \text{ demand}}}, \tag{2}$$

$$p_2^M = c + \frac{1}{\eta(m_2)} + \underbrace{\delta\frac{EV'(p_2^M)}{Q'(m_2)}}_{\substack{\text{effect of } \uparrow p_2^M \\ \text{on continuation profits}}}. \tag{3}$$

The Medicare pricing decisions are not independent across time because m_2 depends on p_1^M; the optimal launch price depends on the period 2 price and vice versa. The margin in period 2 will depend on the reimbursement level, which is determined by launch price. In turn, period 1 price depends on the profit margin the firm anticipates in period 2. (Suppose– outside the model– the firm expected to have to price at marginal cost in period 2. Then, there would no longer be an incentive to raise launch price above the static monopoly price in period 1.)

The first order condition for the choice of launch price shows that the difference between static monopoly pricing and optimal prices depends on the marginal effect of launch prices on future demand. Launch prices affect future demand by changing effective margin to physicians in period 2. This impact on margin depends on share of Medicare patients μ, the ASP reimbursement multiplier $1 + A$, and weight λ on reimbursement versus price in physician's effective margin.

We make four technical assumptions formalized in the Theoretical Appendix. First, we assume that the physician puts a positive weight on reimbursement and that the patient

out-of-pocket share is constant. Second, we assume that conditions hold such that the pharmaceutical's pricing problem is globally convex. Third, we assume that continuation value profits are not too negative in the period 2 Medicare price. Fourth, we assume that the firm cannot make infinite profits in the future by raising current prices (e.g. continuation value of future profits are not convex in the period two Medicare price).

5.4 Results

Our theoretical results show when the Medicare lagged-price reimbursement system will lead to declining prices over time, as opposed to the flat prices in the private sector. Proposition 1 provides an intuitive condition for the necessary and sufficient conditions for lagged-price reimbursement will lead to a declining Medicare price path: so long as the semi-elasticity of demand in period 2 is not too much more inelastic, price will decline over time. The larger the ASP add-on $(1 + A)$, the discount rate, and the share of Medicare patients, the more semi-elasticity of demand can differ.

Proposition 1 *The equilibrium Medicare price will decrease over time ($p_1^M > p_2^M$) if and only if:* $\frac{\eta(m_1)}{\eta(m_2)} < \frac{1+\delta(1+A)\lambda\mu\frac{Q(m_2)}{Q(m_1)}}{1+\delta\frac{EV'(p_2^M)}{Q(m_2)}}$.

Proof. The difference between the optimal Medicare prices in period 2 and period 1 from equations (3) and (4) can be written as:

$$p_2^M - p_1^M = \frac{1}{\eta(m_2)}\left[1 - \delta\frac{Q'(m_2)}{Q'(m_1)}(1+A)\lambda\mu\right] - \frac{1}{\eta(m_1)} + \delta\frac{EV'(p_2^M)}{Q'(m_2)}$$

This is negative if and only if $\frac{1}{\eta(m_2)}\left[1 - \delta\frac{Q'(m_2)}{Q'(m_1)}(1+A)\lambda\mu + \delta\frac{EV'(p_2^M)}{Q(m_2)}\right] < \frac{1}{\eta(m_1)}$. Given that $\eta > 0$, and that $\frac{Q'(m_2)}{Q'(m_1)} = \frac{\eta(m_2)Q(m_2)}{\eta(m_1)Q(m_1)}$, we can rearrange to yield the condition to yield $\left(1 + \delta\frac{EV'(p_2^M)}{Q(m_2)}\right) < \frac{\eta(m_2)}{\eta(m_1)}\left(1 + \delta(1+A)\lambda\mu\frac{Q(m_2)}{Q(m_1)}\right)$. Given that $\left(1 + \delta\frac{EV'(p_2^M)}{Q(m_2)}\right) \geq 0$ by construction (see Assumption (iii) in Theoretical Appendix), can further rearrange to yield the condition
$\frac{\eta(m_1)}{\eta(m_2)} < \left(1 + \delta(1+A)\lambda\mu\frac{Q(m_2)}{Q(m_1)}\right) / \left(1 + \delta\frac{EV'(p_2^M)}{Q(m_2)}\right)$. ■

To see the intuition underlying the condition, consider the case where profits after period 2 are not impacted by period 2 price, so $EV'(p_2^M) = 0$. Then, the condition reduces to $\frac{\eta(m_1)}{\eta(m_2)}$ being less than 1 plus an additional positive term that increases in A (ASP add on) and μ (the fraction of Medicare patients). It is thus always satisfied when the semi-elasticities with

respect to margin are constant or larger in period 2. It is more likely to be satisfied when period 1 demand is relatively inelastic $\eta(m_1) < \eta(m_2)$, when Medicare is more generous (A is larger) and more important (μ is larger).

Note that the theory also allows for time-invariant differences in Medicare versus private reimbursement and demand. Private reimbursement may be higher or lower, and private demand may be more or less elastic than Medicare demand, and the private market price would still be constant, while the Medicare price would decline over time if and only if the condition in Proposition 1 holds.

To facilitate application of the theory to our empirical results, we have the following corollary:

Corollary 1 *Prices for drugs with positive Medicare market share ($\mu > 0$) will have a larger decline in average price ($\bar{p}_2 - \bar{p}_1$) over time, compared to drugs with no Medicare market share ($\mu = 0$).*

When $\mu = 0$, the theory tells us average price $\bar{p}_t$ is constant, since it is determined by the private market, while when $\mu > 0$, price is declining ($\bar{p}_1 - \bar{p}_2 > 0$) since it is an average of the constant price price and the declining Medicare price.

Empirically, we see rising drug prices on average over time, in the private sector. However, consistent with our theory, Medicare restrains those price increases: recall that Table 2 shows that $\bar{p}_t$ has a smaller increase for drugs with above median Medicare market share, as compared to drugs below the median. The corollary is applicable, as the average Medicare market share in the below median group is close to zero– only 6%, compared to 48% in the above median group all. The below median group experiences about 8% price growth after 12 quarters, compared to a decline of about 3% in the above median Medicare market share group.

The link between the empirical application and the theory though, is more subtle. Medicare reports the *quantity-weighted* average sales price at each point in time, which is an equilibrium outcome. Not only is the Medicare price changing over time, Medicare's weight in the average also changes over time. (In contrast, $\bar{p}_t$ in the theory weighs by a constant μ, the fraction of individuals with Medicare coverage.) When the Medicare market share is constant, it is clear the quantity-weighted price will decline overtime if $\mu > 0$. Appendix Proposition A.1 shows the condition for the quantity weighted price to decline overtime with $\mu > 0$, essentially showing the market shares cannot vary too much over time compared to the price variation.[11]

[11] A stronger theoretical claim would be the price decline increases in μ at each level of μ: $\frac{d(\tilde{p_1} - \tilde{p_2})}{d\mu} > 0$, but this is quite complex as μ both changes the Medicare price and Medicare market share.

These results show that the dependence of drug reimbursement rates on lagged prices distorts optimal pricing decisions so that firms charge high prices at launch, and lower prices in subsequent periods. The reason is that margins, more so than prices, are what determines quantity sold: setting a high price and lowering it gives a physician more margin in later periods.

6 Conclusion

Understanding the dynamic pricing incentives in lagged-price reimbursement contracts is important. Our model and empirical analysis show that these contracts can shape the market prices that they in turn rely on. We find that lagged cost-based reimbursement in Medicare Part B creates incentives to launch at high prices and then lower them over time.

Future theoretical work should explore the impact of price dispersion and negotiation in the model. Future empirical work should examine how providers respond to changes in margin and how that affects patient health. Moreover, because Medicare Part B reimbursement design affects prices and thus drug profitability, it may have impacted innovation.

Understanding how payment policy affects the pricing of pharmaceuticals is necessary to evaluate policy reforms, such as reforms included in the 2022 Inflation Reduction Act. The impact depends on both policy parameters and the elasticity of demand. Our model can be used by policy-makers with context-specific estimates to predict how the design of contracting in Medicare Part B will impact overall costs. It could also enrich models of external reference pricing (in which countries set prices based on lagged-prices in other countries, see e.g. Maini and Pammolli (2023)) and can be used for other non-pharmaceutical industries.

References

Bajari, Patrick and Steven Tadelis, "Incentives versus Transaction Costs: A Theory of Procurement Contracts," *The RAND Journal of Economics*, 2001, *32* (3), 387–407.

Bosio, Erica, Simeon Djankov, Edward Glaeser, and Andrei Shleifer, "Public Procurement in Law and Practice," *American Economic Review*, April 2022, *112* (4), 1091–1117.

Crocker, Keith J. and Kenneth J. Reynolds, "The Efficiency of Incomplete Contracts: An Empirical Analysis of Air Force Engine Procurement," *The RAND Journal of Economics*, 1993, *24* (1), 126–146.

Cutler, David M., "Medicare Enters the Pharmaceutical Purchasing Business," *JAMA Health Forum*, September 2022, *3* (9), e223630.

Decarolis, Francesco, "Medicare part d: Are insurers gaming the low income subsidy design?," *American Economic Review*, 2015, *105* (4), 1547–1580.

Desai, Sunita and J Michael McWilliams, "Consequences of the 340B drug pricing program," *New England Journal of Medicine*, 2018, *378* (6), 539–548.

Dubois, Pierre, Ashvin Gandhi, and Shoshana Vasserman, "Bargaining and International Reference Pricing in the Pharmaceutical Industry," *National Bureau of Economic Research Working Paper 30053*, May 2022.

Duggan, Mark and Fiona Scott Morton, "The Effect of Medicare Part D on Pharmaceutical Prices and Utilization," *American Economic Review*, March 2010, *100* (1), 590–607.

Ericson, Keith M, "Consumer inertia and firm pricing in the Medicare Part D prescription drug insurance exchange," *American Economic Journal: Economic Policy*, 2014, *6* (1), 38–64.

Farrell, Joseph and Carl Shapiro, "Dynamic Competition with Switching Costs," *The RAND Journal of Economics*, 1988, *19* (1), 123–137.

Gaynor, Martin, Nirav Mehta, and Seth Richards-Shubik, "Optimal Contracting with Altruistic Agents: Medicare Payments for Dialysis Drugs," *American Economic Review*, June 2023, *113* (6), 1530–1571.

Ginsburg, Paul and Steven Lieberman, "Medicare payment for physician-administered (Part B) drugs," *USC-Brookings Schaeffer Initiative for Health Policy Working Paper*, February 2021.

Government Accountability Office, "Physician-administered Drugs: Comparison of Payer Payment Methodologies," *GAO-16-780R Report*, 2016.

Howard, David H., Peter B. Bach, Ernst R. Berndt, and Rena M. Conti, "Pricing in the Market for Anticancer Drugs," *Journal of Economic Perspectives*, February 2015, *29* (1), 139–162.

Ippolito, Benedic N and Joseph F Levy, "The Influence of Medicare Part D on the List Pricing of Brand Drugs," *Health Services Research*, 2023.

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*, 2010, *29* (7), 1391–1399.

Ji, Yunan and Parker Rogers, "The Dynamic Effects of Health Care Price Reform," *Working Paper*, 2023.

Kang, Karam and Robert A Miller, "Winning by Default: Why is There So Little Competition in Government Procurement?," *The Review of Economic Studies*, May 2022, *89* (3), 1495–1556.

Kosmopoulou, Georgia and Xueqi Zhou, "Price Adjustment Policies in Procurement Contracting: An Analysis of Bidding Behavior," *The Journal of Industrial Economics*, 2014, *62* (1), 77–112.

Krasnokutskaya, Elena and Katja Seim, "Bid Preference Programs and Participation in Highway Procurement Auctions," *American Economic Review*, October 2011, *101* (6), 2653–2686.

Lakdawalla, Darius N., "Economics of the Pharmaceutical Industry," *Journal of Economic Literature*, June 2018, *56* (2), 397–449.

Maini, Luca and Fabio Pammolli, "Reference pricing as a deterrent to entry: evidence from the European pharmaceutical market," *American Economic Journal: Microeconomics*, 2023, *15* (2), 345–383.

Medicare Payment Advisory Commission, "Report to the Congress: Medicare and the Health Care Delivery System, Chapter 5," 2016.

_ , "MedPAC July 2022 Data Book, Section 10: Prescription drugs," 2022.

Morton, Fiona Scott and Lysle T Boller, "Enabling competition in pharmaceutical markets," *Hutchins Center Working Paper 30*, 2017.

Polite, Blase, Rena M Conti, and Jeffery C Ward, "Reform of the buy-and-bill system for outpatient chemotherapy care is inevitable: perspectives from an economist, a realpolitik, and an oncologist," *American Society of Clinical Oncology Educational Book*, 2015, *35* (1), e75–e80.

Ridley, David B. and Chung-Ying Lee, "Does Medicare Reimbursement Drive Up Drug Launch Prices?," *The Review of Economics and Statistics*, December 2020, *102* (5), 980–993.

_ **and Su Zhang**, "Regulation of Price Increases," *International Journal of Industrial Organization*, 2017, *50*, 186–213.

Solon, Gary, Steven J. Haider, and Jeffrey M. Wooldridge, "What Are We Weighting For?," *Journal of Human Resources*, March 2015, *50* (2), 301–316.

Yurukoglu, Ali, Eli Liebman, and David B. Ridley, "The Role of Government Reimbursement in Drug Shortages," *American Economic Journal: Economic Policy*, May 2017, *9* (2), 348–382.

Table 1: Descriptive Statistics of Drugs

	Full Sample		Above Median MMS	Below Median MMS
	Mean	*Std Dev*	*Mean*	*Mean*
Medicare Market Share (MMS) at $\tau = 1$	0.270	0.261	0.480	0.062
Relative ASP at $\tau = 8$	1.058	0.335	1.032	1.083
Average Year of Introduction	2010.7	3.8	2011.4	2010.1
Compound Annual Growth Rate over first 6 years	0.0409	0.1000	0.0196	0.0572
Compound Quarterly Growth Rate over first 6 years	0.0092	0.0239	0.0041	0.0131
N (Unique HCPCS)	215		107	108

Notes: Source: Authors' calculations from CMS Data 2006-2019. Median Medicare Market Share at Launch = 0.193

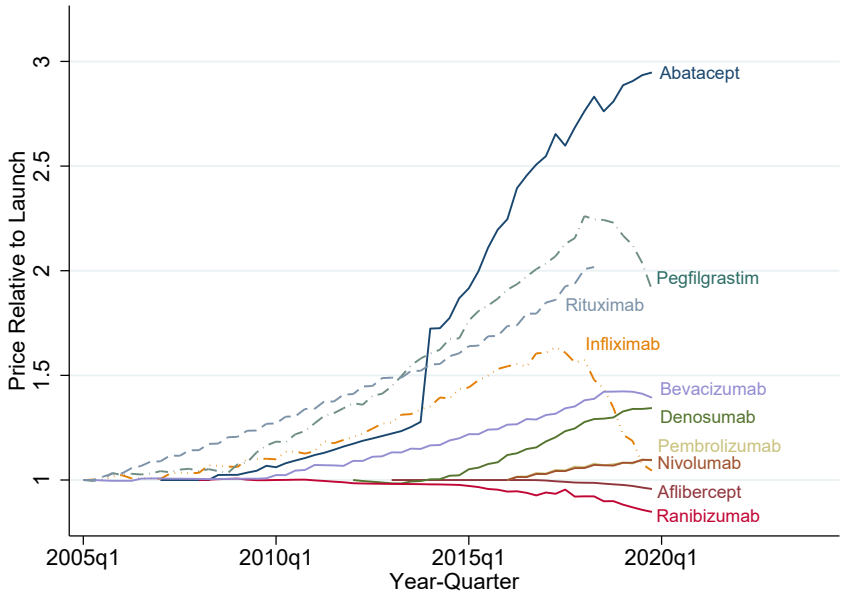
Table 2: Summarizing the Effect of MMS on Price Evolution

	(1)	(2)	(3)	(4)
	Analysis Sample		Balanced Panel	
τ	0.007		0.008***	
	(0.005)		(0.002)	
$\tau\times$ MMS	-0.008*		-0.015***	
	(0.005)		(0.005)	
$\tau > 12$		0.079**		0.033**
		(0.035)		(0.014)
$\tau > 12 \times AboveMedianMMS = 1$		-0.111**		-0.030***
		(0.051)		(0.005)
Drug Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.070	0.087	0.383	0.364
N	4502	4502	588	588

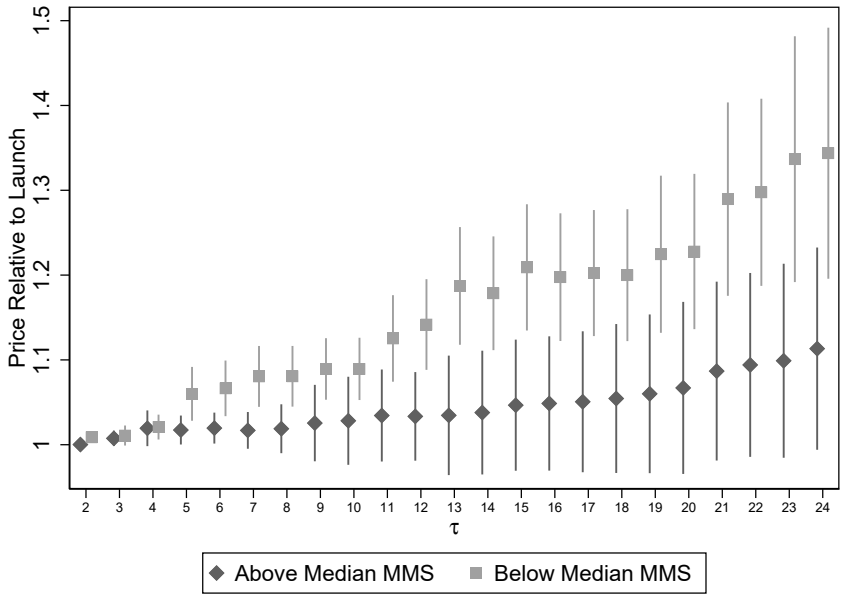
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Dependent variable: $\ln p_{jt}$. Robust standard errors clustered at the HCPCS level. Balanced panel only uses observations with $\tau \leq 16$ and requires that all drugs have at least $\tau = 16$.

Figure 1: Price Evolution of Medicare Part B Drugs

(A) Price Evolution of Top 10 Medicare Part B Drugs



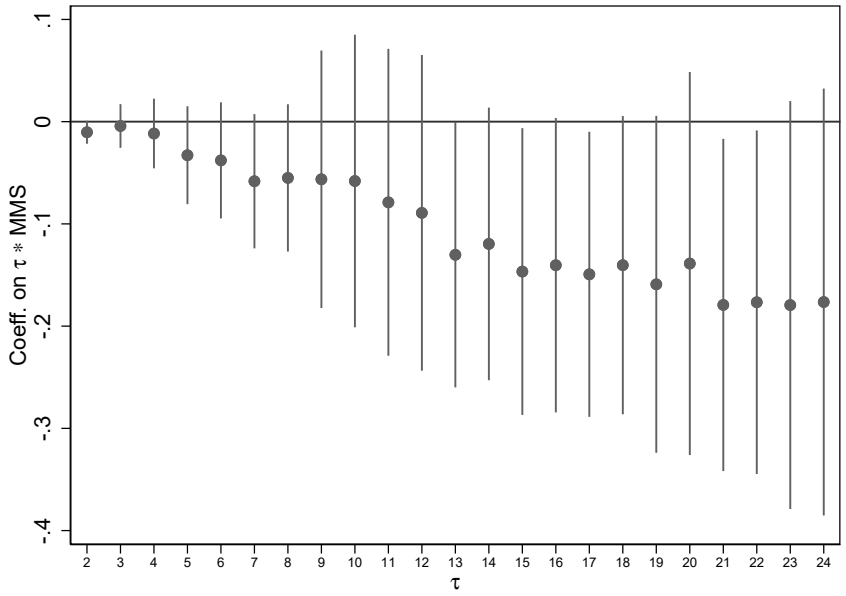
(B) Price Evolution of Drugs by Exposure to Medicare Part B



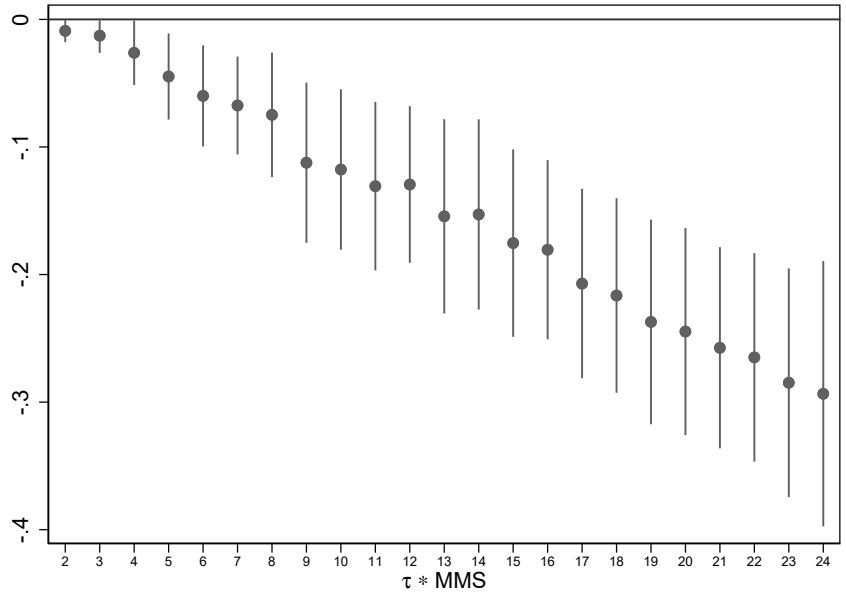
Notes: Panel A: Selects the top 10 Part B drugs by Medicare revenue 2015-2019. Panel B: Price relative to launch by exposure to Medicare. Relative price is ASP in quarter τ divided by ASP in quarter $\tau = 1$. Plots the results of a regression of relative quantity against quarter τ fixed effects and year fixed effects weighted by total drug market size.

Figure 2: Exposure to Medicare Part B and Drug Prices

(A) Estimates of MMS Interaction Effect: Full Sample



(B) Estimates of MMS Interaction Effect: Newly Approved Molecules



Notes: Panel A: Plots point estimates and 95% confidence intervals for coefficients estimated by the regression given in Equation 1 on the Analysis Sample weighted by total drug market size. Panel B: Same as panel A, but estimated on sample of newly approved molecules. Robust standard errors clustered at the HCPCS level.

Online Appendix For: "Lagged-Price Reimbursement Contracts: The Impact of Medicare Part B on Pharmaceutical Price Growth"

Angie Acquatella, Keith Marzilli Ericson, and Amanda Starc

I Theoretical Appendix

Assumptions

Formally, the assumptions we make about the demand system are given by:

(i) effective margin is increasing in reimbursement ($\lambda > 0$), and the patient out-of-pocket share is constant, $\frac{oop(r_t)}{r_t} = k \ \forall r_t$ for some $k \in \mathbb{R}^+$.

(ii) that $Q''(m_t) \geq 0$ and bounded above such that the second order conditions for both the static and dynamic monopoly pricing problem hold at every period t:

$$(p_t - c)Q''(m_t) - 2Q'(m_t) \leq 0, \qquad \forall\ t \tag{A.1}$$

$$(p_1 - c) \cdot Q''(m_1) - 2Q'(m_1) + \delta\lambda^2(1 + A)^2 Q''(m_2) \leq 0, \tag{A.2}$$

(iii) the marginal continuation value profits with respect to the period 2 Medicare price are bounded below by the negative inverse semi-elasticity, $\delta\frac{EV'(p_2^M)}{Q'(m_2)} \geq -\frac{1}{\eta(m_2)}$;

(iv) and that the effect of p_2 on continuation profits is non-convex, such that $EV''(p_2^M) \leq 0$.

I.A Quantity Weighted Price

As noted in the text, when the Medicare price is declining, it is clear that the average price (weighted by the share of the population on Medicare) is declining, since private price is constant. However, the quantity weighted price is more complicated: it is also the case that the Medicare market share is changing over time. Moreover, even though the Medicare price is falling, because quantity depends on price relative to reimbursement, it may not be the case that Medicare market share rises over time.

Here, we examine the quantity weighted price. Let the equilibrium Medicare market share in period t be $s_t = \frac{\mu Q_t^M}{\mu Q_t^M + (1-\mu)Q_t^P}$, and then let the quantity weighted average sales price be $\tilde{p_t} \equiv s_t p_t^M + (1 - s_t)p_t^P$.

When the Medicare market share is constant over time s_t, then quantity weighted price clearly declines over time ($\tilde{p_2} - \tilde{p_1} < 0$). Proposition A.1 shows how much s_t can vary overtime and still have quantity weighted price decline. We think the most empirically relevant case is case (a), which assumes that the private price is higher than the Medicare price, since private insurance tends to set higher reimbursement rates than Medicare (Government Accountability Office 2016), thus allowing pharmaceutical firms to charge higher prices to physicians who treat privately insured patients.

Proposition A.1 *The quantity weighted average sales price declines over time ($\tilde{p_2} - \tilde{p_1} < 0$) if:*

(a) the private price exceeds the Medicare price in the first period ($p^P > p_1^M$) and Medicare market share is weakly increasing such that shares satisfy $\frac{s_1}{s_2} \leq \left(1 - \frac{p_2^M}{p^P}\right) / \left(1 - \frac{p_1^M}{p^P}\right)$;

(b) the private price exceeds the Medicare price in the first period ($p_1^M > p^P$) and Medicare market share is weakly decreasing such that shares satisfy $\frac{s_1}{s_2} \geq \left(1 - \frac{p_2^M}{p^P}\right) / \left(1 - \frac{p_1^M}{p^P}\right)$;

(c) the Medicare price in the first period exceeds the private price, and both exceed the Medicare price in the second period ($p_1^M > p^P > p_2^M$).

Proof. To begin, first note that the difference in the quantity weighted average sales price can be written as: $\tilde{p_2} - \tilde{p_1} = s_2 p_2^M - s_1 p_1^M + (s_1 - s_2) p^P$. Divide by p^P and rearrange. Then, the quantity weighted average sales price is declining iff:

$$\tilde{p_2} - \tilde{p_1} \propto s_1 \left(1 - \frac{p_1^M}{p^P}\right) - s_2 \left(1 - \frac{p_2^M}{p^P}\right) < 0 \tag{A.3}$$

In case (a), $p^P > p_1^M$ implies that $\left(1 - \frac{p_1^M}{p^P}\right) > 0$. It then follows that $p^P > p_1^M$ and condition $\frac{s_1}{s_2} < \left(1 - \frac{p_2^M}{p^P}\right) / \left(1 - \frac{p_1^M}{p^P}\right)$ jointly imply that $(A.3)$ holds.

In case (b), $p_1^M > p^P$ implies that $\left(1 - \frac{p_1^M}{p^P}\right) < 0$. It follows that $p_1^M > p^P$ and condition $\frac{s_1}{s_2} > \left(1 - \frac{p_2^M}{p^P}\right) / \left(1 - \frac{p_1^M}{p^P}\right)$ jointly imply that $(A.3)$ holds

Finally, in case (c), $p_1^M > p^P$ implies that $\left(1 - \frac{p_1^M}{p^P}\right) < 0$. Since $p^P > p_2^M$ implies $\left(1 - \frac{p_2^M}{p^P}\right) > 0$, $(A.3)$ always holds. ■

Table A1: Effect of MMS on Price Growth: Early Versus Late Cohorts

	(1)	(2)	(3)	(4)
	Early Cohort (2005-2011)		Late Cohort (2012-2019)	
τ	0.004		0.008***	
	(0.007)		(0.002)	
$\tau \times$ MMS	-0.007		-0.011***	
	(0.008)		(0.004)	
$\tau > 12$		0.112		0.057**
		(0.071)		(0.027)
$\tau > 12 \times AboveMedianMMS = 1$		-0.152*		-0.062**
		(0.087)		(0.031)
Drug Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.072	0.104	0.199	0.171
N	2945	2945	1557	1557

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable: $\ln p_{jt}$. Data: Analysis Sample, limited to observations with non-missing PMSOI. "Private Market Share of Older Individuals" is created for each HCPCS-year as the total revenue for the older age category (age 56 to 64) over the total revenue for the older and younger (26 to 44 years old) age categories summed. Robust standard errors clustered at the HCPCS level.

Table A2: Descriptive Statistics, Split By Private Market Share of Older Individuals

	Full Sample		Above Median PMSOI	Below Median PMSOI
	Mean	*Std Dev*	*Mean*	*Mean*
Private Market Share of Older Individuals (PMSOI) at $\tau = 1$	0.591	0.326	0.866	0.319
Relative ASP at $\tau = 8$	1.041	0.293	1.022	1.059
Average Year of Introduction	2010.9	3.8	2011.3	2010.5
Compound Annual Growth Rate over first 6 years	0.0382	0.0933	0.0247	0.0505
Compound Quarterly Growth Rate over first 6 years	0.0086	0.0227	0.0053	0.0117
N (Unique HCPCS)	197		98	99

Notes: Source: Authors' calculations from CMS Data 2006-2019 and aggregate Truven Marketscan spending by age. "Private Market Share of Older Individuals" (PMSOI) is created for each HCPCS-year as the total revenue for the older age category (age 56 to 64) over the total revenue for the older and younger (26 to 44 years old) age categories summed. Number of observations is lower than in the Analysis Sample due to missing data (HCPCS with no private spending). Median Private Market Share of Older Individuals at Launch = .69

Table A3: Private Market Share of Older Individuals (PMSOI) and Price Growth

	(1)	(2)
τ	0.020***	
	(0.005)	
$\tau\times$ PMSOI	-0.021***	
	(0.006)	
$\tau > 12 = 1$		0.081**
		(0.033)
$\tau > 12\times$ Above Median PMSOI =1		-0.134**
		(0.057)
Drug Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
R^2	0.111	0.105
N	4080	4080

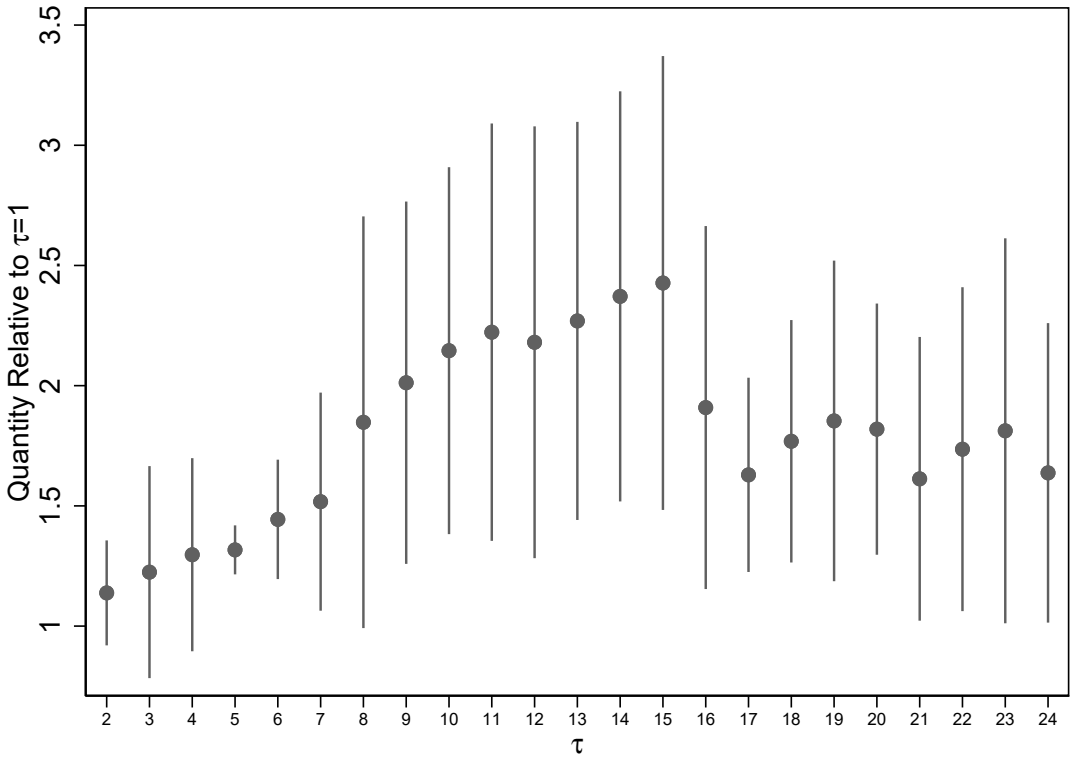
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable: $\ln p_{jt}$. Data: Analysis Sample. Robust standard errors clustered at the HCPCS level.

Table A4: Effect of MMS on launch price

	(1)	(2)	(3)	(4)
	Weighted		Unweighted	
MMS	2.650***		1.021	
	(0.875)		(0.729)	
Above Median MMS		0.639		0.503
		(0.449)		(0.349)
Drug FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
τ FE	Yes	Yes	Yes	Yes
τ FE $\times$ MMS	Yes	No	Yes	No
τ FE $\times$ Above Median MMS	No	Yes	No	Yes
R-squared	0.220	0.060	0.020	0.020
N	4502	4502	4502	4508

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable: $\ln p_{jt}$. Data: Analysis Sample. Robust standard errors clustered at the HCPCS level.

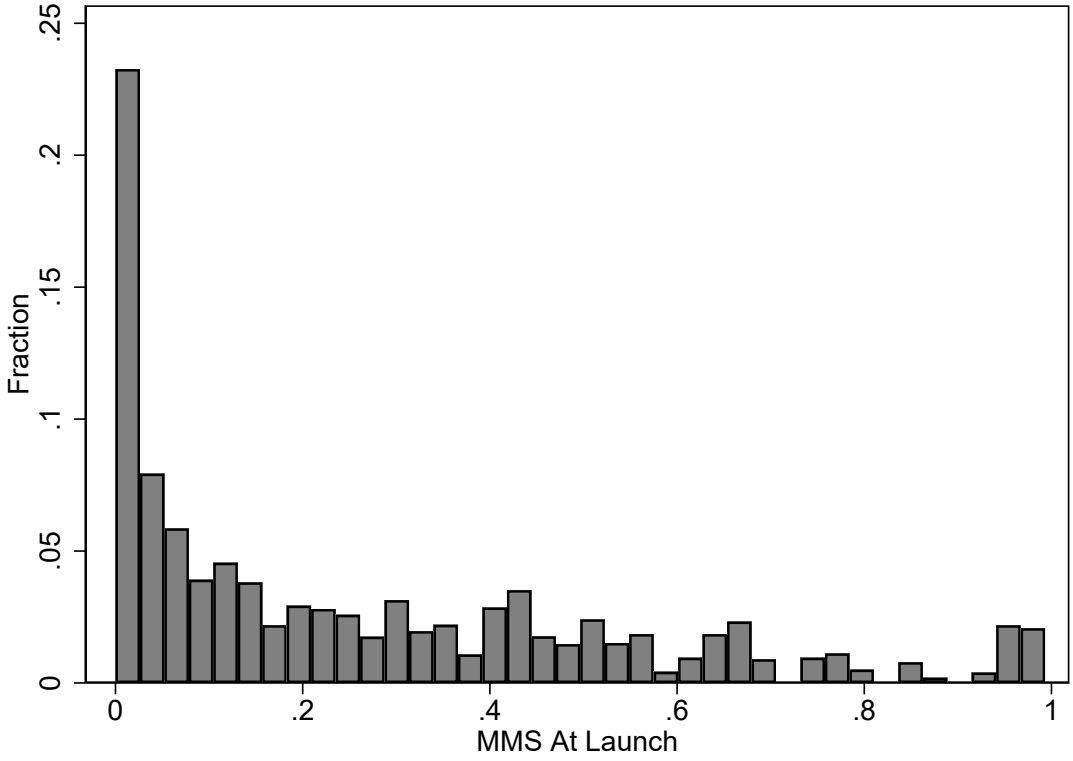
Figure A0: Medicare Quantity Sold, Relative to Launch Period



Notes: Data: Analysis Sample. Quantity in each quarter is calculated as total Medicare revenue divided by ASP. Relative quantity is quantity in quarter τ divided by quantity in quarter $\tau = 1$. Relative quantity is winsorized at the 1st and 99th percentiles due to outliers. Plots the results of a regression of relative quantity against quarter τ fixed effects and year-quarter fixed effects weighted by total drug market size. Point estimates and 95% confidence intervals of the quarter τ fixed effects are present. Standard errors clustered at the HCPCS level.

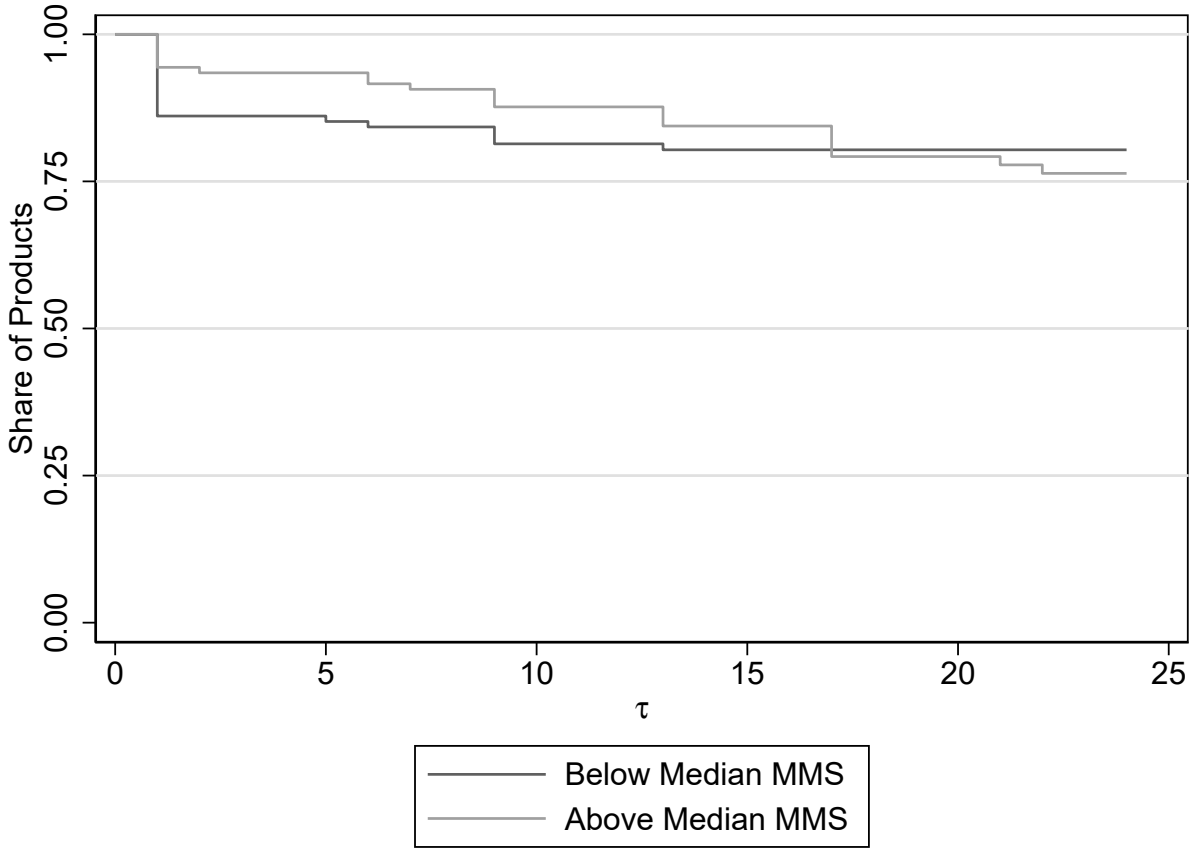
Note that 2 years after launch, median quantity sold is very similar to quantity at launch (relative quantity=0.99), while the 99th percentile of relative quantity is over 20. This accounts for the jump in standard errors in the figure beginning 2 years after launch.

Figure A1: Distribution of MMS at Launch



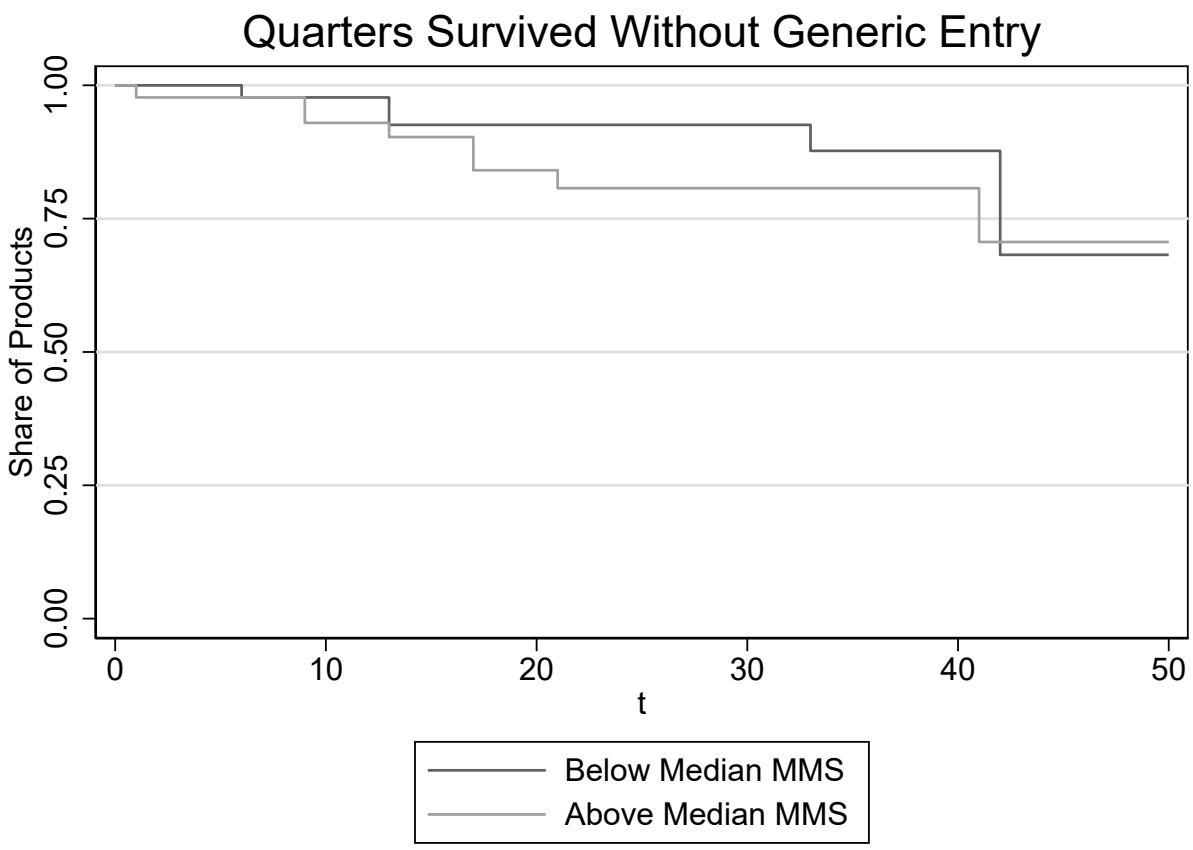
Notes: Data: Analysis Sample

Figure A2: Time Until Competitor Entry in Billing Code



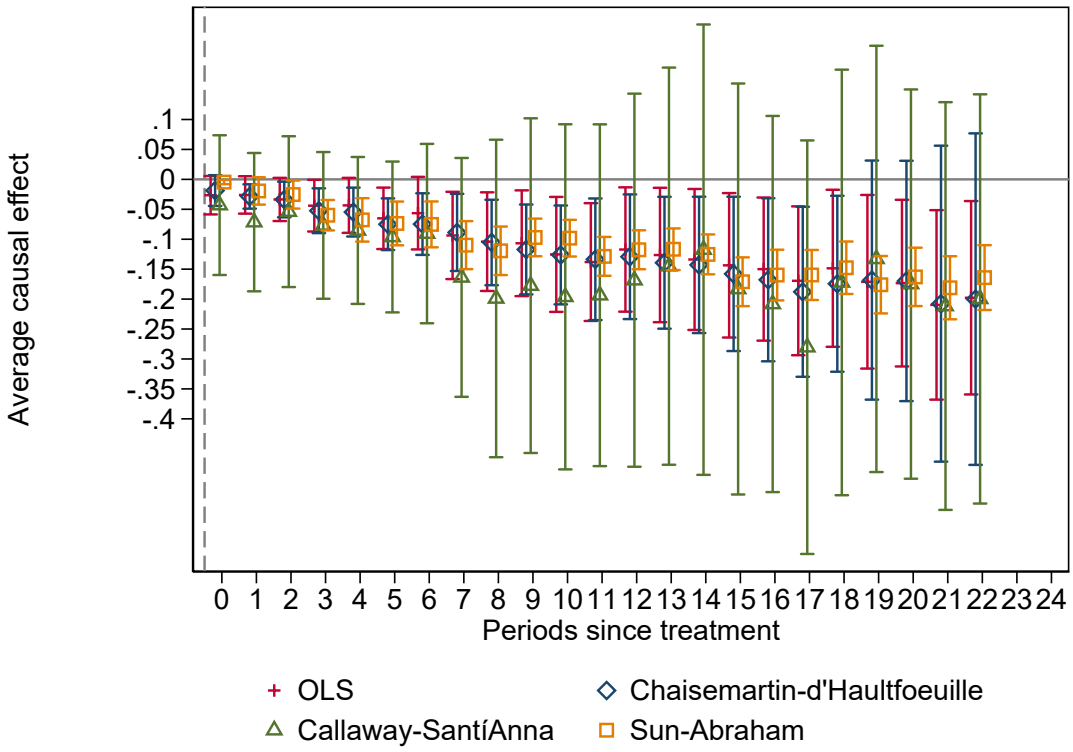
Notes: Plots Kaplan-Meier survivor function for being billing code monopolist split by above versus below median Medicare market share. Early entry due in part to new J-Codes that have old products. In Cox proportional hazard model, above median MMS products are more likely to have entry, but this different is not statistically significant (Hazard ratio 0.975, 95% CI 0.54 to 1.75). Data: Analysis Sample.

Figure A3: Time Until Competitor Entry in Billing Code: Sample of Newly Approved Molecules



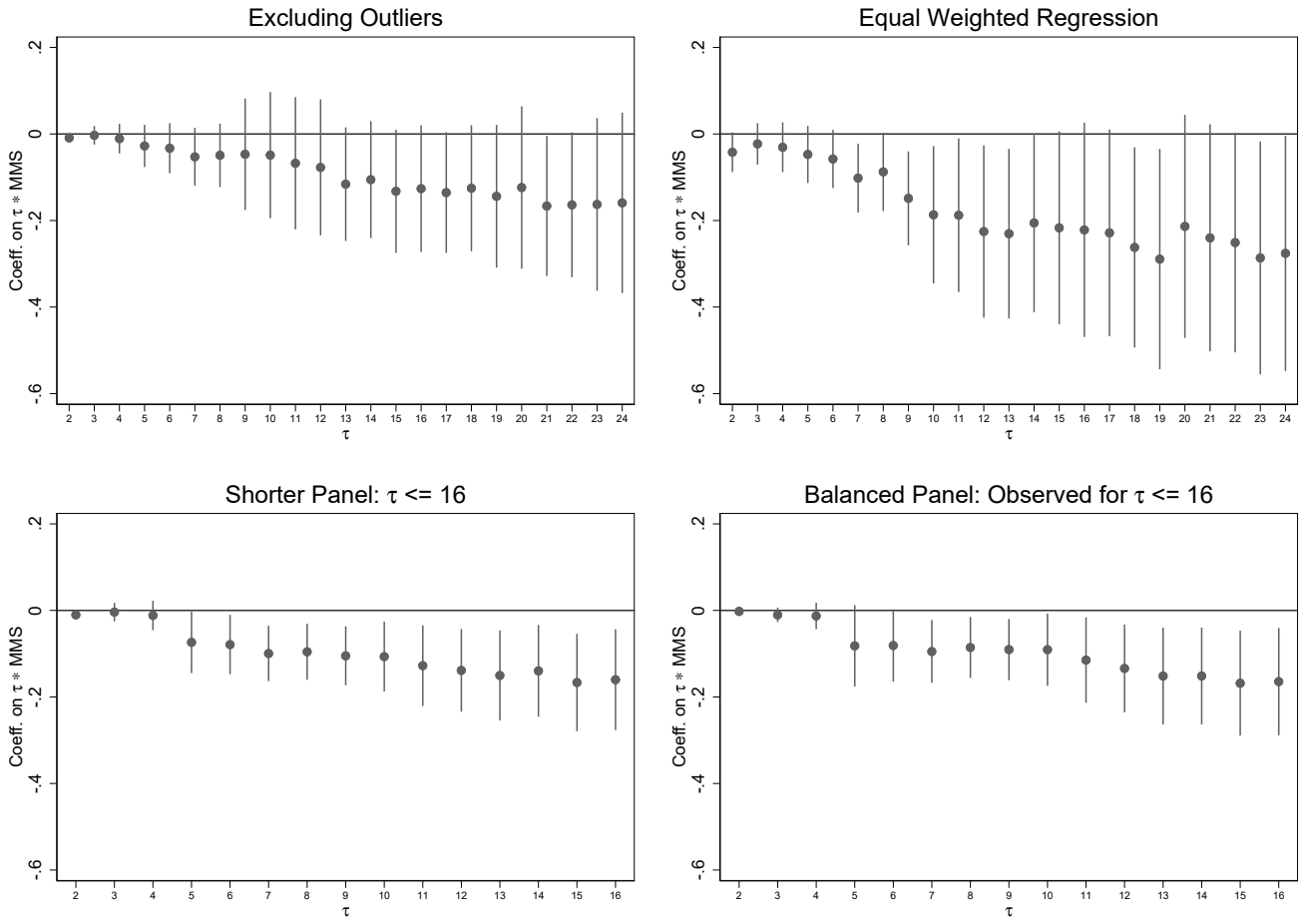
Notes: Plots Kaplan-Meier survivor function for being billing code monopolist.

Figure A4: Robustness Checks



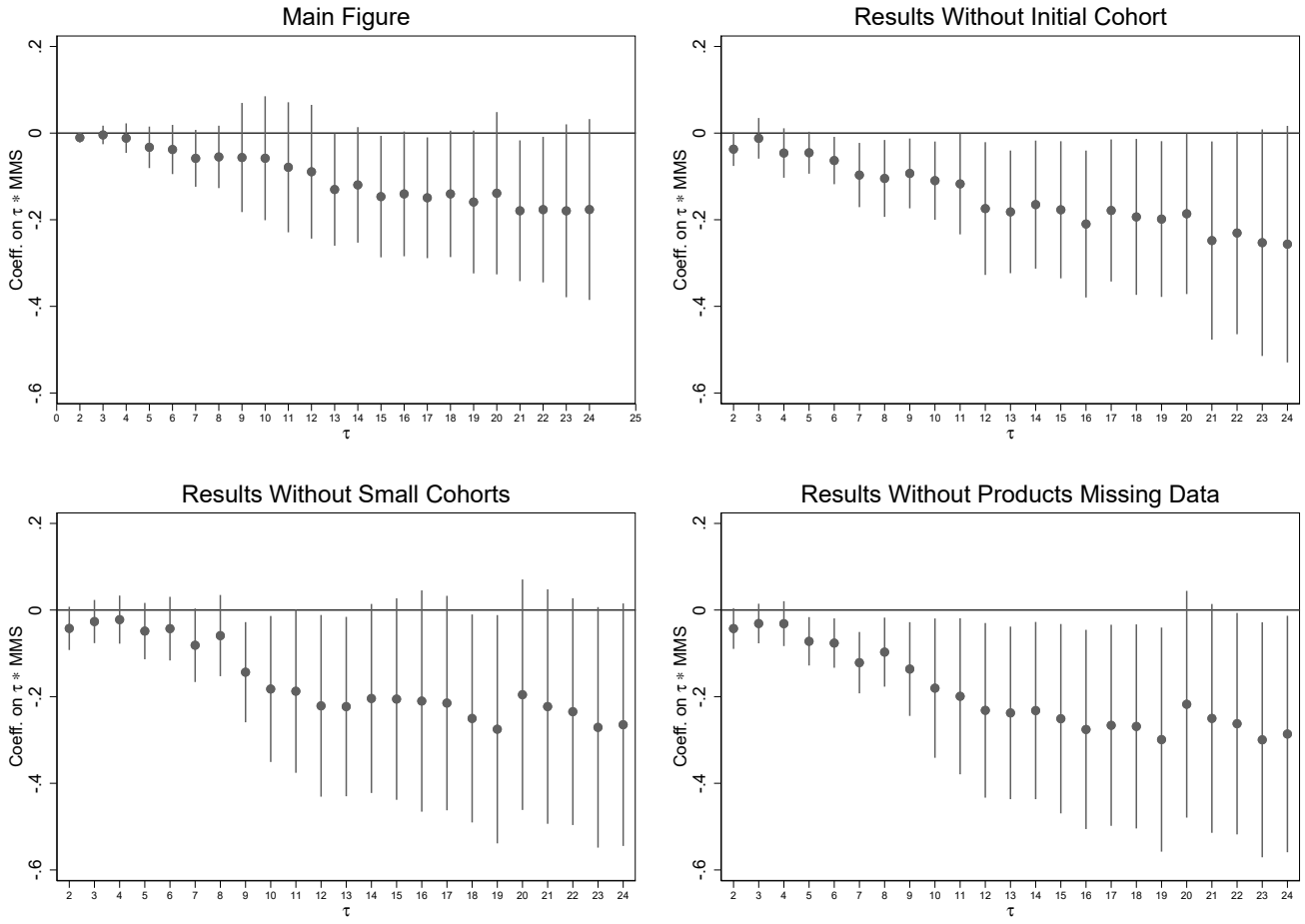
Notes: Plots point estimates and 95% confidence intervals for coefficients from four different estimators. OLS is estimated by regression Equation 1 in which treatment is discretized into above versus below median MMS. Then, results from three additional two-way fixed effects estimators are presented: Callaway and Sant'Anna (2021), Chaisemartin and d'Haultfoeuille (2020) and Sun and Abraham (2021). Data: Analysis Sample. Robust standard errors clustered at the HCPCS level.

Figure A5: Robustness Checks



Notes: Plots point estimates and 95% confidence intervals for coefficients estimated by regression Equation 1. Data: Analysis Sample with modifications as shown in each subfigure's title. Robust standard errors clustered at the HCPCS level.

Figure A6: Additional Robustness Checks



Notes: Plots point estimates and 95% confidence intervals for coefficients estimated by regression Equation 1. Data: Analysis Sample, with modifications as follows. Main Figure recreates the estimates of Figure 2 on a common axis for reference. Results "Without Initial Cohort" estimates the effects without the earliest (and largest) treatment cohort (7.9% of observations). Results "Without Small Cohorts" estimates the effects without cohorts of two or fewer products (3.8% of observations). Results "Without Products Missing Data" estimates the effects without products which are missing any quarter of data (6.8% of observations). Robust standard errors clustered at the HCPCS level.