Provider Altruism and Discarded Anticancer Drugs*

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JOB MARKET PAPER

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January 12, 2026

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Abstract

We study altruism among health care providers—the extent to which they consider the welfare of others when making treatment decisions—in a setting where choice of treatment quantity affects provider profit and public spending, but not patient health. In our setting, providers choose dosages of anticancer drugs around vial-size cutoffs. These drugs are dosed variably and packaged in large and expensive single-use vials ($1,180 for the average vial in our sample). A typical infusion uses a small number of vials and the excess in the last vial is thrown away. Because Medicare pays for the infused and discarded portion of the vial, costs increase substantially at vial-size cutoffs. Using bunching methods in Medicare claims data, we find that 9% of the 3.8 million claims in our sample have doses manipulated *down* across these cutoffs. Our results strongly suggest that providers sacrifice profit in order to lower costs for patients and/or Medicare. Treatment guidelines recommend this dose manipulation and state that small dose reductions ($\leq 10\%$) are unlikely to affect health outcomes. 46% of claims in these narrow windows have their doses reduced. Using Medicare reimbursement rates, we can quantify that a provider who manipulates down foregoes $0.056 in profit for every $1 of reduced patient and Medicare expenses. This provides a novel revealed preference quantification of provider altruism.

Keywords: Altruism, Medicare, Oncology

JEL Codes: I11, I13, I18

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1 Introduction

To what extent do health care providers consider the welfare of others when deciding how to treat a patient? Provider altruism is a key feature of healthcare markets, as evidenced by its prominence in economic models of physician behavior (Arrow, 1963; Ellis and McGuire, 1986; McGuire, 2000; Chandra et al., 2011) and in guidance from professional societies (American Medical Association, 2025). However, outside of laboratory and stated-preference approaches (see, e.g., Hennig-Schmidt et al., 2011; Godager and Wiesen, 2013; Kesternich et al., 2015; Li et al., 2022; Attema et al., 2023), empirical evidence for provider altruism is very limited.[1]

In this paper, we study provider altruism in a context where treatment *quantity* directly affects both provider profit and *public* spending (including patient out-of-pocket (OOP) costs and public health insurance expenditures), without affecting patient health. This allows us to advance the literature on provider altruism in two ways. First, we provide a revealed preference test of whether providers internalize social costs. Second, we consider altruism from a different set of providers, typically hospitals or health systems, towards society, not just the treated patient. From an economic perspective, this wider notion of altruism resembles models of voluntary contributions to public goods (e.g., Charness and Rabin, 2002): Reducing spending with no health value benefits society, but comes at a private financial cost to the provider. From a medical perspective, this reflects growing concerns about the overuse of low-value care (see, e.g., Morden et al., 2014).

We study provider dosage choice for infused anticancer drugs in Medicare claims data. This setting is of interest for several reasons. First, these drugs are expensive, with prices often above $10,000 per infusion (Bach, 2009). Second, patients, Medicare, and providers face strong volume-dependent financial incentives. Providers—typically hospitals or health systems—purchase these drugs from pharmaceutical distributors, administer them to patients within a medical facility, and receive a fixed reimbursement from Medicare for each unit (e.g., milligram) of the drug used (see, e.g., Werble, 2017). Medicare patients pay up to 20% of these costs out-of-pocket (OOP). Therefore, OOP costs, Medicare spending, and provider revenue all increase with drug doses. Third, these drugs are typically dosed variably by body-size and packaged in large single use vials. Most infusions use a small number of vials and the excess in the last vial is thrown away. Since providers are reimbursed for the full vial, including discarded portions (Bach et al., 2016), a 1.01 vial infusion costs twice as much as a 0.99 vial infusion.

[1] Chen and Lakdawalla (2019) and Wu (2019) show that physicians respond more to reimbursement changes when patients have higher socioeconomic status (and are less affected by OOP expenses). Hellerstein (1998); Lundin (2000); Carrera et al. (2018) and Crea et al. (2019) show that physicians prescribe more branded drugs when patient OOP costs are lower (imposing some cost on the insurer for an increase in patient utility).

Medicare's reimbursement of discarded infused anticancer drugs creates an opportunity and incentive for providers to influence the cost of care. On the one hand, providers may "overbill"—manipulate doses up by small amounts to receive reimbursement for an additional vial. On the other hand, altruistic providers may wish to reduce patient OOP expenses (Chen and Lakdawalla, 2019) or control healthcare costs more generally (especially for public payers, as in, e.g., Riggs et al., 2017). A sufficiently altruistic provider would value these social benefits more than the revenue from an additional vial and choose the lower dose. Importantly, professional societies recommend reducing doses for exactly these altruistic reasons and state that these slightly lower than normal doses are unlikely to negatively impact health outcomes (see Fahrenbruch et al. 2018). This implies that providers in our setting are primarily trading off their revenue against patient and payer costs.

Using bunching methods and administrative Medicare claims data, we find that 9% of the 3.8 million claims for 32 leading infused cancer drugs in our sample are manipulated down. CMS has required providers to bill separately for the infused and discarded portion of each claim since 2017. Since we cannot observe a patient's body-size, we analyze distributions of infused doses. Infused doses are directly determined by body-size via dosing regimens (e.g., 1 mg of drug per kg of body weight) and would be smooth at vial size cutoffs in the absence of dose manipulation. We instead observe a substantial missing mass of claims just above nearly every vial-size cutoff in our sample. This suggests that some providers reduce doses to avoid the use of an additional vial. We estimate that the 347,048 claims with manipulated doses constitute roughly 46% of the claims that could have been manipulated (i.e., those that would have had doses just above a cutoff in the absence of manipulation). In total, these avoided vials save Medicare and patients a combined $388 million in provider reimbursement.

We interpret this behavior as novel revealed preference evidence of provider altruism, and support this interpretation in three steps. First, we argue that dose manipulation is financially costly for providers. Providers purchase these drugs from distributors and Medicare sets reimbursement at 106% of the average sales price (ASP) of those transactions. Variable costs per infusion other than these acquisition costs are negligible, so any provider whose acquisition cost is less than 106% of the ASP earns a positive profit on each vial. Some providers face acquisition costs above reimbursement, but dose manipulation varies little with proxies for acquisition costs. Theoretically, reducing the cost of an infusion could increase patient demand for future infusions. However, we show with a simple back-of-the-envelope calculation that an implausibly large (in absolute value) demand elasticity of -1 is necessary for this to increase profit overall.[2]

[2]Goldman et al. (2006) and Goldman et al. (2010) estimate price-elasticities of demand for similar drugs of -0.01 and -0.04 to -0.11, respectively. Such low values are plausible because the treated conditions are severe,

We also note that many patients are insulated from costs via supplemental insurance coverage, which makes our back-of-the-envelope calculations conservative.[3] Further, using methods from Diamond and Persson (2016), we show that heterogeneity in which claims are manipulated is inconsistent with this explanation. Dose manipulation does not vary meaningfully with patient or market-level characteristics that are correlated with price-sensitivity such as dual-eligible status, race, zip-code level median income, or provider market concentration ratios.

Second, we argue that providers have three plausible motivations for this behavior, all of which are altruistic: reduction of Medicare spending, reduction of patient OOP costs, and avoidance of discarded drugs. Our ability to distinguish between these explanations is limited, but heterogeneity in bunching provides some suggestive evidence. Since dose manipulation is common for drugs with a wide variety of vial sizes, we conclude that dose-manipulating providers are not primarily concerned with reducing waste itself. As mentioned above, bunching does not vary with patient characteristics that are correlated with patient OOP costs, suggesting that manipulation is likely not driven by concern for patient OOP costs.

Third, we adapt a simple model of voluntary public goods provision (Charness and Rabin, 2002) to show how our bunching results imply lower-bound estimates for the degree of provider altruism. Provider utility is equal to profit, minus payer costs (weighted by an altruism parameter) and a "clinical penalty" term, which penalizes departures from the dose implied by the patient's body size. When a dose is decreased to avoid a vial, lower profits and payer costs create offsetting effects on provider utility. For sufficiently high altruism weights, the latter effect dominates. To minimize assumptions, we focus on the case in which the clinical penalty term is zero—i.e., in which providers expect that small departures from the dose implied by body-size have no impact on drug efficacy. In this case dose manipulation involves a clear tradeoff. A provider manipulates the dose down if their altruism weight exceeds the ratio of lost profit over the payers reduction in costs. Since Medicare sets reimbursement at a fixed markup (6%) over drug acquisition cost (ASP), these values are approximately known and the critical value of the altruism weight is roughly 0.0566.

This provides a clear economic interpretation of our bunching results. For the 46% of relevant claims in our data that have doses manipulated down, we can conclude that providers value a reduction in Medicare and patient costs at at least 5.66% of an equivalent increase in their own profits. Accounting for more realistic penalties for departures from body-size implied doses would increase this number.

Our primary contribution is to the literature on the altruism of health care providers. In

patients overestimate the health benefits of the drugs (Weeks et al., 2012).

[3] 65% of Medicare patients had Medigap, employer, or Medicaid coverage in 2022 (Ochieng et al., 2023).

leading models of physician behavior, patient preferences enter into the physician's utility function, with a weight on patient preferences reflecting the physician's degree of altruism (Arrow, 1963; Ellis and McGuire, 1986; Rochaix, 1989; Jack, 2005; McGuire, 2000; Chandra et al., 2011; Choné and Ma, 2011; Liu and Ma, 2013). Empirical work estimating this degree of altruism primarily elicits preferences via surveys or lab experiments, and finds that physicians are more altruistic than non-physicians (Hennig-Schmidt et al., 2011; Godager and Wiesen, 2013; Kesternich et al., 2015; Li et al., 2022; Attema et al., 2023). However, the large literature on provider responses to financial incentives (e.g., supplier induced demand) makes clear that physicians are not *purely* altruistic (see, e.g., McGuire, 2000; Clemens and Gottlieb, 2014).

We extend this literature in two ways. First, we provide novel revealed-preference evidence of provider altruism. A handful of related studies have analyzed physician prescription choices between generic and brand-name drugs (Hellerstein, 1998; Lundin, 2000; Carrera et al., 2018; Crea et al., 2019). Physicians internalize the patient's welfare and the insurer's expenditures, and altruism is inferred from the relative weight placed on the two. However, these settings capture trade-offs between patient and payer interests rather than between provider self-interest and social cost, since physicians have no direct financial stake in the prescription decision. Similarly, Carrera and Skipper (2025) show that physicians choose different statin drugs for their patients than for themselves, while Chen and Lakdawalla (2019) and Wu (2019) find that providers respond less to financial incentives when treating patients with higher OOP costs.

Second, we go beyond physician's regard for their patient's utility, and consider broader prosocial motivations in the spirit of voluntary contributions to public goods. These prosocial motivations are relevant not just for physicians but also other healthcare providers, like the hospitals and other healthcare facilities whose revenue is typically at stake in our setting. These more general notions of provider altruism have been studied in other work, but sparingly. Li et al. (2022) use a lab experiment to quantify physician altruism for individuals other than their patients in the form of equity-efficiency tradeoffs, and several other lab experiment or stated-preference studies consider non-physician providers such as nurses or dentists (see Galizzi et al., 2023, for a review of this literature).

We also contribute to the extensive medical literature on the so-called financial toxicity of cancer care—the adverse economic impact of cancer treatment and care on patients. A large literature finds that higher cancer treatment costs have strong negative associations with patient well-being (see Sideris et al. 2025 for review). We show that some providers are willing to take personally costly actions to reduce the financial burden of cancer care.

2 Institutional context

2.1 Dosing and reimbursement for infused anticancer drugs

Historically, most cancer drugs were chemotherapies. These drugs work by damaging rapidly dividing cells and have harsh side effects. For this reason, they are typically given through an IV and dosed variably by body size. More recently, targeted drugs, which block specific signals that help cancer grow, and immunotherapies, which help the immune system attack cancer cells, have become common. Many of these newer treatments are biologics (made from large, complex proteins) that would be broken down if swallowed, so they must also be given by infusion. Although these newer drugs work differently than chemotherapy, they can cause serious side effects and are also often dosed variably by body size. Roughly 50% of oncology drugs covered by Medicare are infused and roughly 50% of Medicare oncology drug spending is on these drugs. In 2020, over 1.9 million Medicare beneficiaries received these medications at a cost of $27 billion (Kyle et al., 2022).

Many infused drugs are packaged in single-use vials. As discussed in a recent National Academies report (Nass et al., 2021), this norm appears to be explained by concerns about bacterial growth, although other risks such as staff exposure to toxic compounds and dosing errors may also play a role. Because doses typically increase linearly with body-size (e.g., one additional unit of the drug for every kg of body-weight) this implies that a typical infusion leads to substantial amounts of discarded drug.

Since infused anticancer drugs are provided within healthcare facilities, they are reimbursed under Medicare Part B which follows the so-called "buy-and-bill" model (Werble, 2017). Providers purchase the drugs from wholesalers or other distributors and Medicare reimburses them on a per-unit basis (e.g., mg of the drug used) when the drugs are given to Medicare beneficiaries. CMS tracks the acquisition prices that providers pay in these transactions, and sets reimbursement at 106% of the average acquisition price, known as the average sales price (ASP).[4] ASPs are announced publicly by CMS at the drug-quarter level.

Importantly, Medicare reimburses providers for both the infused and discarded portions of these vials, leading to substantial spending on discarded drug units. Bach et al. (2016) originally called attention to this problem, estimating that $1.8 billion was spent nationally (across all payers) on discarded units of 20 leading cancer drugs in 2016. The previously mentioned National Academies Report (Nass et al., 2021) and several policy interventions followed. CMS now

[4]Our focus is on Medicare patients, but we note that private insurers use similar approaches (although with markups over acquisition prices higher than 6%) (Robinson et al., 2021, 2024) and that the relevant payer for dual (Medicaid + Medicare) eligible Medicare beneficiaries is Medicare.

requires providers to denote discarded units in their claims (Avalere Health, 2022, 2023) and publicly reports Medicare spending on discarded drug at the drug-year level (CMS, 2025). This CMS spending data makes clear that, while not universal, many anticancer drugs have substantial waste (and are therefore both dosed variably and packaged in single use vials). In 2022, at least 1% of Medicare Part B spending on 87 of 262 Part B cancer drugs was for discarded units. These drugs are extremely expensive. For instance, a typical infusion of Abraxane—the drug which accounts for the largest number of claims in our sample—costs about $2,958.[5] Typical infusions for the two most expensive drugs in our sample on a per-vial basis (Adcetris, dosed at 1.8mg/kg and Yervoy, dosed at 3mg/kg) cost roughly $36,000 and $40,000, respectively.

The providers purchasing and administering these drugs include a range of entities—hospital outpatient departments, physician group practices, and independent oncology clinics—but purchases are increasingly concentrated among hospitals and large health systems. This shift has been driven by hospital and health-system acquisition of oncology practices. This means that, in practice, most Medicare provider reimbursement for these drugs accrues to hospitals or health-system–owned clinics rather than to individual physicians.

Many hospitals and other health care facilities receive sizable discounts on acquisition costs (and therefore larger profit margins) via the 340B program. Since 1992 this program has mandated that pharmaceutical distributors provide discounts (estimated at 25–50%) for hospitals that treat large shares of low-income patients (U.S. Government Accountability Office, 2020). Transaction data collected by CMS to calculate ASP *do not* include these discounts. Participation has grown dramatically over the past several decades, with the number of covered facilities increasing by 131% between 2013 and 2021 (Horn, 2025). CMS lowered ASP based reimbursement for some high-cost 340B drugs to ASP minus 22.5% from 2018 to 2022, before the Supreme Court ended the practice. This reduction targeted the minimum discount received, so 340B providers still likely enjoyed a wider profit margin than non 340B providers during this time period, but less so than pre-2018 and post-2022.

On the patient side, traditional Medicare patients without any additional coverage pay 20% coinsurance rates for these drugs (and other Part B services). Medicare Advantage coinsurance rates are generally lower (Ippolito et al., 2024), but still meaningful. However, patient OOP costs for both traditional Medicare and Medicare Advantage are substantially reduced for many patients through additional insurance coverage from Medicaid, Medigap, or employer plans. In

[5] Abraxane is dosed at 1mg per $0.01m^2$ of patient body surface area. Following Bach (2009), we use a body surface area of $1.7m^2$ to approximate an average sized adult cancer patient. Abraxane's reimbursement rate (106% of ASP) in 2024q2 was $14.14 per mg, or $1,479 per 100mg vial. Body surface area is a standardized measure of a person's total skin area, often used instead of simpler measures based on body-weight to better control how much of a drug circulates in the bloodstream.

2022, 65% of Medicare patients had at least one of these sources of additional coverage (Ochieng et al., 2023). Generosity of these supplemental insurance sources varies, and is typically unobservable, but descriptive work using survey data suggests they lower OOP costs for Medicare patients by 50% on average (Kaiser Family Foundation, 2020).

2.2 Provider incentives

Medicare's reimbursement of discarded anticancer drugs creates stark, volume-based incentives for providers, patients, and Medicare. Figure 1 demonstrates this, again focusing on Abraxane, the drug which accounts for the largest number of claims in our sample. Abraxane is packaged in 100mg vials and dosed at 1mg per $0.01m^2$ of body surface area (BSA) for its original FDA-approved indication.[6] Body-size implied doses evolve smoothly through the vial cutoff (panel (a)) but a very small decrease in BSA from $1.01m^2$ to $1m^2$ cuts patient OOP costs, and provider reimbursement in half (panel (b)). Specifically, provider reimbursement decreases by $1,414 (106% of Abraxane's ASP per vial), and patient OOP costs (assuming no supplemental coverage) decrease by 20% of this number ($283).

Importantly, despite the specificity of this dosing regimen (and others in our sample), there is good clinical evidence that moderate departures from the indicated dose for these drugs will not affect patient outcomes. A leading relevant medical professional society, the Hematology/Oncology Pharmacy Association (HOPA), points out that most infused anticancer drugs have substantial pharmacokinetic variability across similarly sized patients (Fahrenbruch et al., 2018). Similarly sized patients naturally receive varying systemic exposures even at the same nominal dose. Based on the amount of this variability that has been observed in pharmacokinetic studies, the HOPA concludes that adjustments of <10% from the recommended dose will not affect health outcomes. Their logic is that the variability in exposure that these dose adjustments would create is much smaller than the variability that similarly sized and identically dosed patients experience in these pharmacokinetic studies.

This implies that provider decision-making in this setting should be primarily concerned with the financial implications of dosage choice. As described in Figure 1 the implications of this decision for provider *revenue* and payer costs are straightforward, below we discuss the implications for provider profit.

Provider profit per claim. A provider, p, receives the following profit Π_{pc} from a given claim c:

[6] BSA is a standardized measure of a person's total skin area, often used instead of simpler measures based on body-weight to better control how much of a drug circulates in the bloodstream. An average cancer patient has a BSA of around $1.7m^2$.

$$\Pi_{pc} = P \cdot Q_{pc} - TC_p(Q_{pc}) = P \cdot Q_{pc} - FC_{pc} - VC_p(Q_{pc}) \tag{1}$$

Here, quantity Q_{pc} is the number of *vials* of the drug required for claim c with provider p. Providers have some discretion over this value for claimants whose body-size is near a vial size cutoff. Price P is set by CMS at 106% of ASP.

An increase in Q_{pc} increases profit if $P > VC_{pc}$. We expect this to be the case because we expect variable costs to consist almost entirely of the acquisition costs for the drug. If VC_{pc} were exactly equal to the acquisition costs, then Medicare's reimbursement at ASP +6% would imply a 6% profit margin for providers who purchase the drug from manufacturers at the average price. Examples of non-drug-acquisition variable costs in this setting are materials costs (e.g., IV tubing or syringes) and staffing costs that vary with the number of vials (e.g., if an additional vial requires additional staff time to set up the infusion, provide it, or discard materials). We view it as highly unlikely that this non-acquisition-cost portion of VC_{pc} is meaningful.

Why would a provider prefer a lower dose? We will provide evidence that providers commonly manipulate doses down. The simple representation of claim-level provider profit in equation 1 would suggest that this *reduces* provider profit in most cases. This is because Medicare reimbursement for these drugs is meant to exceed drug acquisition costs by 6%, and variable costs other than the costs of drug acquisition are likely to be small. This begs the question: Why would a provider prefer less profit? We will consider four possibilities:

1. Dislike of discarded drug units:

   Doses slightly above a vial-size cutoff imply that the vast majority of the final vial is discarded. Providers may be averse to discarding large portions of these expensive products.

2. Preference for lower patient OOP costs:

   This explanation fits most naturally in the existing literature on provider altruism, which is primarily concerned with whether the provider internalizes the effect of treatment choice on patient utility. Large OOP expenses affect patient utility, and an altruistic provider would account for that in their treatment choice.

3. Preference for lower Medicare spending:

   As mentioned above, when a dose increases across a vial-size cutoff, Medicare spending increases by the cost of the vial (minus the proportion paid for by the patient). Since Medicare is a public insurance program, the provider may be altruistically concerned with

controlling these costs. For example, because of the fiscal externality that higher Medicare spending imposes on society.

4. Treat more patients with vials that are currently on-hand:

   Even if the profit-maximizing approach is to restock, this may take time and is occasionally hampered by market shortages. If such delays are important for a given provider, that provider may prefer to stretch their existing stock across a larger number of patients. Manipulating doses down to avoid some discarded units would facilitate this.

We expect that Π_{pc} is increasing in Q_{pc} (i.e., $VC_{pc} \approx$ drug acquisition cost and therefore $VC_{pc} < P$), but it is worth considering situations in which a lower Q_{pc} could *increase* provider profit. Here we list 3 possibilities. Combined with the 4 potential explanations for providers to prefer less profit, this produces a list of 7 potential mechanisms for the dose manipulation that we observe. We discuss these possible mechanisms further in sections 4 and 5.

5. Lower Q_{pc} (number of vials used for claim c), leads to more future claims:

   A smaller number of vials Q_{pc} on claim c means lower patient OOP costs for any patient with nonzero coinsurance rates. This lower OOP cost may make the patient more likely to return for a future infusion. If this offsetting effect on the quantity *of claims* is large enough, lower doses could increase overall profit.

   We do not observe provider profit or patient OOP cost but we do know how these values change in relative terms. This is because both provider revenue and patient OOP cost are proportional to the number of vials. In Appendix B we show that this implies a break-even elasticity of -1. Dose manipulation creates an OOP decrease proportional to the number of vials without manipulation. The offsetting quantity response must be at least as large in percentage terms for profit gained from additional claims to outweigh the profit lost from lower reimbursement per claim. Existing estimates suggest that demand for drugs similar to those in our sample is very price-inelastic, with elasticities of -0.01 (Goldman et al., 2006) and -0.04 to -0.11 (Goldman et al., 2010). This strongly suggests that providers are not manipulating doses down in an effort to increase future demand for infusions.

6. Non-drug-acquisition variable costs are large:

   If non-drug-acquisition variable costs per-vial are large enough then these costs could exceed the roughly 6% margin between drug-acquisition costs and P so that $VC_{pc} > P$ and $\frac{\partial \Pi_{pc}}{\partial Q_{pc}} < 0$. As mentioned above, we view this as unlikely. Infusions with more vials

may require more staff time and more materials, but these differences are likely to be ignorable relative to the cost of acquiring the drug.

7. Provider pays more than ASP +6% to acquire the drug:

   ASPs are averages across all transactions between providers and distributors of the drugs. Transaction level data is hard to come by, but it is clear that these prices vary across providers, and likely that provider size is a key determinant of the price that they pay for the drug. Providers who buy more of the drug have more bargaining power in these transactions and therefore pay less. An additional complication here is that the ASP system operates with a lag. Reimbursement rates paid today are based on ASPs calculated from transactions that occurred 1-2 quarters in the past. This implies that if transaction prices for a given drug increase substantially in a short period of time, providers are temporarily more likely to have paid more for a vial of the drug than Medicare will reimburse (Polite et al., 2015).

3 Data

We use Medicare claims and enrollment data from Centers for Medicare and Medicaid Services (CMS) obtained through virtual access to the Chronic Conditions Warehouse. This data includes all Part B claims for Traditional Medicare (2017-2024) and Medicare Advantage (2017-2022). The data also allow us to identify the physician who treated the patient and the facility where the visit occurred.

To arrive at a list of drugs for our analysis we began with drug-year level discarded drug spending data from CMS (CMS, 2025). This data simply reports all Medicare spending on discarded units of Part B drugs. We limit this list to drugs indicated for the treatment of cancer for which spending on discarded units is at least one percent of total spending, a vial of the drug costs at least $400, and total spending on the drug was at least $10 million. This selection criteria resulted in 48 drugs.

For these 48 drugs (and the remainder of our analysis) we further restrict our attention to claims that comply with a CMS requirement to bill separately for the infused and discarded portion of the dose. This restriction is necessary because our analysis will focus on small changes in the infused dose around vial size cutoffs. Information on the billed dose alone (infused + discarded) would not allow us to observe dose manipulation around these cutoffs (billed doses are almost always multiples of full vials). Since 2017 CMS has required the use of the JW modifier

which specifies what portion of the billed dose was discarded.[7] However, this requirement is not strictly enforced and compliance is incomplete. Importantly, this implies that we cannot differentiate doses with zero discarded units from those that have discarded units but simply decided not to use the JW modifier. Since the JW modifier is not required for doses with zero discarded units these two types of claims will appear identically in the data.

When the billed and discarded doses are separately reported we can infer infused dose (billed minus discarded). We use this to visually inspect the infused dose distribution for these 48 drugs. Based on this visual inspection, we dropped two drugs (Jevtana and Velcade) which rarely require more than one vial (because their vial sizes are large enough to exceed the vast majority of body-size-implied doses). We also discarded several drugs for which the distribution of infused doses was too sparse to allow for bunching methods.

This leaves us with 32 drugs which we focus on in our analyses. Roughly 17% of the claims in the data for these drugs use the JW modifier, allowing us to observe the infused dose, which is critical for our analyses as mentioned above. Table 1 displays some basic information about these drugs. Notably, the cost (to Medicare) for each vial of the drug. These values range from \$496 (Kyprolis) to \$11,993 (Adcetris) and are the amounts of revenue that a provider would lose by manipulating the dose down to avoid an additional vial. Table 2 shows the summary statistics of claims included in the analysis sample, and claims for the same drugs that do not use the JW modifier (and are therefore excluded from our sample).

We link detailed physician and facility characteristics to each claim from different sources. The CMS Healthcare Cost Information Report System contains facility level info such as revenue, ownership, and size for hospitals (RAND Corporation, 2018). Some other hospital characteristics such as teaching status are obtained from the Comparative Health System Performance Initiative maintained by the Agency for Healthcare Research (Agency for Healthcare Research and Quality, 2025). Data from the Health Resources and Services Administration is used to identify hospital 340B status (Health Resources and Services Administration, 2022). Medical personnel and clinic characteristics come from the Medicare Data on Provider Practice and Specialty. We also obtain the median household income in each ZIP code from the American Community Survey. These facility, doctor, and patient characteristics are used to characterize providers who manipulate doses and patients whose doses are manipulated.

[7] In 2023, CMS strengthened the guidance by requiring the use of a separate JZ modifier if zero units were discarded. Not following the new guidance could result in claims being subject to audits or being returned as unprocessable.

4 How many claims have doses manipulated?

4.1 Methods

To estimate the number of manipulated claims, we implement standard bunching methods as described in Kleven (2016). The distribution of infused doses for Abraxane in Figure 2 illustrates the method. We present four distributions. Two for the cutoff between 1 and 2 vials (top row), and two for the cutoff between 2 and 3 vials (bottom row). Because these distributions exhibit substantial heaping at doses that are multiples of 5 and 10 units, we also show separate plots which exclude these round number bins for clarity (left column).

We are interested in estimating the number of infused doses that are manipulated across the vial size cutoff (potentially in either direction). The key assumption underlying bunching methods is that the distribution of infused doses would be smooth through the vial size cutoff in the absence of such manipulation. To make use of this assumption, we first identify a manipulation region—the range of the infused dose within which dose manipulation is considered possible—and then use the distribution outside of the manipulation to extrapolate a counterfactual distribution without manipulation through the manipulation region. We can then estimate the number of doses manipulated as the difference between the counterfactual and actual distributions within the manipulation region.

To implement this approach, we begin by estimating the following regression for each drug X vial-size cutoff:

$$n_d = \sum_{g=1}^{2} 1\{\text{round number group} = g\} \cdot \left[\sum_{q=0}^{Q} \alpha_{qg} d^q + \sum_{i=\underline{d}}^{\bar{d}} \delta_{ig} 1\{d = i\} \right] + \upsilon_d \tag{2}$$

where d is the infused dose in units, $[\underline{d}, \bar{d}]$ is the excluded range, q is the order of polynomial, g separates infused doses into groups based on the type of round number (multiples of 5 ($g = 1$), multiples of 10 ($g = 2$), neither ($g = 0$, omitted)) and is used to allow the fitted distribution to differ for round numbers, n_d is the number of claims with infused dose d. Standard errors are calculated using a bootstrap procedure by randomly resampling bin-level residuals. We choose the excluded range and bandwidth by visually inspecting the distribution of claims and following guidance from professional societies that suggest reducing the dose within 10% of the vial cutoff. Specifically we begin with a manipulation window equal to 10% of the cutoff dose, and then reduce that window for some drugs in which manipulation is clearly limited to a shorter window. These shorter windows are primarily used for drugs with smaller vials, in

which a 10% manipulation window would span a large proportion of a vial.

We prefer to estimate equation 2 for each cutoff of the given drug. For some drugs, however, the vials are very small resulting in a very small manipulation region, bandwidth, and hence number of observations per regression. For these drugs we estimate one regression for multiple cutoffs.[8,9] The manipulation region in this pooled regression consists of three separate manipulation regions.[10] To obtain the number of missing claims at the drug level, we then sum the number of missing claims at each cutoff or cutoff group. We assume that manipulation is bounded (e.g., movement not to or from far away from the threshold), and that the distribution of units is well-behaved (e.g., counterfactual distribution is smooth across threshold).

Two key caveats unique to our setting are worth noting. First, if doses are manipulated down (to avoid wasted drug from a mostly unused additional vial) we will be unable to observe the excess mass without additional assumptions. (The size of the excess mass should be equal to the size of the missing mass, and this is a common check on the validity of bunching estimates.) Imagine a drug which is packaged in 100 unit vials and two patients receiving this drug. Patient A has a 101 unit dose and patient B has a 80 unit dose. Patient A's provider manipulates their dose down to 100 units to avoid discarding 99 units in a second vial and therefore bills for 100 units of the drug, none of which are recorded as waste. Patient B's provider correctly bills for 100 units of the drug (Medicare pays for discarded units) but neglects to bill separately for the 20 units that were discarded. These claims are indistinguishable for our purposes and are both dropped from our analysis.

Second, it is possible for manipulation to occur in both directions. All providers have a private financial incentive to manipulate doses up across vial size cutoffs, while altruistic providers also have an offsetting social incentive to manipulate doses down. This implies that our estimates will be interpretable as the net manipulation.

We will provide evidence that providers manipulate doses down across cutoffs. As discussed in subsection 2.2 there are several potential explanations for this behavior. Determining which of these potential explanations explain the dose manipulation that we observe will be critical to our analysis because different explanations have drastically different implications for provider altruism. In Section 5, we rely on heterogeneity across drugs, providers, and patients, to further

[8] One-cutoff-per-regression drugs: Abraxane, Adcetris, Enhertu, Folotyn, Halaven, Kadcyla, Onivyde, Polivy, Poteligeo, Trodelvy, Yervoy, Zepzelca.

[9] Multiple-cutoffs-per-regression drugs: Alimta, Avastin, Cyramza, Erbitux, Herceptin, Imfinzi, Kanjinti, Kyprolis, Mvasi, Ogivri, Ontruzant, Riabni, Rituxan, Ruxience, Sarclisa, Treanda, Truxima, Vectibix, Yondelis, Zirabev.

[10] Assume for example that there are 3 cutoffs, the size of the vial is 10 units, and the manipulation region is 2 units. One regression per cutoff would consist of 10 observations: 5 units below the cutoff, 5 units above the cutoff, 2 units in the manipulation region region, and 8 units outside of the manipulation region. The pooled regression would consist of 30 observations and three manipulation regions with 2 units each.

disentangle these mechanisms.

4.2 Results

The results suggest that the "altruistic" dose manipulation by providers is common in our setting. Providers—either physicians or facilities or both—decrease doses which are just above vial-size cutoffs in order to avoid the use of an additional vial. Since these drugs are expensive, and providers are reimbursed purely based on volume by Medicare, this behavior in effect transfers substantial sums from providers to patients and the Medicare program. A single vial of a typical drug in our sample costs $1,000s of dollars—each dose manipulated down across a vial size cutoff loses the provider this amount in Medicare reimbursement.

We illustrate our results for Abraxane in figure 2 and Avastin in figure 3—the drugs with the highest number of claims in each drug-type (one cutoff per regression, or mulitple cutoffs per regression) group. Appendix figures A.1-A.30 contain similar plots for each of the remaining 30 drugs in our sample. Figure 2 and 3 shows the dose distribution of Abraxane and Avastin, respectively. The left panel in each figure shows doses distributions with doses in round number bins (multiples of 5) removed for clarity. Heaping is due to rounding in the reporting of these doses by providers. The blue line represents the counterfactual distribution estimated as described in section 4.1 and the black line is the actual dose distribution. For Abraxane, we estimate one regression for each vial cutoff. The results suggest clear dose manipulation right after the first and second vial cutoff. Providers manipulate down 7,228 (se: 2,357) claims around the first vial and 34,533 (se: 3,447) claims around the second vial cutoff. This manipulation translates to $50.2 million lost in revenue for the providers or saved for Medicare or patient.[11] For Avastin we estimate separate regressions for the first three, next three, and the last four cutoffs. Providers manipulated 25,457 (se: 2,433) claims on the first three, 10,629 (se: 1,247) claims on the next three, and 7,014 (se: 965) claims on the last four cutoffs. The number of manipulated claims for Avastin results in $31.8 million in revenue forgone or cost saved.

Figure 4 shows the results for the remaining drugs (see table 3 for more details). The number of manipulated claims ranges from 45 to 43,223. Out of 32 drugs, the estimated number of manipulated claims is not statistically significant at conventional levels for only four drugs. The total number of manipulated claims is 347,048 which implies $388.4 million in revenue forgone or cost saved. The fraction of revenue lost out of total revenue per drug ranges between 0.002 for Folotyn and 0.04 for Kadcyla, Onivyde, and Polivy. To quantify the extent of manipulation, we scale the number of manipulated claims by number of claims that could have been manipulated

[11] We obtain the revenue lost by multiplying the number of manipulated claims by the median cost of a vial of the drug during the analysis period.

(i.e., the sum of the counterfactual distribution across all bins in the manipulation region). The share of manipulated claims relative to counterfactual claims ranges from 0.13 to 0.59 with an average and median of 0.45. We also use a more conservative measure and scale the number of manipulated claims by the total number of claims for a given drug. The fraction of manipulated claims relative to the total number of claims ranges between 0.01 and 0.21 with an average and median of 0.09. The scaled estimates of manipulation suggest that the extent of missing claims is meaningful even when we use the most conservative measure.

The estimated number of manipulated claims is likely to be an undercount for the true number of missing claims and revenue lost or cost savings because of several reasons. First, we are only able to estimate dose manipulation for the 17% of claims that separately bill for waste. Second, we only focus on traditional Medicare and Medicare Advantage and therefore omit patients covered by private insurance and Medicaid. Third, in our analysis we use only the 32 leading anticancer drugs and remove smaller drugs. Fourth, the empirical approach requires a minimum number of observations and hence omits vial-size cutoffs with a small number of observations.

5 Which claims have doses manipulated?

5.1 Methods

We use methods from Diamond and Persson (2016) to evaluate which providers manipulate the doses and which patients are affected by the manipulation. We characterize manipulated claims by observing how claim characteristics change through the region of the dose distribution where manipulation occurs. Since we observe bunching in number of claims, unless manipulators are randomly selected we expect to see bunching in the binscatter of characteristics that drive the bunching behavior in the region where manipulation occurs. Figure 5 illustrates intuition by showing a binscatter when a characteristic is not driving the manipulation in panel (a) and when a characteristic is driving the manipulation in panel (b).

We therefore compare the mean among manipulators to the counterfactual mean for a given characteristics in the manipulation region. The mean of the characteristics for the manipulator group can be derived using the relationship between counterfactual, manipulation, and actual mean of the given characteristic. Shown in equation 3 the counterfactual average of the characteristic x_d^C in each bin d is a weighted average of the manipulator average of the characteristic x_d^M in each bin d and the actual average of the characteristic x_d^L in each bin d. The weights is the number of manipulation n_d^M and actual n_d^L claims in each bin. We then solve for the

average of the characteristic among manipulators in each bin (see equation 4) and calculate a weighted average of the characteristic across all bins in the manipulation region to obtain the statistic of interest (see equation 5). The weight of each bin is the number of missing claims in the bin n_d^M divided by the total number of missing claims in the manipulation region N^M.

$$x_d^C = \frac{x_d^M \cdot n_d^M + x_d^L \cdot n_d^L}{n_d^M + n_d^L} \tag{3}$$

$$x_d^M = x_d^C \cdot \frac{n_d^M + n_d^L}{n_d^M} - x_d^L \cdot \frac{n_d^L}{n_d^M} \tag{4}$$

$$\bar{x}^M = \sum_{d=\underline{d}}^{\bar{d}} \frac{n_d^M}{N^M} \cdot x_d^M \tag{5}$$

To obtain the counterfactual mean in each bin we use a similar approach to calculating the number of manipulated claims, except that the dependent variable is the characteristic of interest:

$$x_d = \sum_{g=1}^{2} 1\{\text{round number group} = g\} \cdot \left[\sum_{q=0}^{Q} \beta_{qg} d^q + \sum_{i=\underline{d}}^{\bar{d}} \theta_{ig} 1\{d = i\} \right] + \epsilon_d \tag{6}$$

where d are the bins of infused drug units, $[\underline{d}, \bar{d}]$ is the excluded range, p is the order of polynomial, g is the type of bins (multiples of 5, multiples of 10, neither), x_d is the average of characteristics in bin d. Standard errors are calculated using a bootstrap procedure and the regression is weighted by number of claims when the characteristics is not missing.

Extrapolating a counterfactual relationship between the characteristic and the infused dose through the manipulation region allows us to estimate the mean of that characteristic in the manipulation region in the absence of bunching and in the presence of bunching. The difference can be combined with our above estimates of the number of claims that were manipulated to construct an estimate of the mean of that characteristic among the manipulated claims.

Similar to obtaining the number of missing claims, we estimate equation 6 for each cutoff for the one-cutoff-per-regression drugs and multiple cutoffs for the multiple-cutoffs-per-regression drugs. We then calculate the overall average of the characteristic across all cutoffs and drugs by calculating the weighted average of the mean of the characteristic at each cutoff or cutoff group with the fraction of claims as weights at the corresponding cutoff or cutoff group.

5.2 Results

We now characterize the providers who manipulate doses and the patients with manipulated claims to understand what could be driving the manipulation of the dose. This heterogeneity analysis allows to understand whether providers reduce the infused dose to benefit themselves, the patient, or Medicare. The parameter of interest is the average of the characteristic among the manipulators relative to the counterfactual average of the characteristic in the absence of bunching. Therefore, if the ratio between the mean among manipulators and the counterfactual mean is less than one, the characteristic is less likely to explain the manipulation. Figure 8 illustrates this approach for Abraxane using two characteristics - dual status and national cancer institute. The top panel of the figure shows the actual (or non-manipulation) and counterfactual fraction of claims in each bin of dual eligible beneficiaries and the bottom panel of the figure shows the actual (or non-manipulation) and counterfactual fraction of claims in each bin from a national cancer institute. The share of actual and counterfactual claims for dual eligible beneficiaries is very similar in the manipulation region. In contrast, the fraction of actual claims from a national cancer institute is much higher than the counterfactual mean suggesting that the manipulation mean is lower for this characteristic and that the providers in national cancer institutes are less likely to reduce doses.

Dislike of discarded drug units. If providers were motivated by the amount of drug discarded, we would expect manipulation to be more common for drugs supplied in larger vials, where waste is greater. Instead, we observe dose manipulation across drugs with vial sizes from 10 to 100 units (see table 1). This pattern suggests that concern about discarded units is unlikely to be a main factor in providers' behavior.

Preference for lower patient OOP costs. To assess whether providers adjust doses to lower patients' OOP spending, we compare the mean among manipulators and non-manipulators for patient and provider characteristics that proxy for OOP liability. As reported in table 4, manipulators do not systematically treat patients who differ in race/ethnicity, dual eligibility, ZIP-code median income, or Medicare coverage type from the counterfactual average.[12] In figure 7, we also show that the proportion of manipulated claims among patients with Traditional Medicare and Medicare Advantage are not different. The characteristics of the medical specialist that treat the patient shown in table 5 are also not affecting the decision to manipulate the dose. In addition according to Ochieng et al. (2023), 90% (40%) of patients in Traditional Medicare (Medicare Advantage) have supplemental insurance that insulates patients from OOP

[12]We define dually eligible beneficiaries as those enrolled in any Qualified Medicare Beneficiary, Specified Low-Income Medicare Beneficiary, Qualified Disabled Working Individual, Medicare-Qualifying Individual program, or otherwise eligible for Medicaid.

costs. Taken together, these results suggest that patient OOP costs are unlikely to be a primary driver of providers' dosing decisions

Preference for lower Medicare spending. We have limited direct evidence that providers bunch to reduce Medicare spending. However, since neither aversion to discarded drug units nor concern about patients' OOP costs appears to explain the manipulation, a natural interpretation is that providers' behavior is primarily motivated by a desire to limit Medicare—and more generally public—spending.

Treat more patients with vials that are currently on-hand. One potential mechanism is that binding supply constraints induce providers to lower infused doses so that an existing stock of vials can cover more patients. Because drug shortages can emerge at several points in the supply chain—ranging from inputs and manufacturing capacity to product- or drug-specific presentations and local distribution—observed scarcity may reflect national, regional, or facility-level frictions, and generic infused anticancer drugs are especially exposed to such disruptions (Malta et al., 2025). However, figure 4 shows similar manipulation rates for generic and brand-name drugs, which makes a drug-level shortage explanation less compelling. We also examine directly whether drug-level shortages affect provider behavior by incorporating information on the timing of shortages from the American Society of Health-System Pharmacists.[13] Because we document dose manipulation for drugs that are never in shortage, supply-side constraints are unlikely to be the primary driver of this behavior. Consistent with this interpretation, the manipulation and counterfactual mean of claims billed during shortage periods are very similar, providing further evidence against drug shortages as an explanation for the observed bunching (see table 7). Consistent with this evidence, figure 7 shows no discernible difference in the proportion of manipulated claims between shortage and non-shortage periods. Moreover, shortages can be unevenly distributed across facilities due to allocation rules, distributor networks, or purchasing contracts, and smaller providers—because of weaker bargaining power, lower inventories, and fewer sourcing options—are more likely to experience facility-level shortages than large systems. We assess this channel in two ways: first, by testing for higher manipulation at the end of inventory cycles (last week of the month or quarter; see table 4); and second, by comparing manipulation across facilities of different size, proxied by beds, providers, or patients (see table 6 and figure 7). In both cases we find no evidence consistent with facility-level shortages driving dose manipulation.

Lower Q_{pc} (number of vials used for claim c) leads to more future claims. If

[13]During the analysis period, three drugs are affected by supply constraints. Abraxane is in shortage 09/16/2021–09/04/2022 and 04/27/2023–04/28/2023, Treanda is in shortage 02/15/2018–03/19/2018, and Zirabev is in shortage 09/04/2023–02/06/2025.

providers reduced doses above the cutoff to stimulate future demand—because patients could switch to other local providers—we would expect more manipulation in concentrated markets or for higher-priced drugs. We use a back-of-the-envelope calculation (see appendix B) and show that the point-elasticity of demand ranges between -1 and -2 which is substantially higher than the very low price elasticity of demand for similar anticancer therapies estimated in existing literature.[14] In addition the high prevalence of supplemental coverage among Medicare beneficiaries make this mechanism less compelling.[15] We nonetheless examine it by comparing manipulation across markets with different degrees of concentration, measured by the Herfindahl–Hirschman Index (HHI) and price of the drugs. The patient's market is defined as the hospital referral region (HRR) by year, and we also test a definition at the HRR–year–drug level.[16] As shown in table 7, HHI levels among manipulators mirror the counterfactual HHI, and the differences in vial prices—both in levels and relative to other vials of the same drug—are similarly small.[17] Taken together, these patterns suggest that providers are unlikely to be manipulating doses in order to boost future demand.

Non–drug-acquisition variable costs are large. Hospital-based and other large integrated infusion settings incur higher non–drug variable costs than physician-office sites because of more resource-intensive staffing, pharmacy, and compliance requirements (Kalidindi et al., 2018). We therefore examine whether hospitals are more likely to manipulate doses, but table 4 shows no evidence consistent with this channel.[18]

Provider pays more than ASP + 6% to acquire the drug. Because Medicare reimbursement is tied to an average price, providers can incur losses under the buy-and-bill program if their acquisition cost exceeds ASP plus the 6% add-on. Providers with weaker bargaining power and without drug discounts are more exposed to this risk. To capture bargaining power, we use the number of claims at the facility–drug–year level and compare manipulation across this measure (see table 7). Manipulation is more common when claim volume—and thus likely bargaining power—is higher.

Claims volume could be an imperfect proxy for supplier bargaining power because many providers procure drugs via group purchasing organization (GPO) contracts. GPOs pool demand and negotiate prices based on aggregate member volume and compliance-based tiers,

[14]The price elasticity of demand ranges from –0.01 to –0.11 for comparable anticancer drugs (Goldman et al. 2006; Goldman et al. 2010).

[15]Ochieng et al. (2023) report that 90% (40%) of beneficiaries in Traditional Medicare (Medicare Advantage) had some form of additional coverage in 2022.

[16]HHI values are taken from the Dartmouth Atlas of Health Care and linked to claims using the patient's ZIP code, year, and drug.

[17]Absolute vial price is the ASP per vial; the relative price is the ASP per vial divided by the total price of all vials observed for that drug.

[18]See also figure 7 for direct comparison of proportion of manipulated claims in hospitals and clinics.

which can decouple an individual provider's claims volume from its effective acquisition price.[19]

Motivated by this concern, we test whether manipulation is more likely when providers face negative reimbursement spreads, i.e., when acquisition costs exceed reimbursement. Under buy-and-bill, a drug is "underwater" when the provider's purchase price is higher than the insurer payment (Polite et al., 2015). One mechanism is reimbursement lag: Medicare Part B pays based on the drug's ASP, updated quarterly but constructed from sales data with an approximately six-month delay. As a result, following an upward price shock, providers may face higher contemporaneous acquisition costs while reimbursement remains tied to an earlier, lower ASP until subsequent updates incorporate the increase.

To proxy periods in which a drug is likely to be underwater, we identify quarters with unusually large quarter-to-quarter percentage increases in ASP and examine manipulation in the preceding six months.[20] Table 7 and figure 7 shows that the manipulation-counterfactual-mean ratio and proportion of manipulated claims are nearly identical in these windows, consistent with little evidence that manipulation is driven by concerns about acquisition costs exceeding reimbursement.

In table 6 and figure 7, we also compare the behavior of providers in hospitals with and without 340B status.[21] The 340B shares (ratio 1.05) and proportion of manipulated claims are nearly identical, implying that providers with access to discounted drugs manipulate doses at least as much as others, which is inconsistent with a simple profit-maximization explanation.

Administrative costs increase with Q_{pc} (number of vials used for claim c). Larger doses can raise the facility's administrative burden, so providers might have an incentive to lower doses to avoid incremental non–drug costs. Infusion of oncology drugs typically involves pharmacy preparation, pre-infusion verification, venous access, administration, monitoring, and post-infusion care; among these, infusion time is the component most likely to scale with dose for products that specify a maximum infusion rate (e.g., rituximab), whereas for drugs with fixed infusion times (e.g., Abraxane) only pharmacy-related steps may lengthen slightly. To test whether providers manipulate doses to shorten infusions, we compare manipulation rates at cutoffs requiring different vial counts. As shown in Figure 6, manipulation does not increase with the number of vials, indicating that administrative burden is unlikely to be the primary mechanism.

[19] Dobson et al. (2019) finds that 96–98% of U.S. hospitals participate in GPO contracts and that GPO-mediated purchasing accounts for roughly 60% of hospital non-labor spending.

[20] For each drug, we define a "large" ASP increase as a quarter-to-quarter percentage change above the 95th percentile. Approximately 3% of claims occur in windows classified as likely underwater.

[21] The 340B Drug Pricing Program requires manufacturers to offer discounted outpatient drugs to safety-net providers. We can identify hospitals, but not clinics, participating in 340B using CMS certification numbers from HRSA daily reports or 340B-related modifiers such as JG and TB.

Concerns about CMS audits Providers could also be concerned about audits by CMS due to excessive amounts of waste and therefore manipulate the dose to reduce the discarded amount of the drug. To ensure accountability, prevent fraud, and promote accurate budgeting, the CMS clearly allows and encourages to bill for waste since CMS pays for the infused and discarded portion of the drug. The providers are supposed to use a JW modifier since 2017 that indicates how much of the drug was discarded and a JZ modifier since 2023 that shows whether no waste occurred. The guidance by CMS suggest that failing to use these modifier if needed could be subject to review since 2017 and subject to audits or returned as processable since 2023. Taken together, the CMS guidance does not imply any negative implications if drug waste is reported. However, if providers interpret CMS to penalize discarded amounts of the drug, the consequences are worse when CMS started to require providers to report whether no amount was discarded. We therefore check if manipulation is more likely to happen when JZ modifier is required, but find no difference between manipulation and counteraction mean shown in table 4.

Accountable Care Organization. In Medicare, an Accountable Care Organization (ACO) is a contractual arrangement in which groups of providers (e.g., physician practices and hospitals) are made jointly accountable for the total Part A and Part B spending and quality outcomes of a panel of beneficiaries, relative to a risk-adjusted expenditure benchmark, while day-to-day care continues to be reimbursed under fee-for-service. Beneficiaries are eligible for attribution if they are enrolled in traditional (fee-for-service) Medicare with both Part A and Part B and are not enrolled in Medicare Advantage, and are assigned to an ACO based on where they receive the plurality of their primary care. Providers may participate through different ACO models that vary in the degree of financial risk—most prominently the Medicare Shared Savings Program (MSSP), with "one-sided" (upside-only) and "two-sided" (upside-and-downside) tracks, and higher-risk Innovation Center models (e.g., Pioneer, Next Generation, ACO REACH, kidney-specific models, and state all-payer ACO demonstrations), which differ primarily in their risk levels, attribution rules, and payment mechanisms. These contracts create population-level incentives by allowing the ACO to retain a share of any savings (and sometimes bearing a share of losses) relative to the benchmark, conditional on meeting quality targets, thereby partially internalizing payer spending. In settings such as buy-and-bill chemotherapy, this structure can change dose decisions at vial thresholds: because the ACO ultimately bears part of the marginal cost of an additional vial, small dose reductions that keep the prescribed amount just below a vial-size cutoff reduce expected total spending and increase expected shared savings, so a provider group could rationally reduce doses for financial reasons

even in the absence of altruistic concern for payer or patient costs.

To assess whether ACO participation drives dose reduction, we focus on beneficiaries and providers in the MSSP and the Next Generation ACO model, which together account for the dominant share of Medicare ACO activity over our study period. Between 2017 and 2024, approximately three-quarters to nearly all Medicare beneficiaries and about 70–95 percent of providers participating in ACO or ACO-like payment models were in either MSSP or Next Generation ACO, with this combined share peaking before 2022 and then declining as newer Innovation Center models expanded (MedPAC 2024; Parashuram et al. 2024). Table 7 and figure 7 shows that both the manipulation and the counterfactual mean as well as the proportion of manipulated claims are very similar across claims with and without ACO participation, suggesting that ACO affiliation is unlikely to be the primary driver of the observed manipulation.

6 Using dose manipulation to quantify provider altruism

In our setting, a healthcare provider chooses the dose d of a physician-administered drug. The provider's choice affects their own revenue and costs, the financial burden on Medicare, and the patient's financial exposure through OOP costs.

We assume the provider maximizes a utility function that combines private financial returns with altruistic concern for payer and patient spending, as well as adherence to clinical norms:

$$U(d) = \underbrace{R(d) - C_p(d)}_{\text{net private payoff } \Pi(d)} - \gamma \underbrace{B(d)}_{\text{social cost}} - \underbrace{\psi(d; d^*)}_{\text{clinical appropriateness cost}} \tag{7}$$

The first term, $R(d) - C_p(d)$, represents the provider's net private payoff: reimbursement $R(d)$ from the payer minus the cost $C_p(d)$ of purchasing and administering the drug. The second term captures altruism: the provider internalizes a fraction $\gamma \geq 0$ of the payer's spending $B(d)$. A higher γ indicates stronger concern for payer or patient financial welfare. The final term $\psi(d; d^*)$ penalizes deviations from the clinically appropriate dose d^*, which is determined primarily by the patient's body size. Since we expect that there is little to no effect of the dose adjustments we consider on patient health (Fahrenbruch et al., 2018), this clinical appropriateness term can be interpreted as a professional or ethical cost of deviating from the medically justified dose, or as the providers misperceived health cost of the dose adjustment.

6.1 The reimbursement notch

In the empirical setting, infused anticancer drugs are supplied in large single-use vials. Medicare reimburses providers for the entire vial, including any portion discarded after use. Consequently,

total reimbursement $R(d)$ is discontinuous at the vial boundary $d = c$: increasing a dose slightly beyond the threshold that requires a new vial sharply increases both reimbursement $R(d)$ and payer spending $B(d)$. Thus, the provider's payoff function features a reimbursement notch—a discrete jump in financial returns at the vial boundary.

6.2 Optimal dosing and the role of altruism

Figure 9 illustrates this payoff function. When the provider is purely profit-oriented ($\gamma = 0$), the notch is positive: the utility function jumps upward at the vial boundary, creating an incentive to dose slightly above the cutoff. As γ increases, the altruism term $-\gamma B(d)$ partially offsets the reimbursement gain, shrinking the effective notch. Eventually a value of γ is reached that makes the provider indifferent between $d = c - \epsilon$ and $d = c + \epsilon$. We call this value γ^*. For $\gamma > \gamma^*$, the perceived notch becomes negative, and the provider prefers $d = c - \epsilon$ to $d = c + \epsilon$. Such a provider would manipulate the dose down below the cutoff, reducing payer spending, patient OOP, and their own profit.

6.3 Bounding Altruism When Clinical Penalties Are Negligible

While clinical guidance clearly discourages arbitrary dose changes, it is less clear how to quantify the implicit "clinical penalty", $\psi(d; d^*)$, associated with deviating from the dose d^* implied by the patient's body size. Conceptually, $\psi(d; d^*)$ captures non-pecuniary costs of deviating from the dose implied by a patient's body size or other clinical indicators—such as expected toxicity risks or professional norms. In practice, we expect that the average clinician experiences a positive clinical penalty for *any* deviation from the body-size-implied dose will reduce the effectiveness of the drug. However, the magnitude and functional form of the clinical penalty is uncertain.

As a starting point, we consider the limiting case $\psi(d; d^*) = 0$ within a narrow window around reimbursement cutoffs. This assumption is partly consistent with professional guidance that explicitly allows small dose adjustments (for example, rounding to the nearest vial or modest reductions to avoid waste) (Fahrenbruch et al., 2018). In this simplified setting, the provider faces a straightforward binary decision rule:

$$\text{Manipulate dose down (avoid additional vial)} \iff \gamma \geq \gamma^* = \frac{\Delta\Pi}{\Delta B}$$

where $\Delta\Pi$ is the increase in provider profit from crossing the cutoff, and ΔB is the associated increase in payer (and possibly patient) spending.

To see this, recall the provider's objective function:

$$U(d) = \Pi(d) - \gamma B(d)$$

Where $\Pi(d)$ is the provider's net private profit and $B(d)$ is total spending. A provider who manipulates a dose down across a vial size cutoff experiences the following change in utility:

$$\Delta U = \Delta\Pi - \gamma \Delta B$$

Where $\Delta\Pi$ and ΔB are < 0. The provider chooses a dose below the cutoff (i.e., manipulates down) if doing so increases their utility:

$$\Delta U \geq 0 \quad \Rightarrow \quad \gamma \geq \frac{\Delta\Pi}{\Delta B} \equiv \gamma^*$$

Thus, $\gamma^* = \Delta\Pi/\Delta B$. The degree of altruism that leaves the provider indifferent between the lower and higher doses is equal to the ratio of the provider's profit lost over the payer's cost savings.

Even under the strong assumption of $\psi = 0$, this bounding result remains informative. First, it offers a direct revealed-preference interpretation: γ^* represents the ratio of private profit to social cost at which providers are just indifferent between self-interest and social efficiency. Second, since any positive clinical penalty would only raise the implicit threshold for manipulation, these bounds provide a lower bound on altruism.

Importantly, our setting allows us to approximate the value of γ^*. Since reimbursement per vial is a fixed percentage markup over acquisition cost (e.g., ASP+6%), the profit margin per vial is approximately constant across drugs and providers. Since social spending per vial ΔB is simply the reimbursement, this is approximately constant as well. Specifically, let the per-vial reimbursement be ASP $\times$ (1.06) and assume the provider's acquisition cost is ASP. Then the net private gain from adding a vial is $\Delta\Pi = 0.06 \times$ ASP, while the increase in total spending (payer+patient) is $\Delta B \approx 1.06 \times$ ASP:

$$\gamma^* \equiv \frac{\Delta\Pi}{\Delta B} = \frac{0.06\,\text{ASP}}{1.06\,\text{ASP}} \approx 0.0566$$

Therefore, whenever a dose is manipulated down, we can infer that $\gamma \geq 0.057$. In other words, we can infer that the provider is willing to give up at least ¢5.66 per \$1 of profit to lower Medicare and patient costs.

7 Conclusion

This paper provides new revealed-preference evidence of provider altruism using administrative Medicare data on infused anticancer drugs. In contrast to prior studies that rely on stated preferences or laboratory behavior, we observe real financial trade-offs in a setting where providers can manipulate treatment doses to reduce costs for patients and payers. Nearly half of the potentially manipulable claims in our data involve downward dose adjustments that lower provider profit and reduce public spending. We interpret this as evidence that a substantial share of providers internalize social benefits when making treatment decisions.

We first use bunching methods to quantify the number of claims with manipulated doses. Heterogeneity in this dose manipulation and institutional knowledge strongly suggests that this dose manipulation implies that providers are choosing to sacrifice some profit in order to lower spending by Medicare and/or patients. By adapting models of voluntary contributions to public goods (e.g., Charness and Rabin, 2002), in which providers weigh their own profits against the social value of reduced healthcare spending, we use these bunching results to quantify provider altruism. Under plausible assumptions about provider profit margins per vial we show that observed dose manipulation implies that providers value reductions in public and patient costs at roughly five to six cents per dollar of foregone profit. Based on clinical guidance from professional societies (Fahrenbruch et al., 2018), we assume that these minor deviations from typical doses will not impact patient health outcomes. However, if we assume that providers have a preference for the typical dose—such that they pay a utility cost for deviating from that dose—this would raise these estimates of provider altruism.

Providers' willingness to sacrifice profits to reduce waste and costs parallels recent professional efforts, such as the Choosing Wisely campaign (Morden et al., 2014), to curb the overuse of low-value care. From a policy perspective, this supports reforms or interventions which recognize or reinforce such prosocial motives—rather than assuming purely self-interested behavior. More generally, our results highlight the value of integrating behavioral models of altruism into analyses of public spending and the design of social insurance programs.

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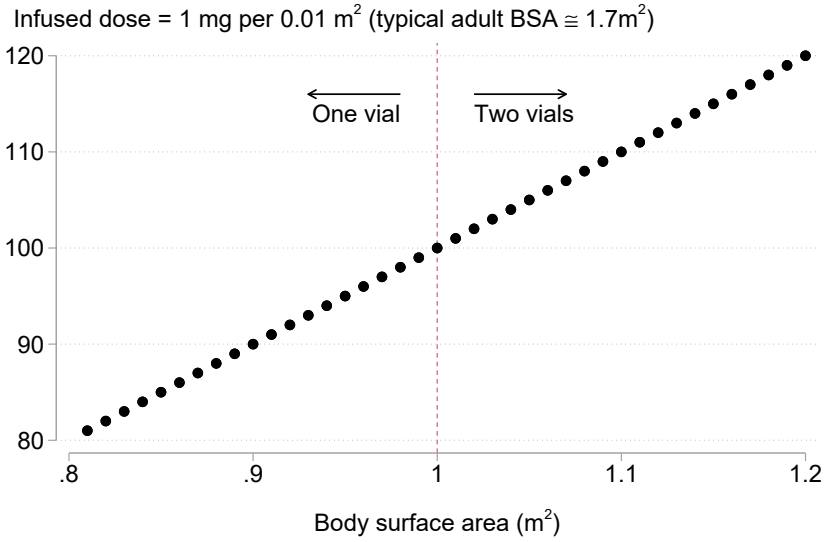
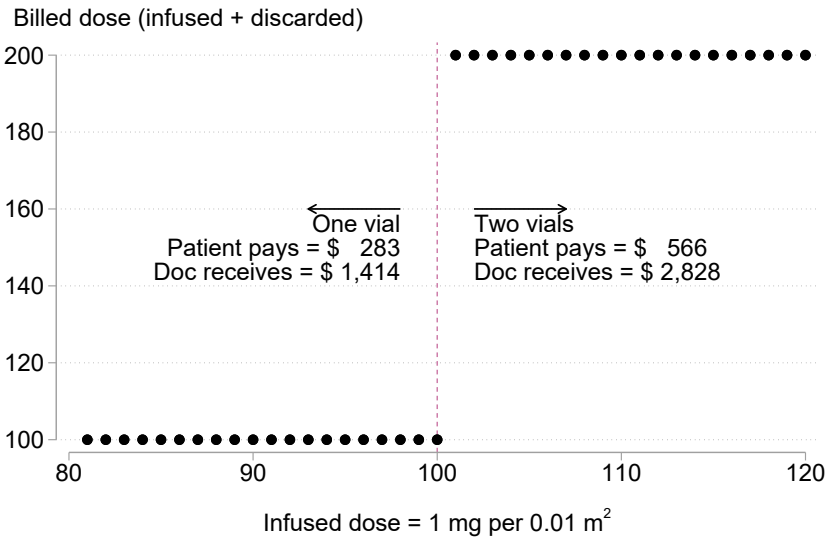
Figures

Figure 1: Incentives to Over and Under-Bill: Abraxane

(a) Relationship between Body Surface and Dose

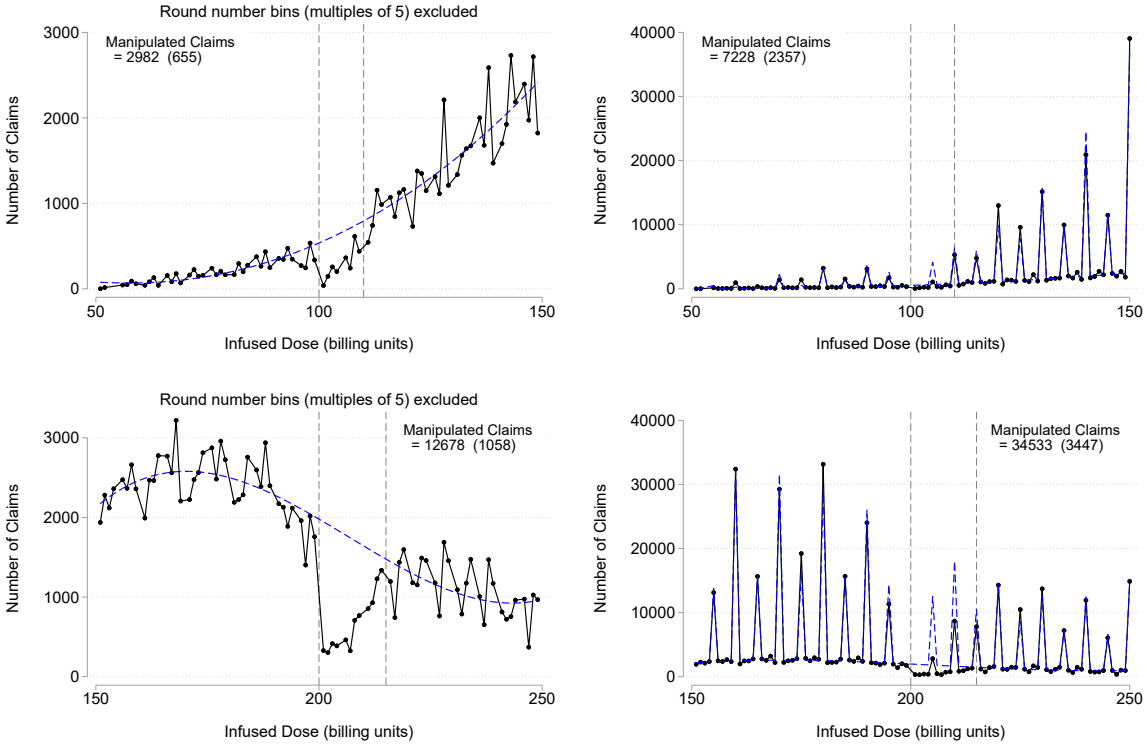


(b) Patient Cost and Provider Revenue



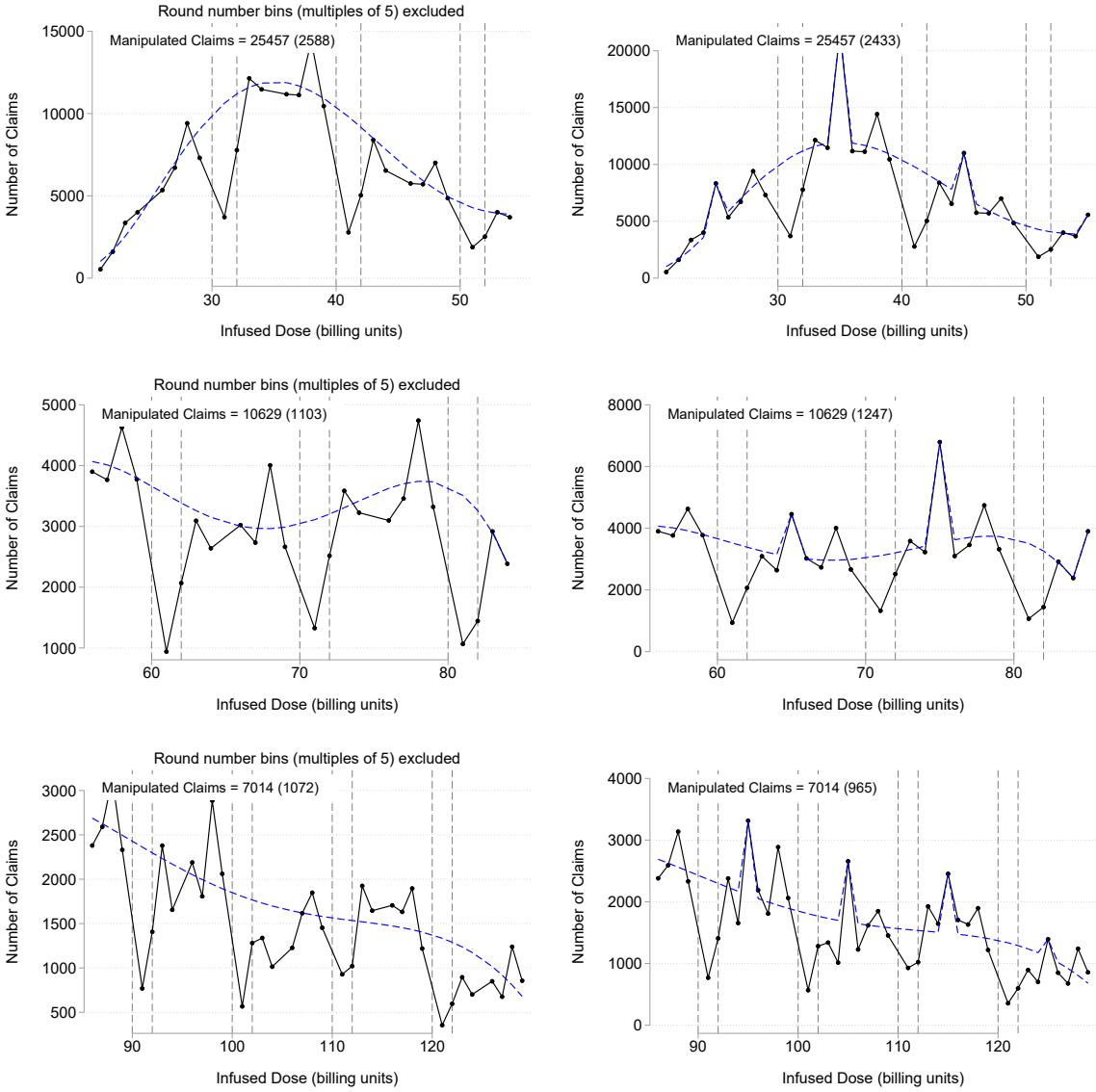
Notes: This figure shows for Abraxane the relationship between body surface (panel a) and the change in out-of-pocket costs for the patient and revenue for the provider (panel b) when one additional vial is needed. The vial size for Abraxane is 100 mg.

Figure 2: Provider Manipulation of Abraxane Doses



Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

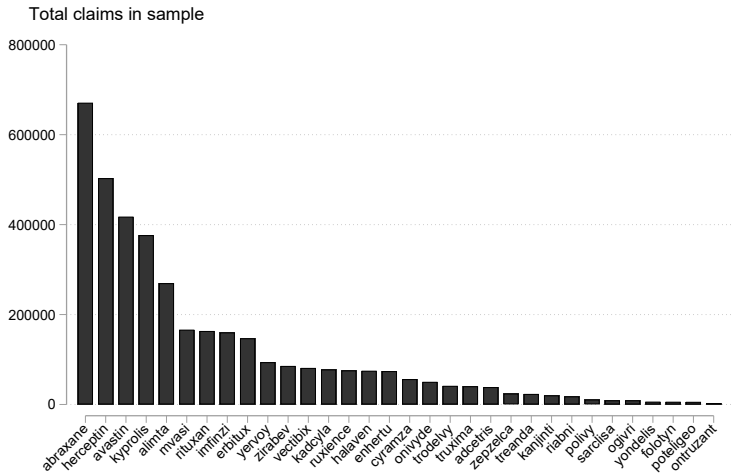
Figure 3: Provider Manipulation of Avastin Doses



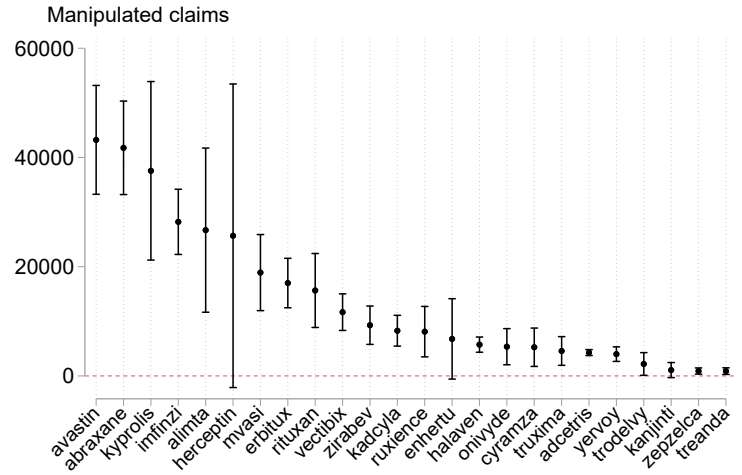
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure 4: Manipulated Claims by Drug

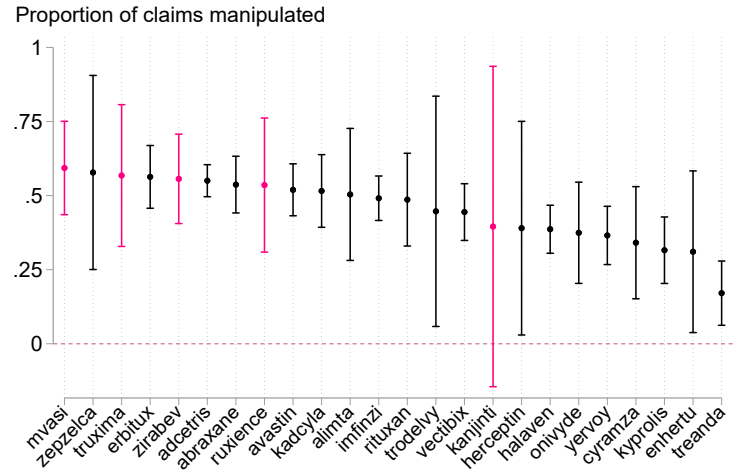
(a) Number of claims



(b) Manipulated claims



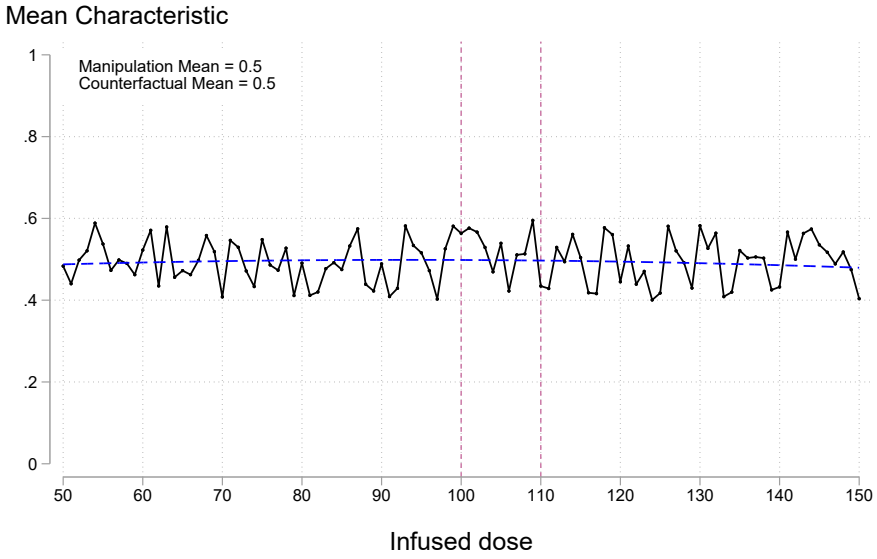
(c) Manipulated proportion



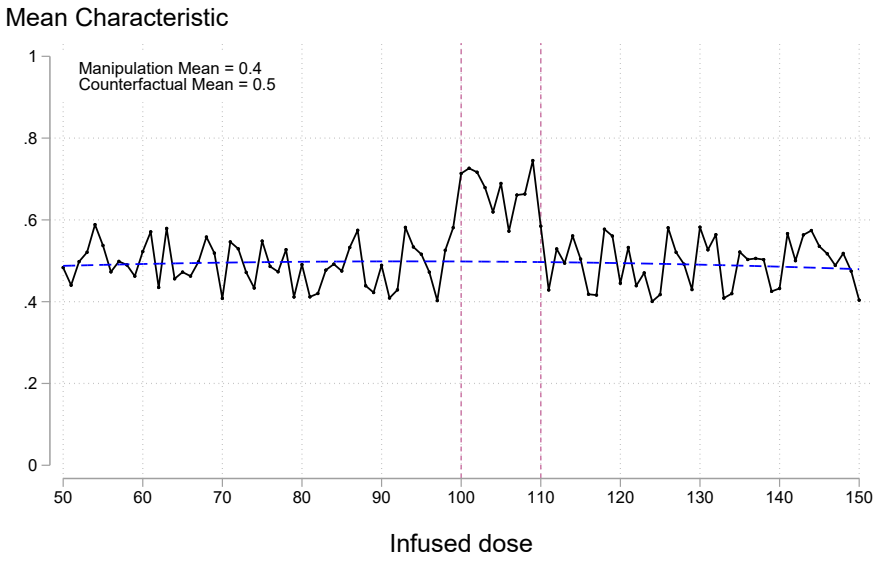
Notes: The figure shows the total number of claims (a), number of manipulated claims (b), and proportion of manipulated claims (c) for drugs with more than 0.05% of claims in the sample. See table 1 and 3 for all drugs in the sample. The number of manipulated claims is calculated using methods described in section 4.1. We obtain the proportion of manipulated claims by dividing the number of missing claims by number of counterfactual claims in the manipulation region. Drugs shown in red in panel (c) are generic drugs. Panel (b) and (c) show 95% confidence intervals.

Figure 5: Relationship between Manipulation and Characteristic

(a) Non-Manipulation Characteristic

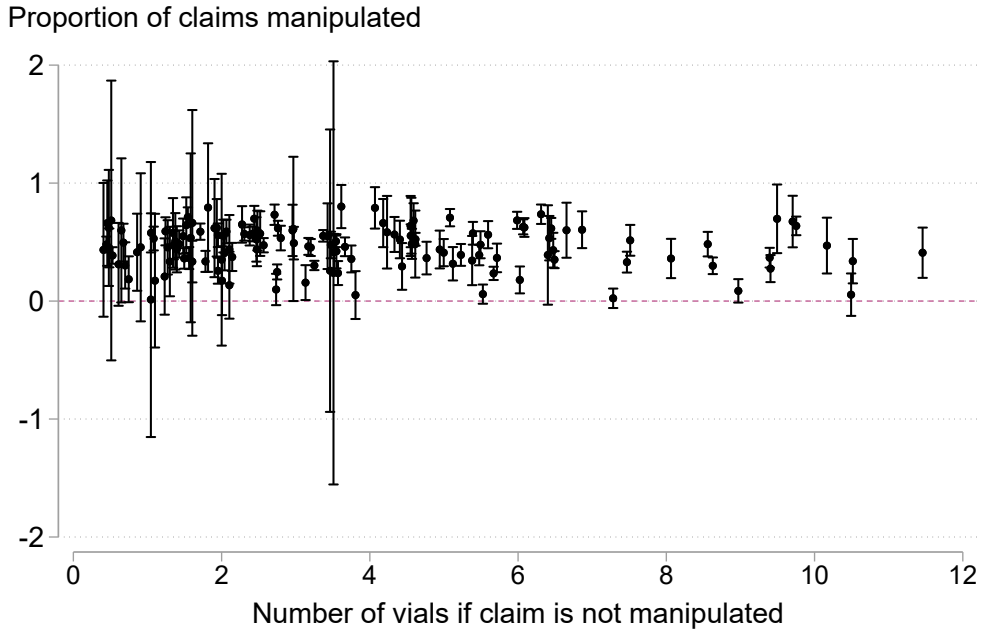


(b) Manipulation Characteristic



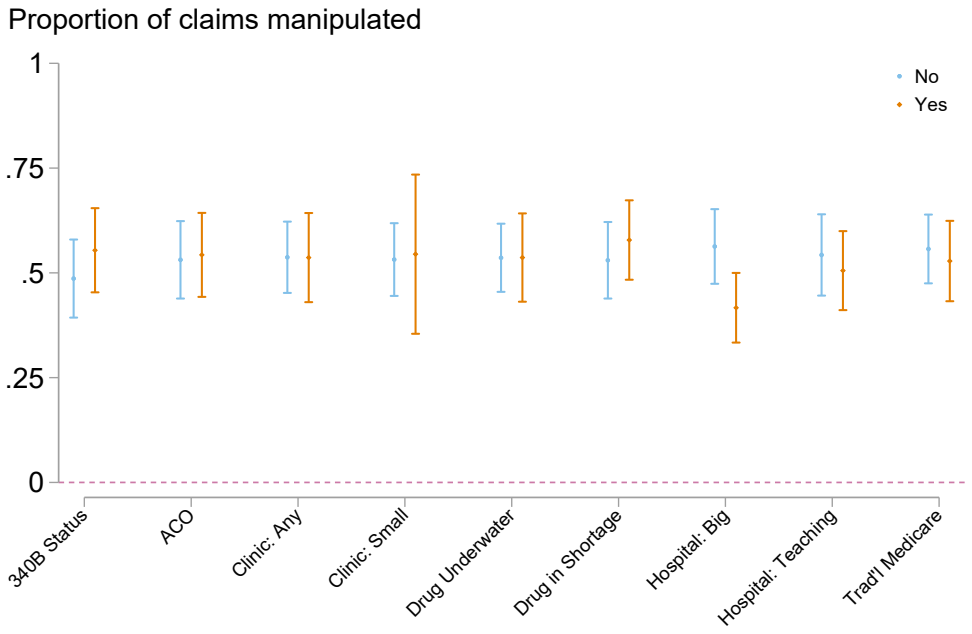
Notes: This figure shows for Abraxane an example when a characteristics is not driving manipulation (panel a) and drives manipulation (panel b). Blue line represent the counterfactual mean estimated as described in Section 5.1. Black line represent the non-manipulation or actual mean. Counterfactual mean is a weighted average of the manipulation and non-manipulation (actual) mean. First vertical line is the dose at which an additional vial is required. The vial size for Abraxane is 100 mg

Figure 6: Proportion of claims manipulated and number of vials



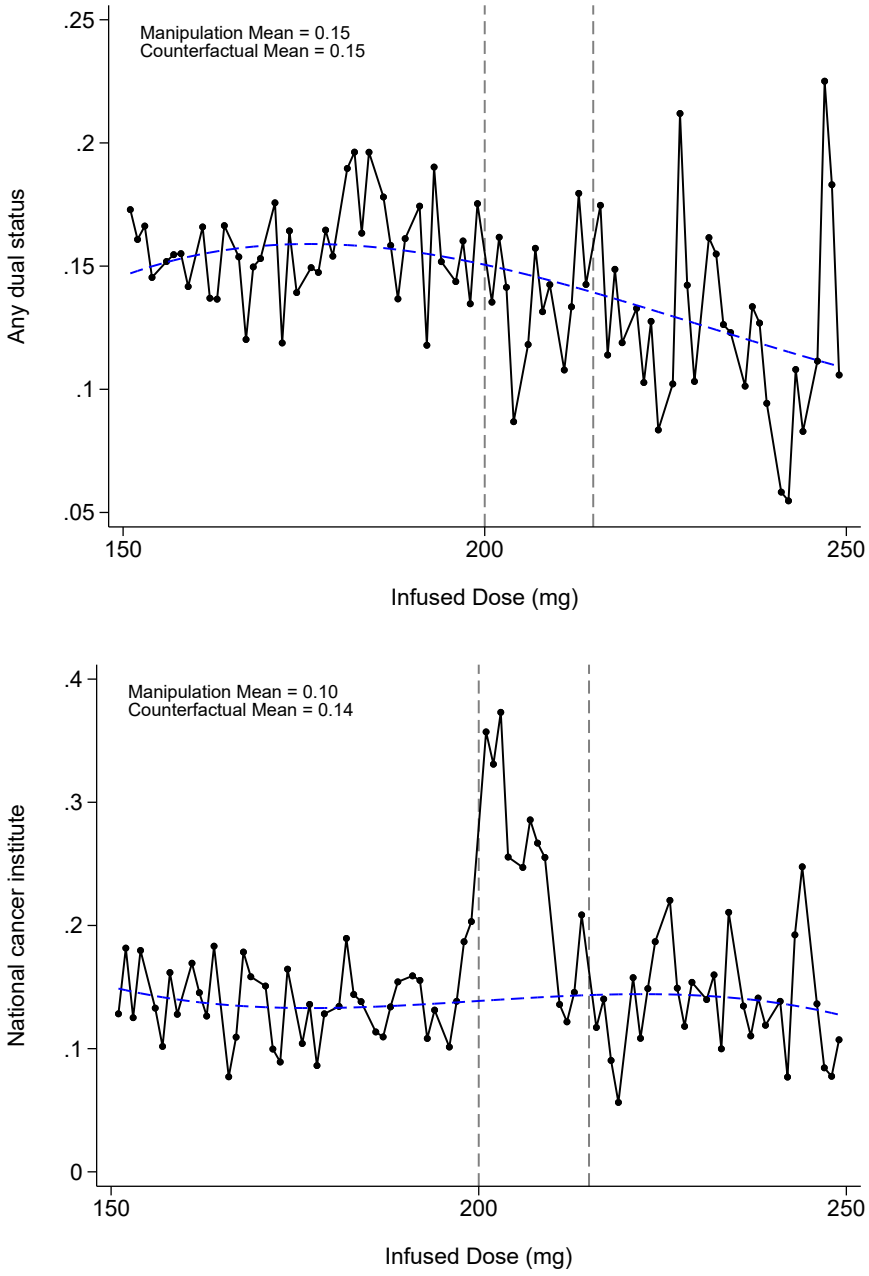
Notes: This figure shows the proportion of claims manipulated and the corresponding 95% confidence intervals at each vial cutoff for all drugs in our sample. The number of manipulated claims is calculated using methods described in section 4.1. We obtain the proportion of manipulated claims by dividing the number of missing claims by number of counterfactual claims in the manipulation region.

Figure 7: Proportion of claims manipulated by groups



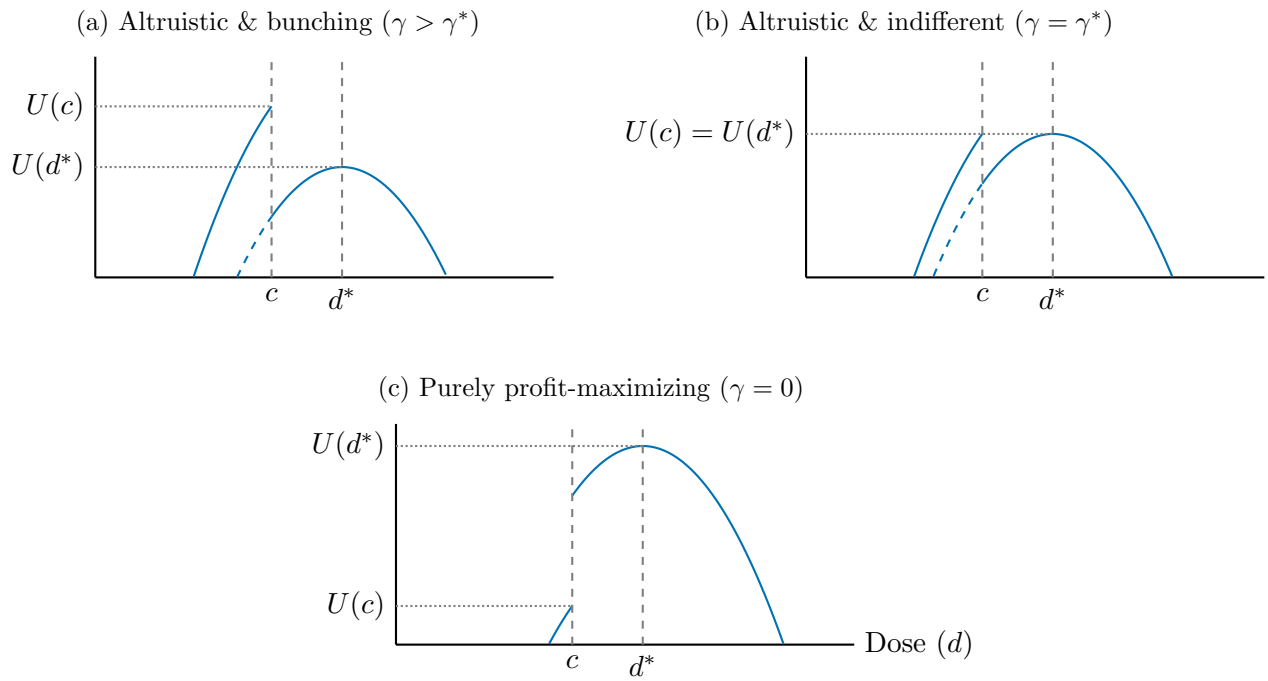
Notes: This figure shows the proportion of claims manipulated and the corresponding 95% confidence intervals for different groups for Abraxane. The number of manipulated claims is calculated using methods described in section 4.1. We obtain the proportion of manipulated claims by dividing the number of missing claims by number of counterfactual claims in the manipulation region.

Figure 8: Heterogeneity Analysis of Manipulation for Abraxane



Notes: This figure shows the actual and counterfactual fraction of claims with dual status (top figure) in each bin and fraction of claims from a national cancer institute (bottom figure) in each bin. Blue = counterfactual mean estimated as described in Section 5.1. Black = non-manipulation or actual mean. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure 9: Provider payoff functions for varying degrees of altruism γ



Notes: Each panel shows the provider's payoff $U(d)$ as a function of dose d, where d^* is the dose implied by the patient's body-size, and c is the nearest vial-size cutoff. γ is the weight that the provider places on the sum of Medicare and patient spending. Reimbursement for the discarded portion of a vial implies that provider revenue increases discontinuously at $d = c$. γ reduces the corresponding notch in the provider's payoff function since γ represents the provider's internalization of the corresponding social costs (higher Medicare and patient OOP spending). Sufficiently high values of γ ($> \gamma^*$) will lead a provider to manipulate the dose down from d^* to c. If d^* were instead just below c, $\gamma < \gamma^*$ would lead the provider to manipulate the dose up to obtain the additional reimbursement.

Tables

Table 1: Drugs Included in Current Analysis

Brand Name	Spending (Million)	Smallest Vial	Billing unit	Cost of Vial	Number of Claims	Percent JW Use	Drug Type	FDA Approval
Abraxane	$336	100	1	$1,479	1,282,162	54.01	Chemo	1992
Adcetris	$191	50	1	$11,993	85,210	54.34	Immuno	2011
Alimta	$459	10	10	$784	960,420	26.98	Chemo	2004
Avastin	$259	10	10	$813	11,510,551	3.38	Immuno	2004
Cyramza	$127	20	5	$1,425	176,327	31.86	Immuno	2014
Enhertu	$264	100	1	$2,781	158,457	57.77	Immuno	2019
Erbitux	$159	10	10	$756	469,105	28.91	Immuno	2004
Folotyn	$21	20	1	$7,475	16,424	49.62	Chemo	2009
Halaven	$44	10	.1	$1,413	163,254	50.83	Chemo	2010
Herceptin	$162	15	10	$1,605	1,262,538	40.12	Immuno	1998
Imfinzi	$585	12	10	$982	654,656	21.44	Immuno	2017
Kadcyla	$175	100	1	$4,045	212,862	39.27	Immuno	2013
Kanjinti	$91	42	10	$3,808	369,961	5.81	Immuno	2019
Kyprolis	$382	10	1	$496	1,025,647	37.71	Chemo	2012
Mvasi	$222	10	10	$698	625,197	26.23	Immuno	2018
Ogivri	$42	15	10	$1,400	111,878	8.92	Immuno	2017
Onivyde	$66	43	1	$2,785	98,327	55.55	Chemo	2015
Ontruzant	$32	15	10	$1,384	46,163	7.9	Immuno	2021
Polivy	$69	30	1	$3,899	32,324	44.04	Immuno	2019
Poteligeo	$63	20	1	$4,777	21,887	38.5	Immuno	2018
Riabni	$28	10	10	$738	58,499	32.67	Immuno	2021
Rituxan	$599	10	10	$954	1,930,329	8.97	Immuno	1997
Ruxience	$250	10	10	$738	380,563	19.68	Immuno	2019
Sarclisa	$43	10	10	$780	48,052	21.06	Immuno	2020
Treanda	$12	25	1	$769	71,299	30.86	Chemo	2008
Trodelvy	$160	72	2.5	$2,497	91,421	57.34	Immuno	2020
Truxima	$210	10	10	$871	329,380	12.32	Immuno	2018
Vectibix	$123	10	10	$1,593	208,194	35.73	Immuno	2006
Yervoy	$453	50	1	$8,844	204,294	50.8	Immuno	2011
Yondelis	$12	10	.1	$3,628	14,600	47.21	Chemo	2015
Zepzelca	$97	40	.1	$8,144	37,881	67.9	Chemo	2020
Zirabev	$248	10	10	$632	322,432	26.73	Immuno	2019

Notes: Many drugs have larger vial sizes which are almost always multiples of the smallest vial. Cost per vial is based on the highest ASP for the drug during the analysis period. The initial list of drugs was constructed using variably dosed drugs packaged in single-use vials with at least one percent of discarded amount, $400 price of vial, and $10 million of total spending. We then exclude drugs which rarely require more than one vial and drugs for which our data appears to have quality issues. Information about total spending, smallest vial, billing unit, and cost of vial is coming from Centers of Medicare & Medicaid Services. Total spending is based on Traditional Medicare Part B claims. Number of claims and JW use is calculated using Traditional and Medicare Advantage Part B claims. Drug type and FDA approval year is obtained from Surveillance, Epidemiology, and End Results Program.

Table 2: Claim-Level Summary Statistics

	All	No JW Use	JW Use
Age of beneficiary	73.85	74.37	71.29
	(10.08)	(10.27)	(8.65)
Race of beneficiary: White	0.77	0.77	0.78
	(0.42)	(0.42)	(0.42)
Race of beneficiary: Black	0.09	0.09	0.10
	(0.28)	(0.28)	(0.30)
Race of beneficiary: Hispanic	0.09	0.09	0.06
	(0.28)	(0.29)	(0.25)
Race of beneficiary: Asian	0.03	0.03	0.03
	(0.17)	(0.17)	(0.16)
Race of beneficiary: AIAN	0.00	0.00	0.00
	(0.06)	(0.06)	(0.06)
Race of beneficiary: unknown	0.01	0.01	0.02
	(0.12)	(0.12)	(0.14)
Sex of beneficiary: male	0.39	0.40	0.38
	(0.49)	(0.49)	(0.48)
Sex of beneficiary: female	0.61	0.60	0.62
	(0.49)	(0.49)	(0.48)
Dual status	0.18	0.18	0.17
	(0.39)	(0.39)	(0.37)
Hospital claim	0.30	0.27	0.42
	(0.46)	(0.44)	(0.49)
Traditional Medicare	0.57	0.54	0.75
	(0.49)	(0.50)	(0.43)
Number of claims	22,980,294	19,136,440	3,843,855
Number of facilities	12,129	12,022	4,547
Number of beneficiaries	2,468,536	2,288,560	516,545

Notes: Table displays summary statistics of Medicare Part B claims. Standard deviations are shown in parenthesis. Data is obtained from Medicare master beneficiary summary file and Medicare Part B claims (carrier and outpatient file). JW refers to the modifier that shows how much of the drug was discarded.

Table 3: Manipulated Claims and Lost Revenue Estimates by Drug

Drug	Cutoffs	Count. claims	Manip. claims	Prop. manip.	Rev. lost	Prop. rev. lost
Abraxane	2 (100, 200)	77,765 (2,751)	41,766 (4,368)	0.54 (0.05)	$50.2 mil	0.03
Adcetris	2 (100, 150)	7,764 (215)	4,272 (278)	0.55 (0.03)	$35.5 mil	0.03
Alimta	7 (50–110)	52,967 (4,312)	26,690 (7,668)	0.5 (0.11)	$17.3 mil	0.01
Avastin	10 (30–120)	83,197 (2,887)	43,223 (5,086)	0.52 (0.04)	$31.8 mil	0.02
Cyramza	6 (80–180)	15,392 (1,017)	5,249 (1,792)	0.34 (0.1)	$6.3 mil	0.01
Enhertu	3 (200, 300, 400)	21,827 (3,636)	6,777 (3,754)	0.31 (0.14)	$17.1 mil	0.02
Erbitux	7 (30–90)	30,198 (1,343)	17,007 (2,311)	0.56 (0.05)	$10.6 mil	0.02
Folotyn	2 (20, 40)	356 (218)	45 (234)	0.13 (3.73)	$0.3 mil	0.002
Halaven	1 (20)	14,825 (448)	5,728 (710)	0.39 (0.04)	$6.6 mil	0.03
Herceptin	4 (15–60)	65,801 (7,818)	25,663 (14,182)	0.39 (0.18)	$35.2 mil	0.02
Imfinzi	6 (48–108)	57,444 (1,893)	28,211 (3,045)	0.49 (0.04)	$26.1 mil	0.03
Kadcyla	2 (200, 300)	16,049 (1,166)	8,275 (1,439)	0.52 (0.06)	$26.2 mil	0.04
Kanjinti	4 (15–60)	2,702 (375)	1,069 (702)	0.4 (0.28)	$0.7 mil	0.02
Kyprolis	11 (30–130)	118,987 (5,193)	37,557 (8,340)	0.32 (0.06)	$14.1 mil	0.01
Mvasi	11 (30–130)	31,898 (1,964)	18,920 (3,554)	0.59 (0.08)	$6.8 mil	0.02
Ogivri	4 (15–60)	1,223 (269)	646 (496)	0.53 (0.42)	$0.5 mil	0.02
Onivyde	2 (86, 129)	14,296 (1,533)	5,353 (1,687)	0.37 (0.09)	$12.5 mil	0.04
Ontruzant	3 (15–45)	420 (72)	245 (133)	0.58 (0.26)	$0.2 mil	0.03
Polivy	3 (90, 120, 150)	2,167 (251)	596 (293)	0.27 (0.11)	$2.1 mil	0.01
Poteligeo	2 (60, 80)	780 (246)	285 (293)	0.37 (0.74)	$1.2 mil	0.01
Riabni	3 (60–80)	3,575 (256)	1,596 (454)	0.45 (0.1)	$0.7 mil	0.01
Rituxan	6 (40–90)	32,169 (1,967)	15,644 (3,456)	0.49 (0.08)	$13.5 mil	0.01
Ruxience	6 (40–90)	15,138 (1,309)	8,106 (2,356)	0.54 (0.12)	$3.4 mil	0.02
Sarclisa	5 (50–90)	1,966 (133)	1,094 (236)	0.56 (0.08)	$0.8 mil	0.02
Treanda	5 (100–200)	5,148 (171)	879 (308)	0.17 (0.06)	$0.5 mil	0.01
Trodelvy	3 (144, 216, 288)	4,895 (636)	2,188 (1,060)	0.45 (0.2)	$5.1 mil	0.01
Truxima	5 (50–90)	8,037 (746)	4,562 (1,341)	0.57 (0.12)	$2.4 mil	0.02
Vectibix	6 (20–70)	26,271 (1,024)	11,675 (1,708)	0.44 (0.05)	$13.8 mil	0.03
Yervoy	4 (50, 100, 150, 200)	10,911 (518)	3,988 (679)	0.37 (0.05)	$30.7 mil	0.02
Yondelis	2 (20–30)	691 (69)	286 (129)	0.41 (0.15)	$0.9 mil	0.02
Zepzelca	1 (40)	1,547 (175)	894 (288)	0.58 (0.17)	$6.7 mil	0.02
Zirabev	11 (30–130)	16,680 (962)	9,282 (1,792)	0.56 (0.08)	$3.9 mil	0.02
Total	160	759,761	347,048	0.46	$387.8 mil	0.02

Notes: Table displays estimates of manipulated claims for each drug in our current sample. A manipulated claim receives a slightly lower dose than the patient would typically receive in order to avoid the use of an additional vial. Revenue (Medicare reimbursement) lost is calculated by multiplying the number of manipulated claims by the cost of a vial of the drug. Total revenue is calculated by multiplying number of vials used (observed in the data) by cost of a vial of the drug. Proportion revenue lost is calculated by dividing revenue lost by total revenue. Cost of the vial is captured by the median average sales price during the analysis period. For manipulated claims and counterfactual claims bootstrapped standard errors are shown in parenthesis.

Table 4: Type of Manipulation Analysis - Beneficiary Characteristics

Characteristic	Manipulation Mean	Counterfactual Mean	Mean Ratio	Manipulation Claims	Counterfactual Claims
Age of beneficiary	71.250	71.318	0.999	320,562	716,338
Beneficiary is male	0.411	0.404	1.017	320,581	716,401
Black / Hispanic	0.175	0.176	0.992	320,581	716,401
Low quartile ZIP	0.174	0.176	0.989	272,757	605,029
Traditional Medicare	0.730	0.740	0.987	320,581	716,401
Hospital	0.412	0.401	1.027	320,581	716,401
Year 2017	0.101	0.117	0.864	320,581	716,401
Year 2018	0.119	0.133	0.892	320,581	716,401
Year 2019	0.167	0.167	1.002	320,581	716,401
Year 2020	0.166	0.159	1.046	320,581	716,401
Year 2021	0.156	0.145	1.074	320,581	716,401
Year 2022	0.149	0.140	1.064	320,581	716,401
Year 2023	0.077	0.075	1.031	320,581	716,401
Year 2024	0.065	0.065	1.009	320,581	716,401
Period when JZ was required	0.142	0.140	1.021	320,581	716,401

Notes: Table displays the manipulation and counterfactual mean of each characteristic and the corresponding number of claims. Information about the beneficiary is obtained from Medicare master beneficiary summary file and Part B claims (carrier and outpatient file).

Table 5: Type of Manipulation Analysis - Personnel Characteristics

Characteristic	Manipulation Mean	Counterfactual Mean	Mean Ratio	Manipulation Claims	Counterfactual Claims
% of line items delivered in office by provider	0.667	0.675	0.988	265,084	594,614
% of line items delivered in inpatient hospital by provider	0.085	0.086	0.997	265,084	594,614
% of line items delivered in hospital outpatient department by provider	0.243	0.235	1.036	265,084	594,614
Provider is physician	0.965	0.966	0.999	265,084	594,614
Provider is non-physician	0.035	0.034	1.026	265,084	594,614
Age of provider	50.081	50.166	0.998	265,084	594,614
Provider is male	0.705	0.704	1.002	265,084	594,614
Provider and beneficiary same sex	0.504	0.500	1.008	265,084	594,614
Number of unique beneficiaries treated by provider	546	553	0.988	265,084	594,614
Number of line items billed by provider	3,257	3,359	0.970	265,084	594,614
Number of allowed charges by provider	320,818	327,923	0.978	265,084	594,614

Notes: Table displays the manipulation and counterfactual mean of each characteristic and the corresponding number of claims. Information about the medical personnel is obtained from the Medicare Data on Provider Practice and Specialty.

Table 6: Type of Manipulation Analysis - Facility Characteristics

Characteristic	Manipulation Mean	Counterfactual Mean	Mean Ratio	Manipulation Claims	Counterfactual Claims
Hospital Characteristics					
340B status	0.745	0.709	1.051	131,266	284,747
Number of hospital beds	470.257	461.507	1.019	113,712	245,938
Number of hospital beds above 75th percentile	0.237	0.244	0.968	113,712	245,938
With any resident physician	0.460	0.486	0.946	126,092	273,420
National cancer institute	0.120	0.176	0.681	131,266	284,747
Cancer hospital	0.067	0.092	0.728	122,721	266,008
Net income of hospital (millions)	97.455	99.038	0.984	122,721	266,008
Allowable disproportionate share percentage of hospital	0.176	0.177	0.995	106,174	220,430
Rural referral center	0.335	0.322	1.041	122,721	266,008
Hospital in health system	0.947	0.942	1.005	110,796	241,091
Non-Profit ownership hospital	0.820	0.811	1.011	122,721	266,008
For-Profit ownership hospital	0.026	0.032	0.800	122,721	266,008
Government ownership hospital	0.155	0.157	0.984	122,721	266,008
Clinic Characteristics					
Number of any providers in clinic	250.166	232.678	1.075	157,302	364,730
Number of doctors in clinic	178.355	167.978	1.062	157,302	364,730
Number of non-physicians in clinic	71.788	64.680	1.110	157,302	364,730
Number of line items billed in clinic	392,364	376,752	1.041	157,302	364,730
Number of allowed charges in clinic	49,575,052	46,176,444	1.074	157,302	364,730
Number of unique beneficiaries in clinic	85,153	81,394	1.046	157,302	364,730
Mean age in clinic	48.260	48.306	0.999	157,276	364,646

Notes: Table displays the manipulation and counterfactual mean of each characteristic and the corresponding number of claims. Hospital characteristics are obtained from Healthcare Cost Report Information System from Centers of Medicare & Medicaid Services, Comparative Health System Performance Initiative from Agency for Healthcare Research and Quality, and Provider of Services Files from Centers of Medicare & Medicaid Services. Clinic characteristics are obtained from Medicare Data on Provider Practice and Specialty.

Table 7: Type of Manipulation Analysis - Miscellaneous Characteristics

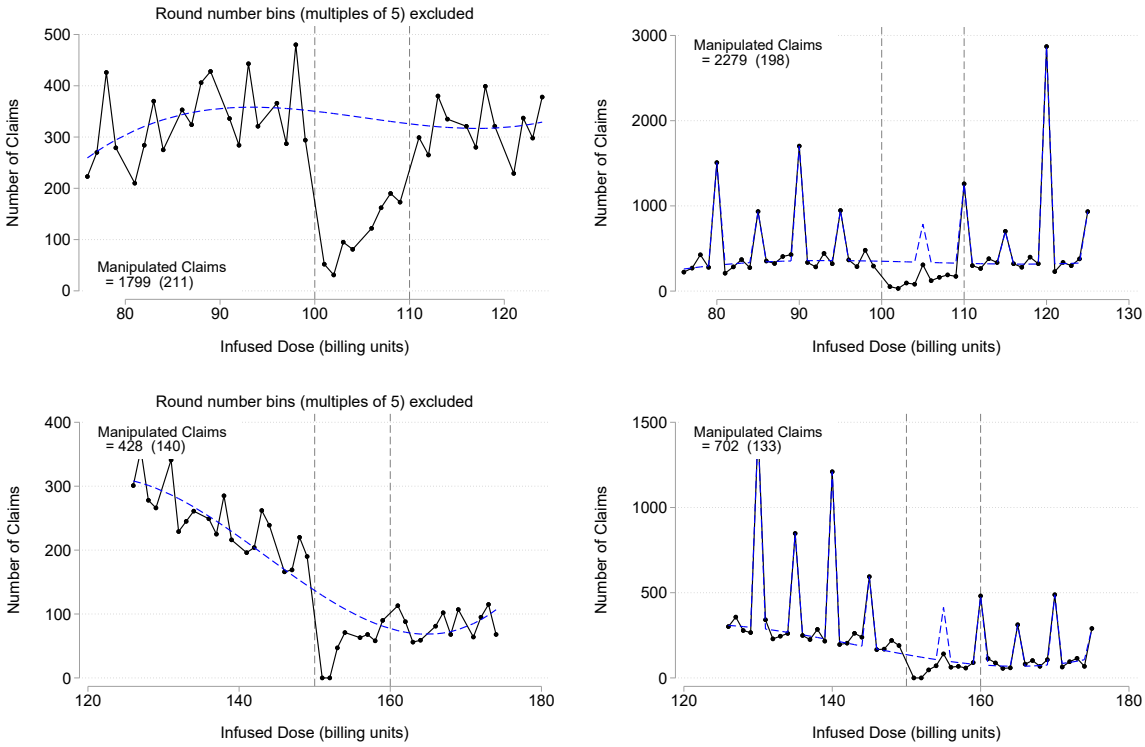
Characteristic	Manipulation Mean	Counterfactual Mean	Mean Ratio	Manipulation Claims	Counterfactual Claims
Market Power					
Number of Claims - average	876.888	826.888	1.060	320,581	716,401
Number of Claims - 1st Quartile	0.011	0.012	0.941	320,581	716,401
Number of Claims - 2nd Quartile	0.038	0.037	1.017	320,581	716,401
Number of Claims - 3rd Quartile	0.129	0.134	0.963	320,581	716,401
Number of Claims - 4th Quartile	0.822	0.817	1.006	320,581	716,401
Market Concentration					
Herfindahl-Hirschman Index (HRR x year)	0.136	0.135	1.003	320,179	713,939
Herfindahl-Hirschman Index (HRR x year x drug)	0.276	0.278	0.995	320,176	713,936
Drug Characteristics					
Chemotherapy drug	0.358	0.387	0.926	320,581	716,401
Immunotherapy drug	0.642	0.613	1.047	320,581	716,401
Age of drug	13.699	12.991	1.055	320,581	716,401
Price of vial (absolute)	1224.984	1260.348	0.972	320,581	716,401
Price of vial (relative)	0.260	0.247	1.055	221,929	518,143
Drug is underwater	0.028	0.025	1.142	320,581	716,401
Drug is in shortage	0.113	0.104	1.094	52,714	99,580
Accountable Care Organization					
Beneficiary or provider is in ACO	0.478	0.469	1.019	320,581	716,401
Beneficiary is in ACO	0.332	0.328	1.012	320,581	716,401
Provider is in ACO	0.295	0.281	1.049	320,581	716,401

Notes: Table displays the manipulation and counterfactual mean of each characteristic and the corresponding number of claims. Number of claims is obtained from Medicare Part B claims (carrier and outpatient file), Herfindahl-Hirschman Index is obtained from the Dartmouth Atlas of Health Care, information about the drugs is obtained from Surveillance, Epidemiology, and End Results Program and Centers of Medicare & Medicaid Services. A drug is considered underwater if the acquisition cost is potentially higher than the reimbursement amount. Participation of the beneficiary in an Accountable Care Organization (ACO) is identified at the beneficiary or facility level using Medicare Shared Savings Program or Next Generation ACO Model.

Appendix

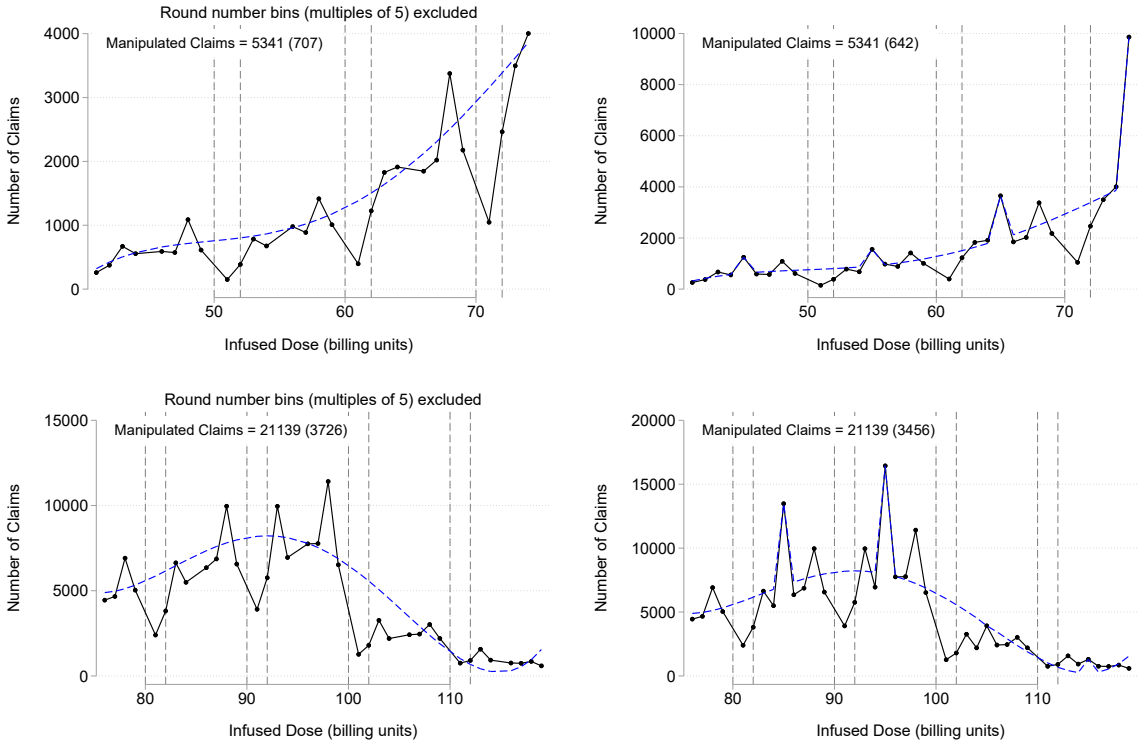
A Supplemental Figures and Tables

Figure A.1: Provider Manipulation of Adcetris Doses



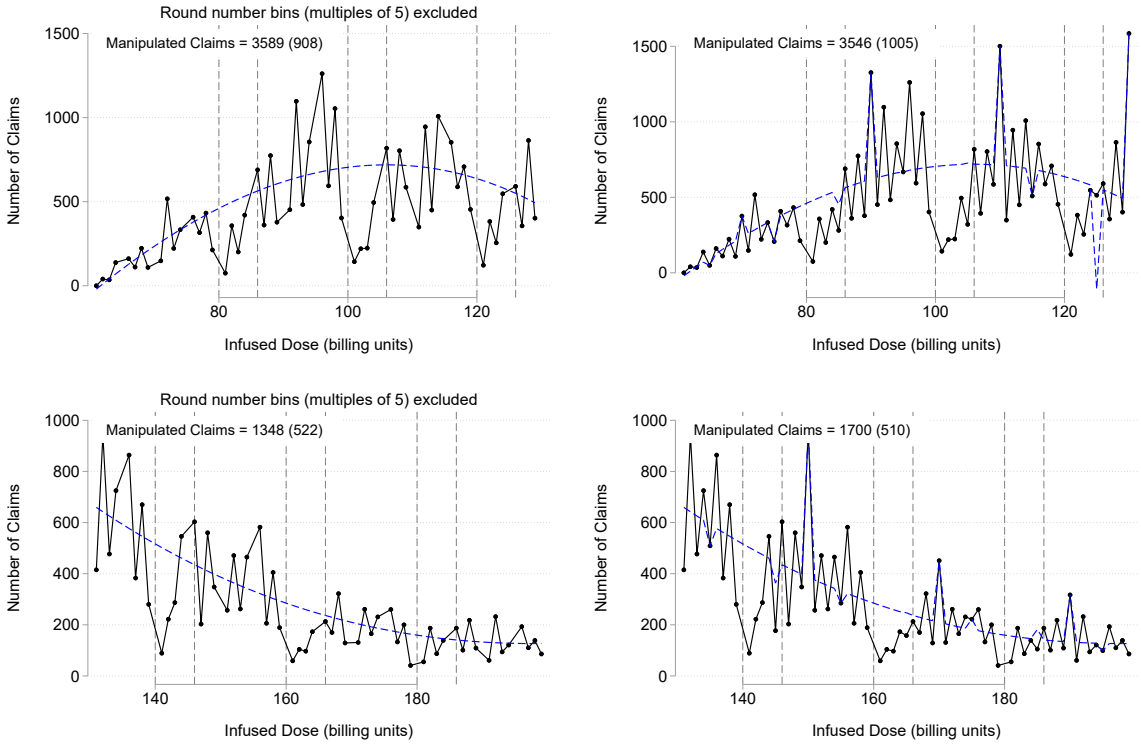
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.2: Provider Manipulation of Alimta Doses



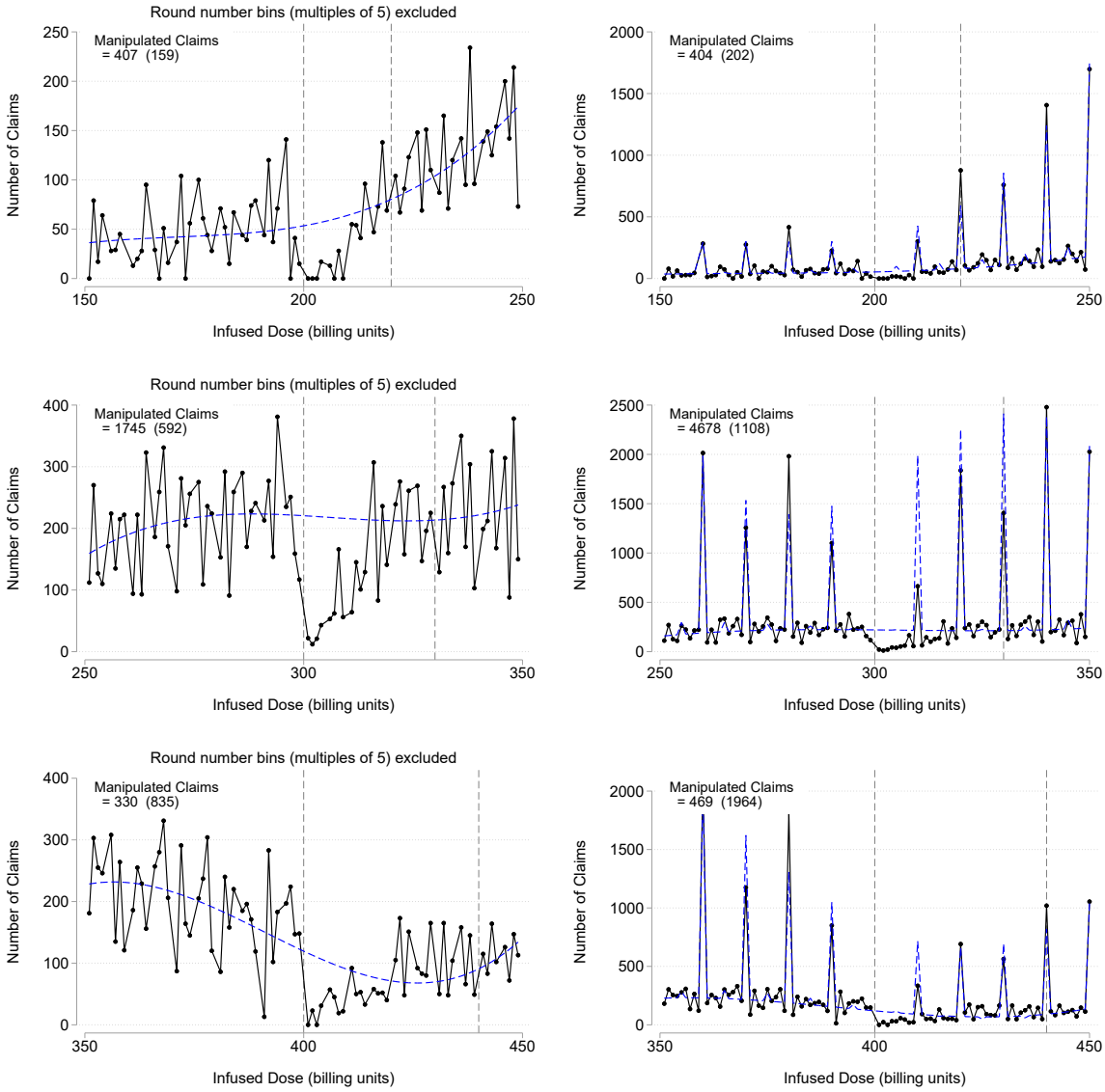
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.3: Provider Manipulation of Cyramza Doses



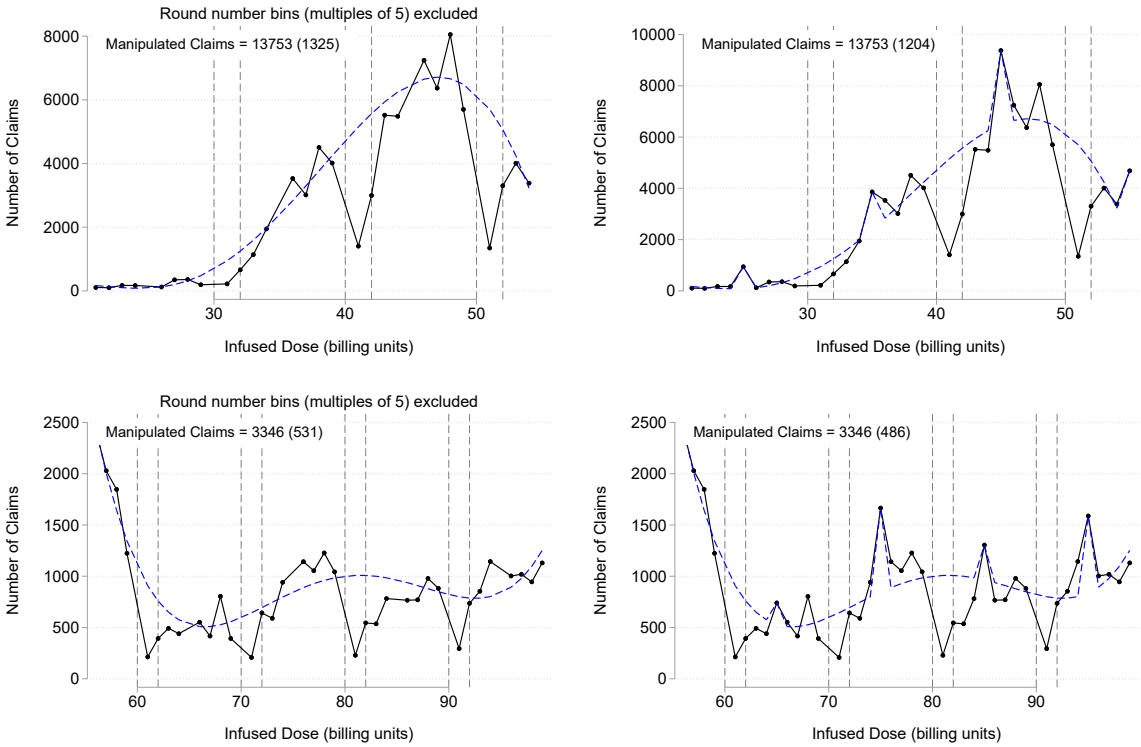
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.4: Provider Manipulation of Enhertu Doses



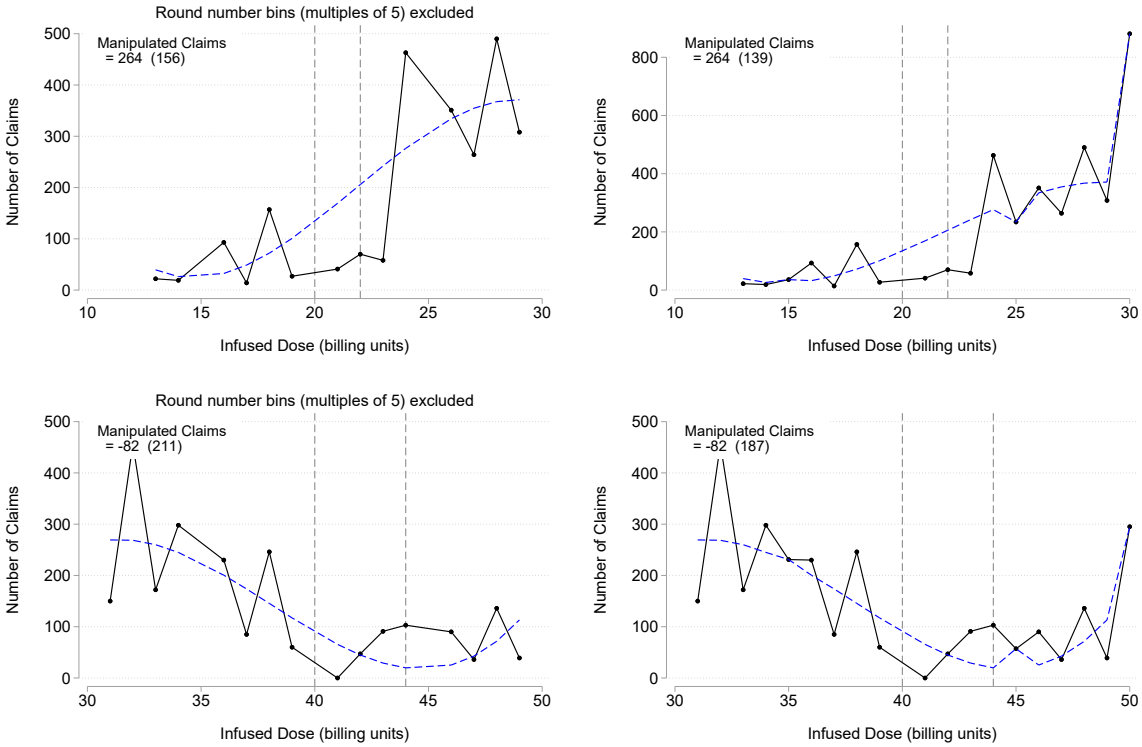
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.5: Provider Manipulation of Erbitux Doses



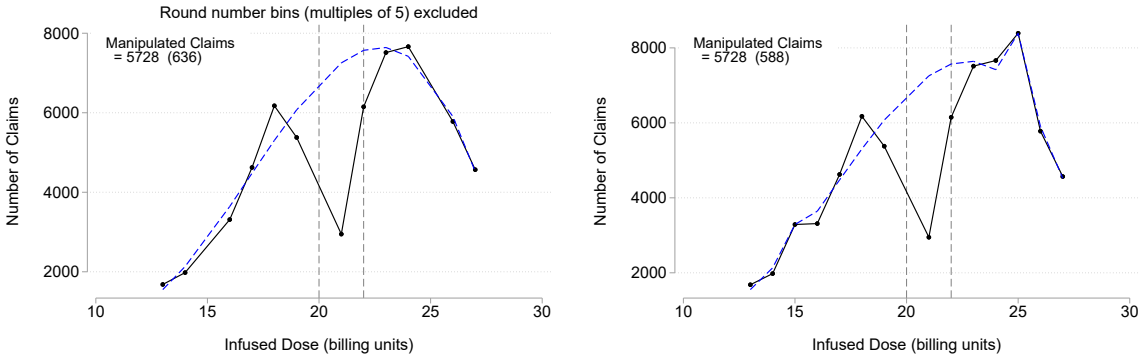
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.6: Provider Manipulation of Folotyn Doses



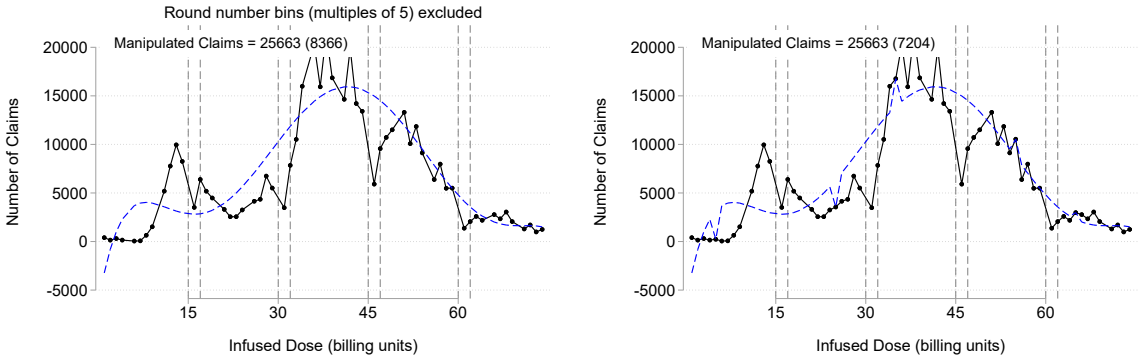
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.7: Provider Manipulation of Halaven Doses



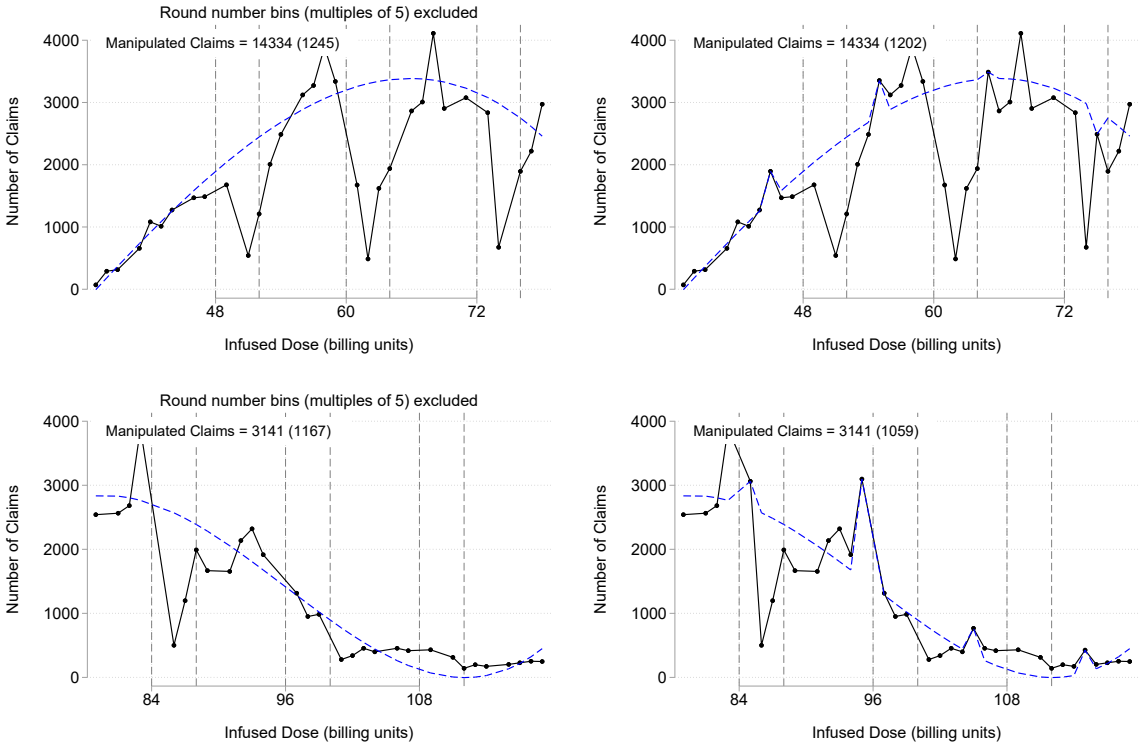
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.8: Provider Manipulation of Herceptin Doses



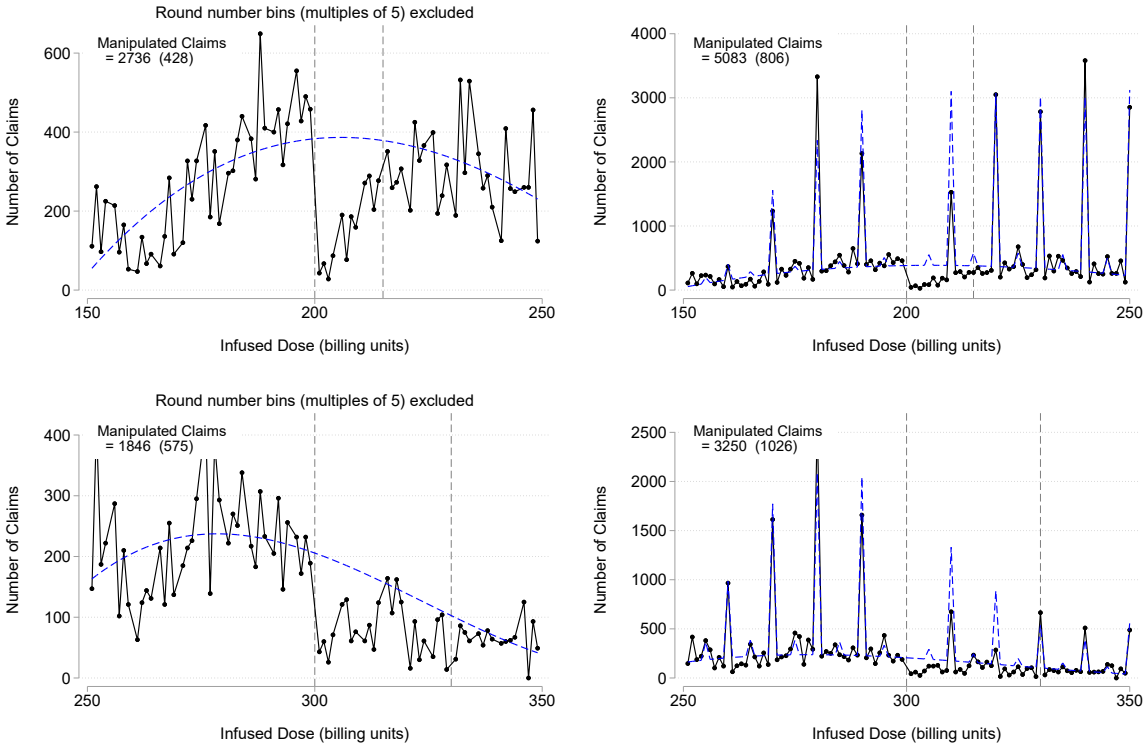
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.9: Provider Manipulation of Imfinzi Doses



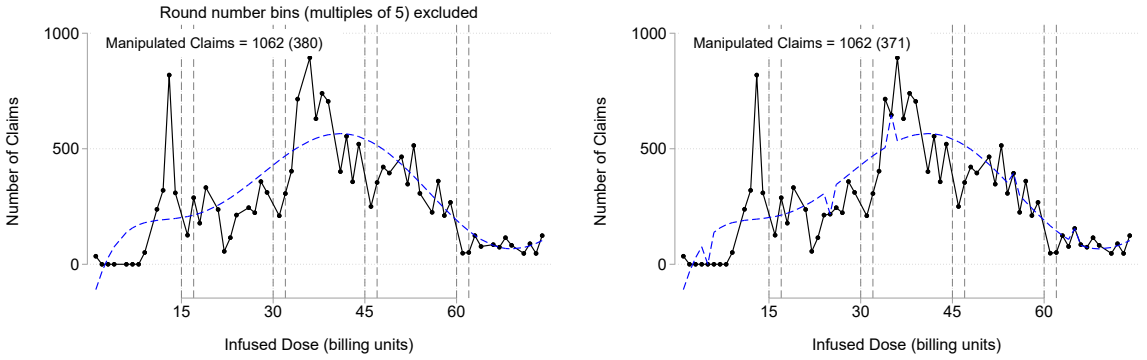
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.10: Provider Manipulation of Kadcyla Doses



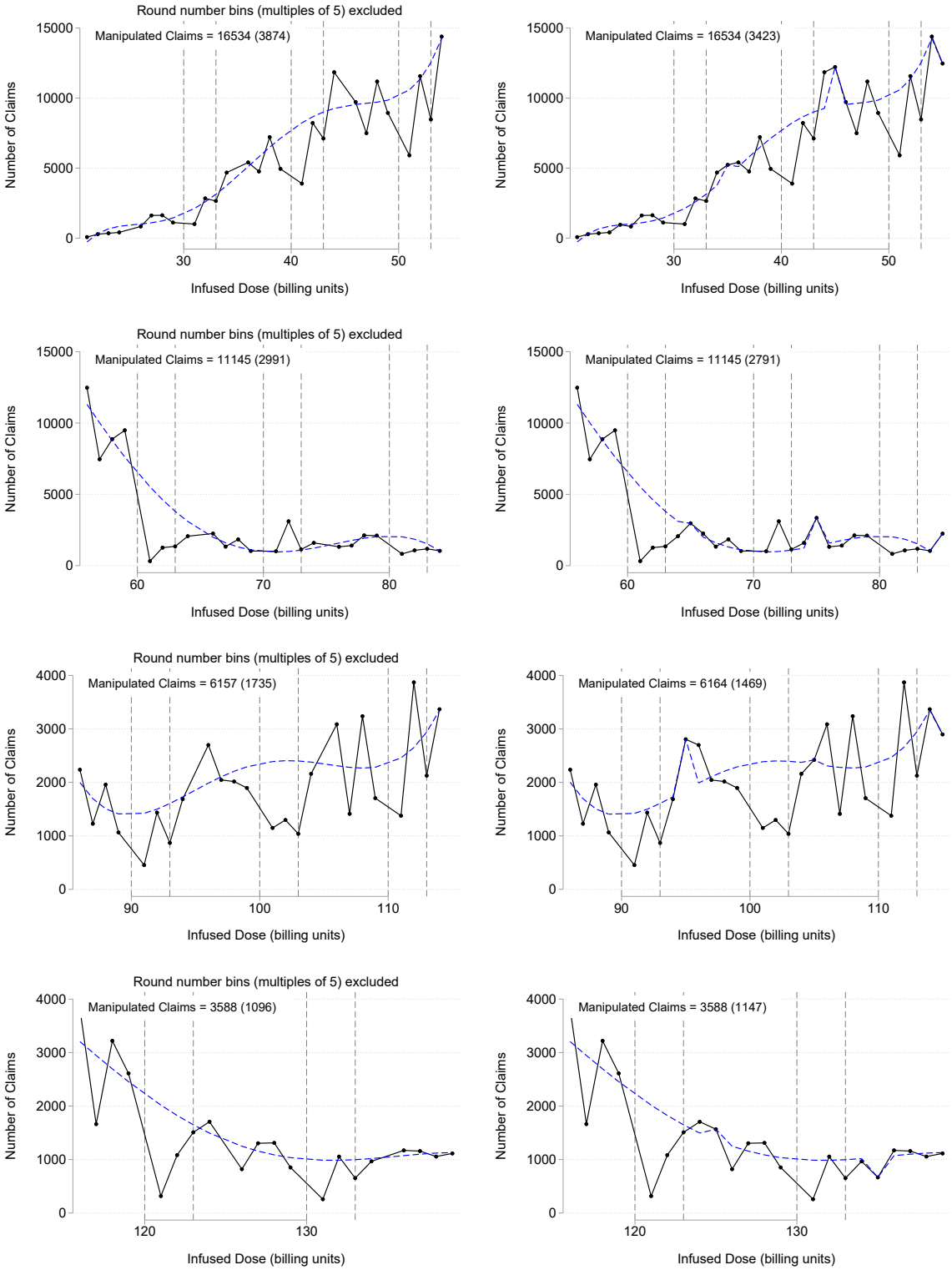
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.11: Provider Manipulation of Kanjint Doses



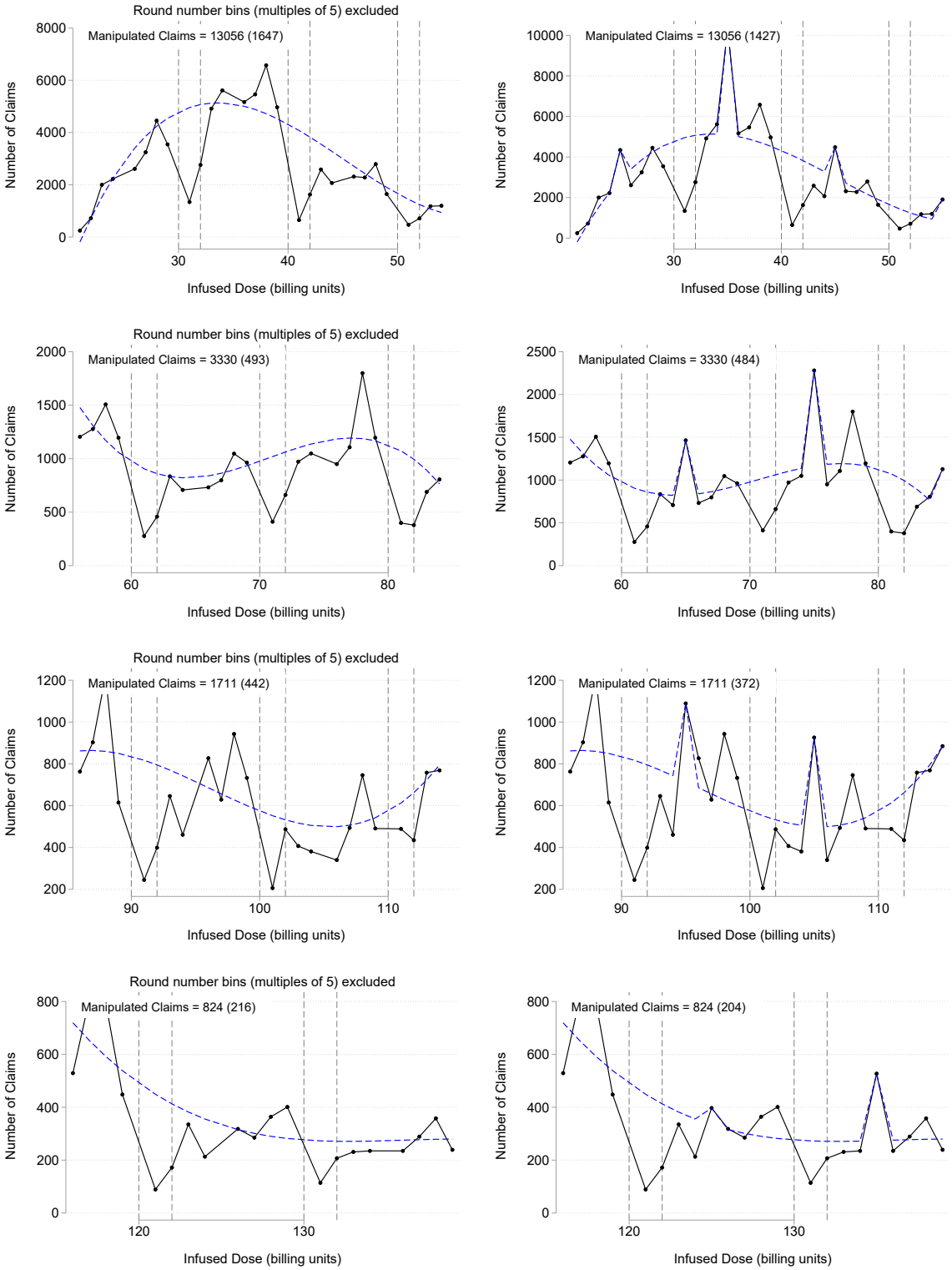
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.12: Provider Manipulation of Kyprolis Doses



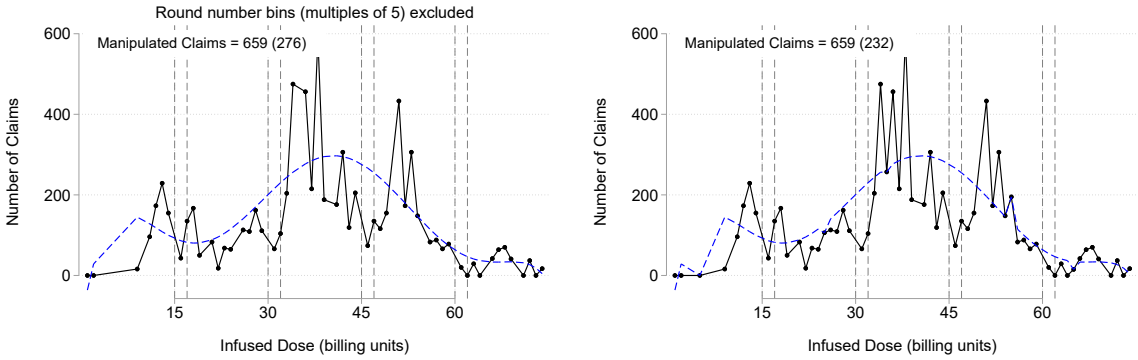
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.13: Provider Manipulation of Mvasi Doses



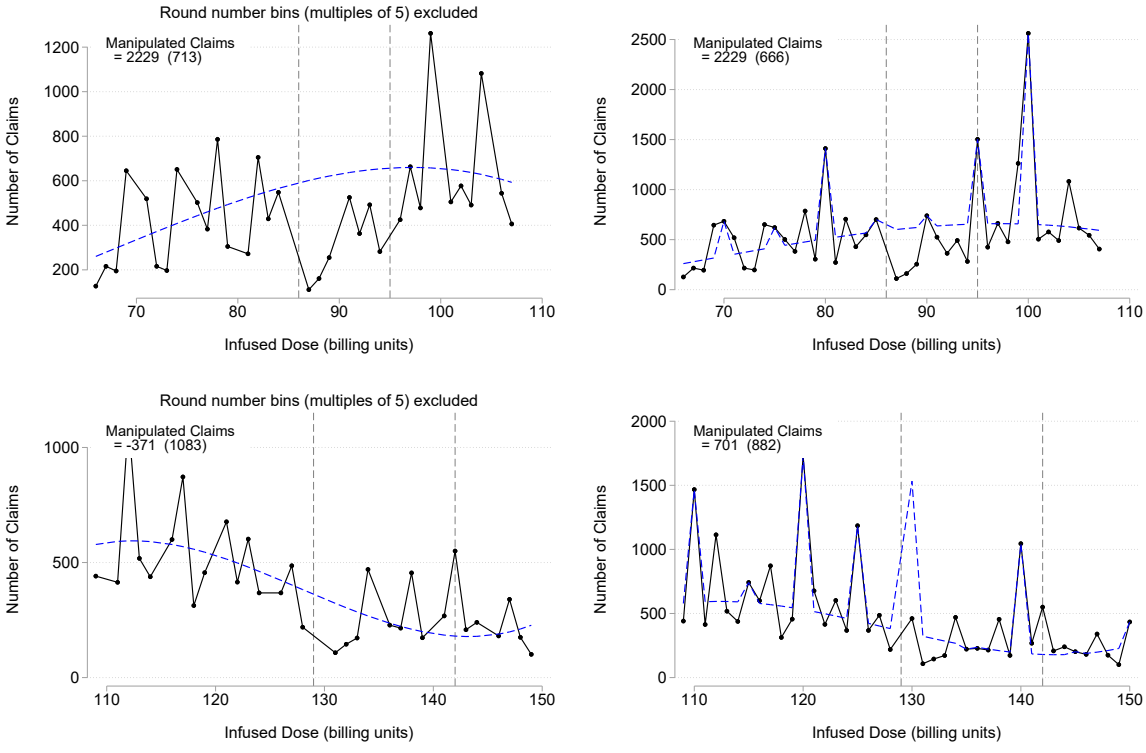
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.14: Provider Manipulation of Ogivri Doses



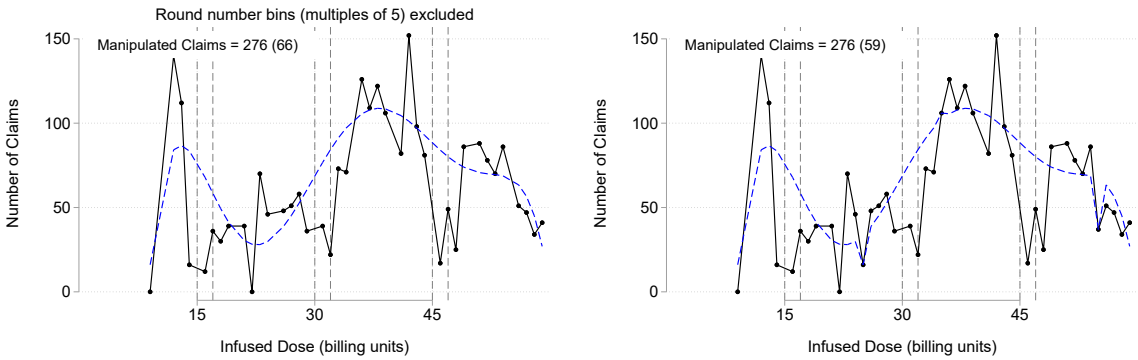
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.15: Provider Manipulation of Ogivri Doses



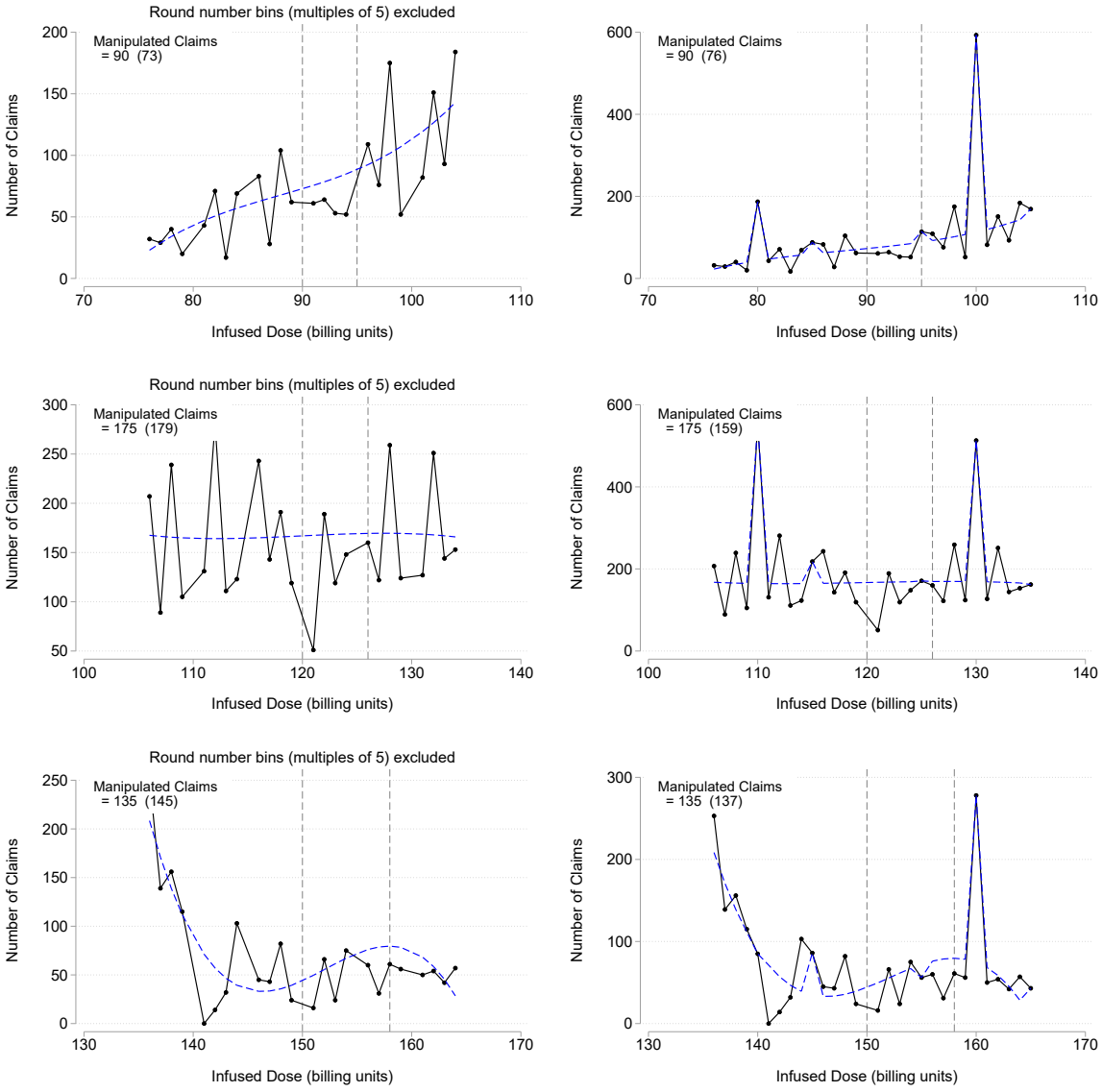
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.16: Provider Manipulation of Ontruzant Doses



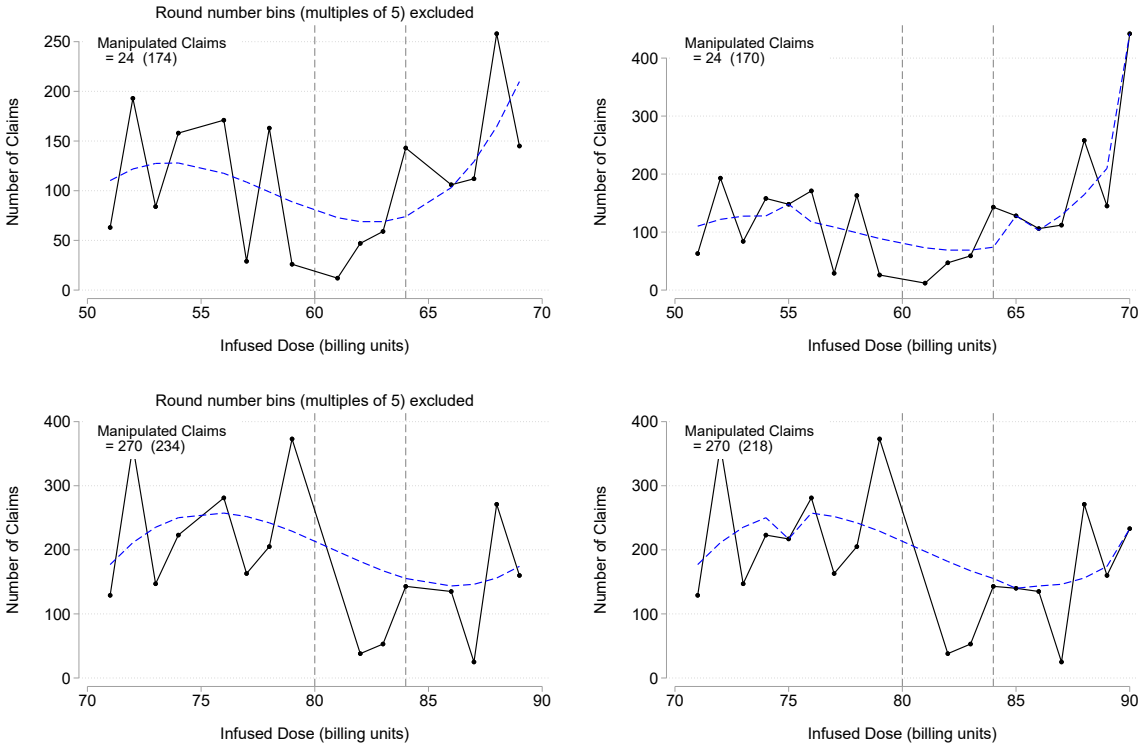
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.17: Provider Manipulation of Polivy Doses



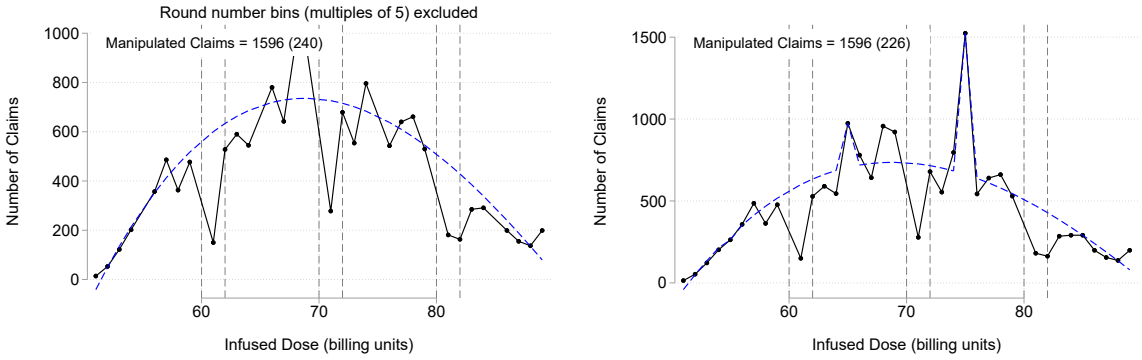
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.18: Provider Manipulation of Poteligeo Doses



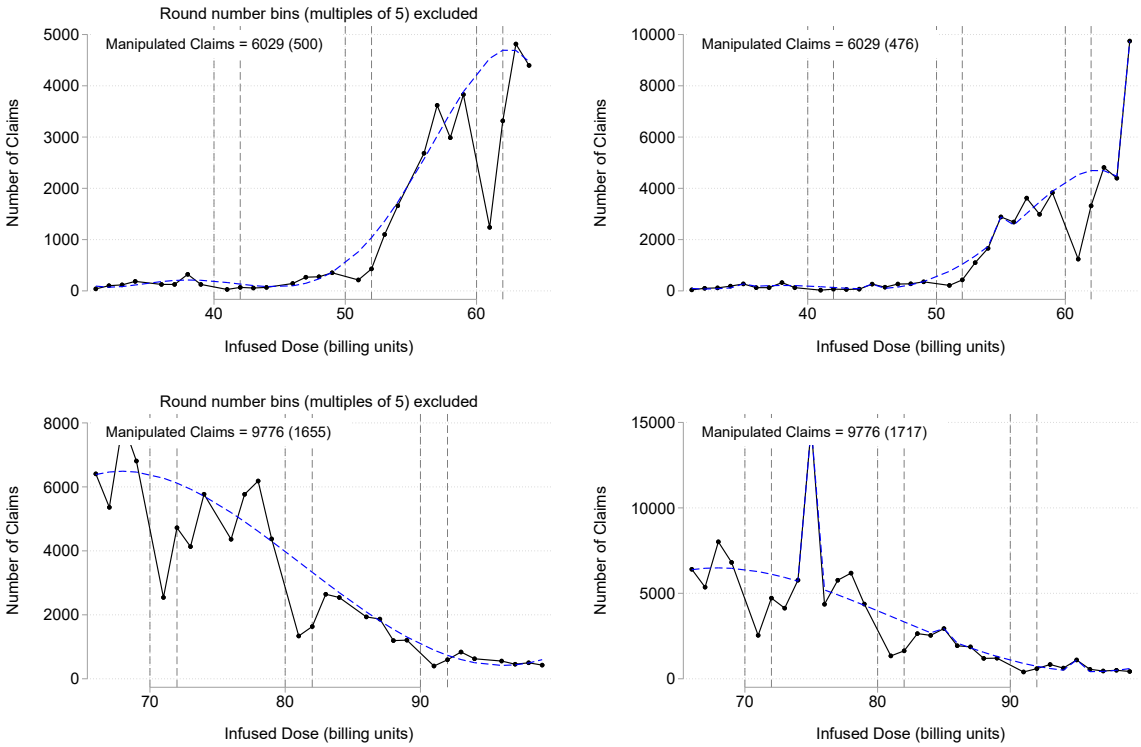
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.19: Provider Manipulation of Riabni Doses



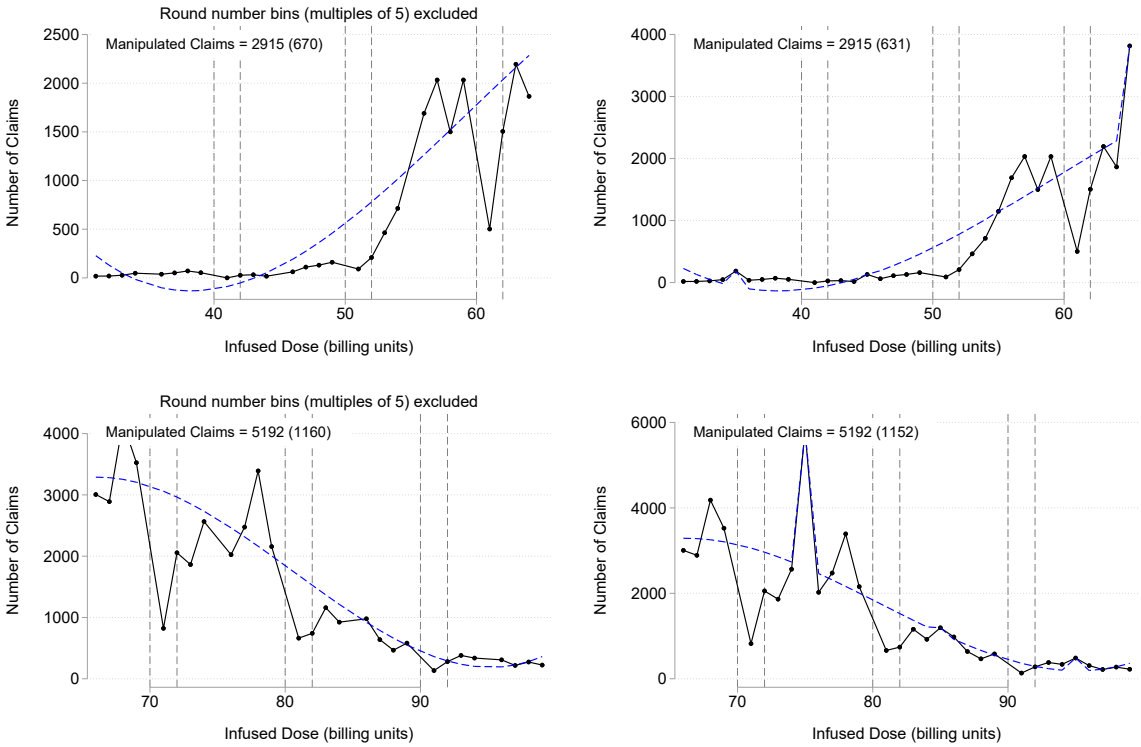
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.20: Provider Manipulation of Rituxan Doses



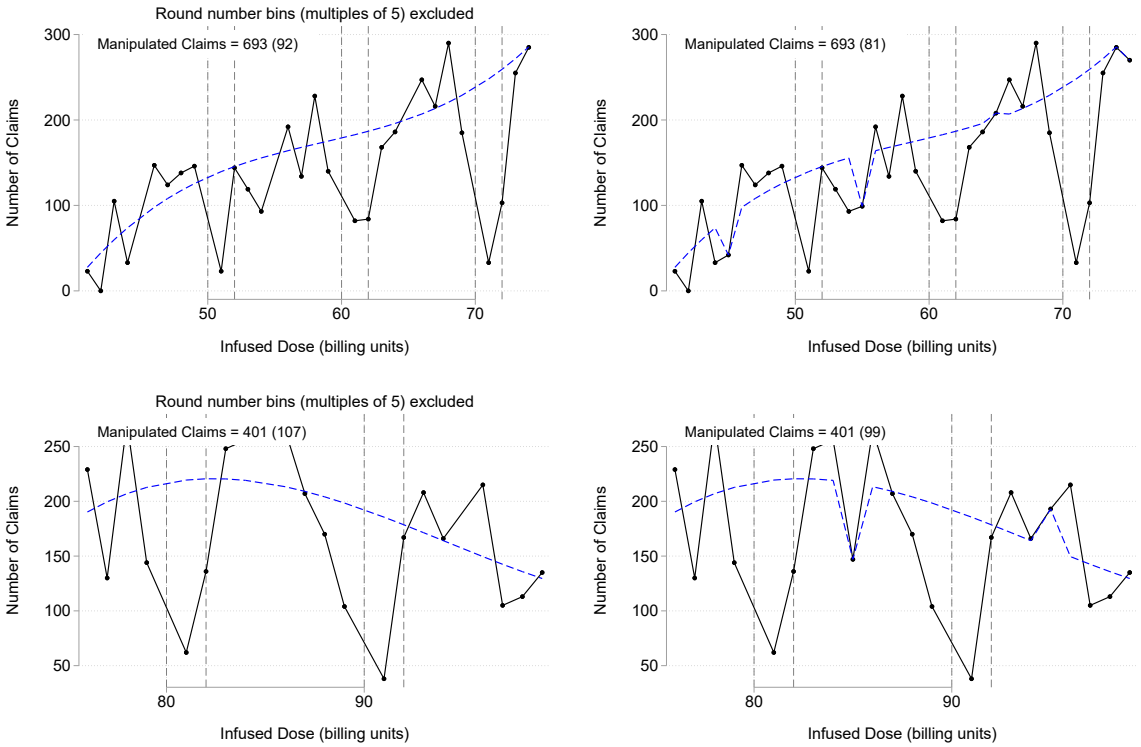
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.21: Provider Manipulation of Ruxience Doses



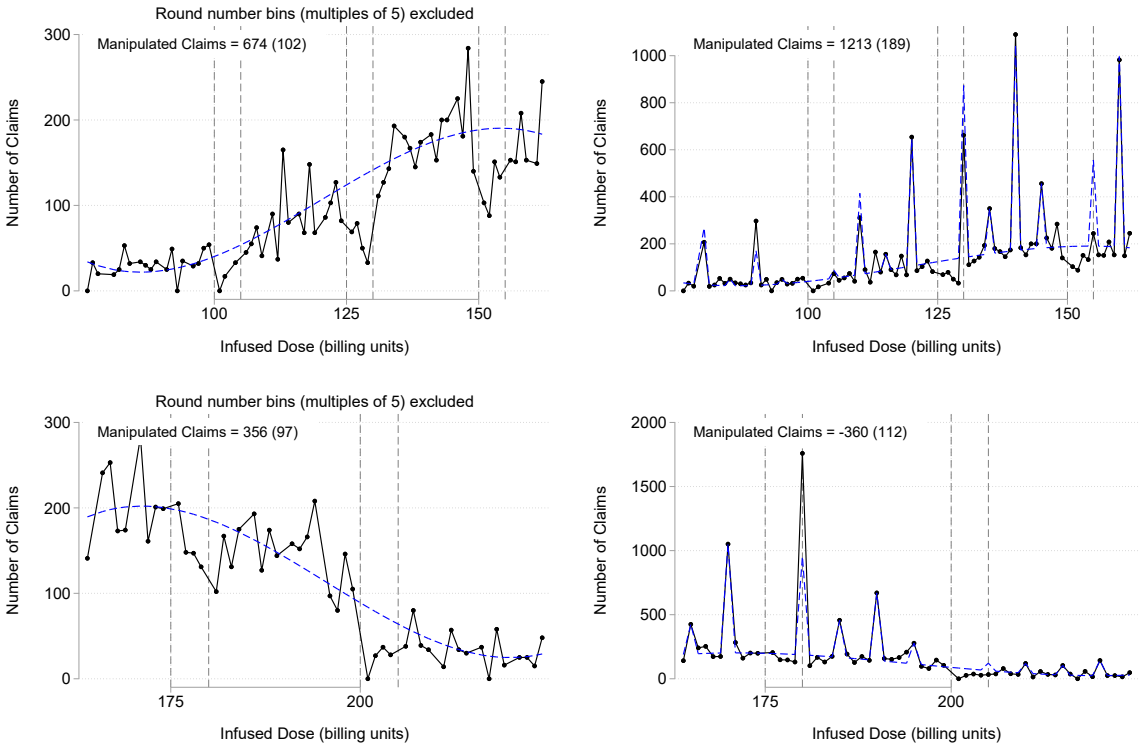
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.22: Provider Manipulation of Sarclisa Doses



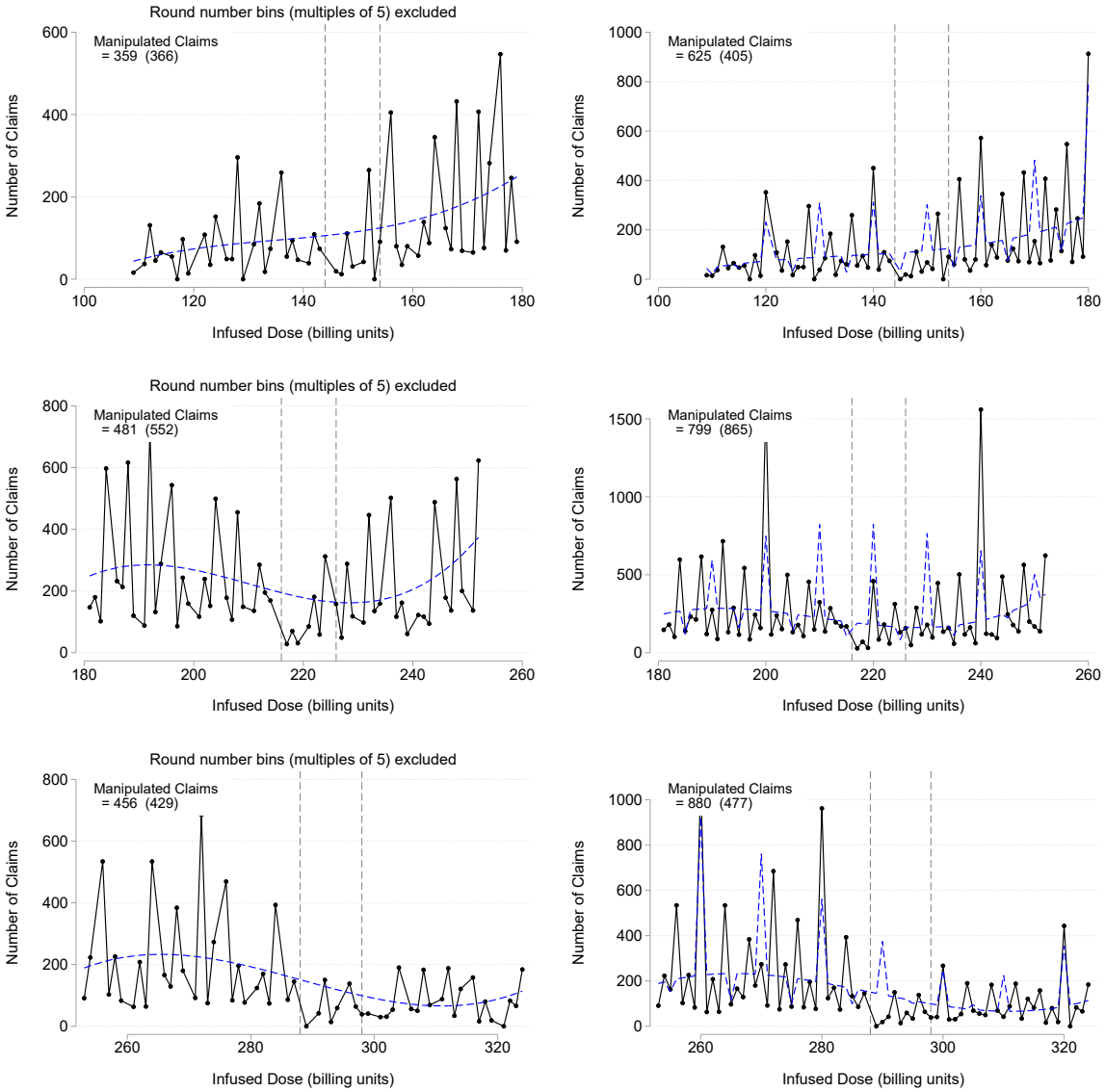
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.23: Provider Manipulation of Treanda Doses



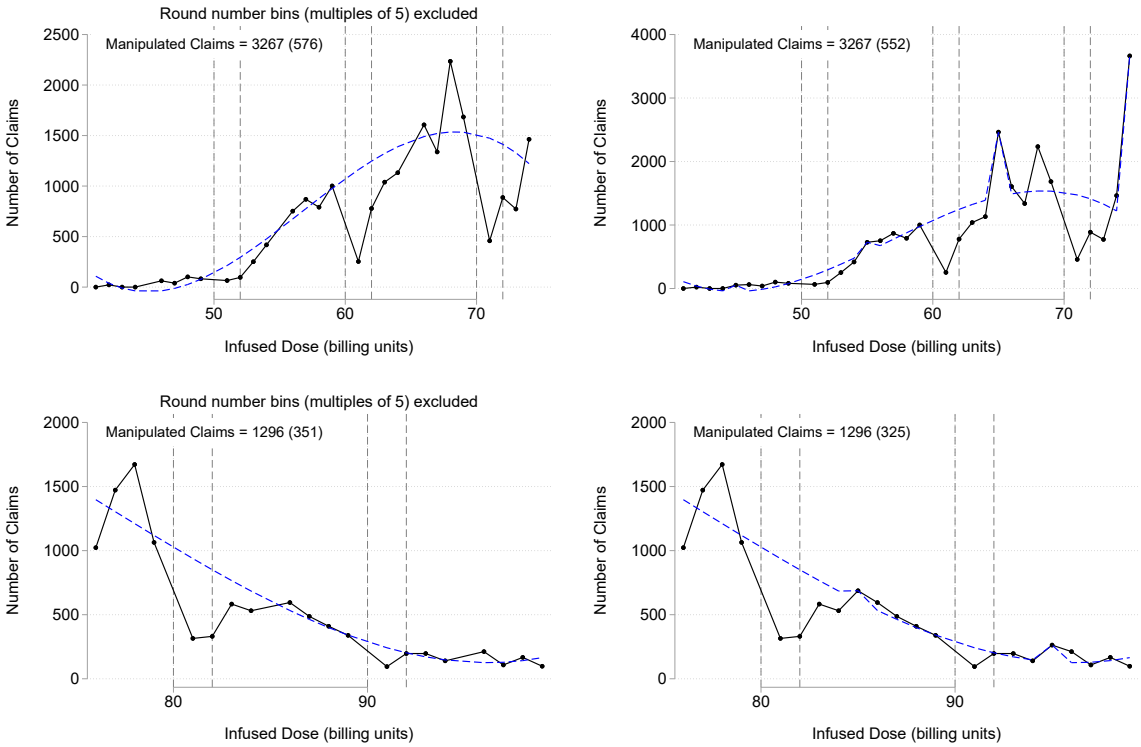
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.24: Provider Manipulation of Trodelvy Doses



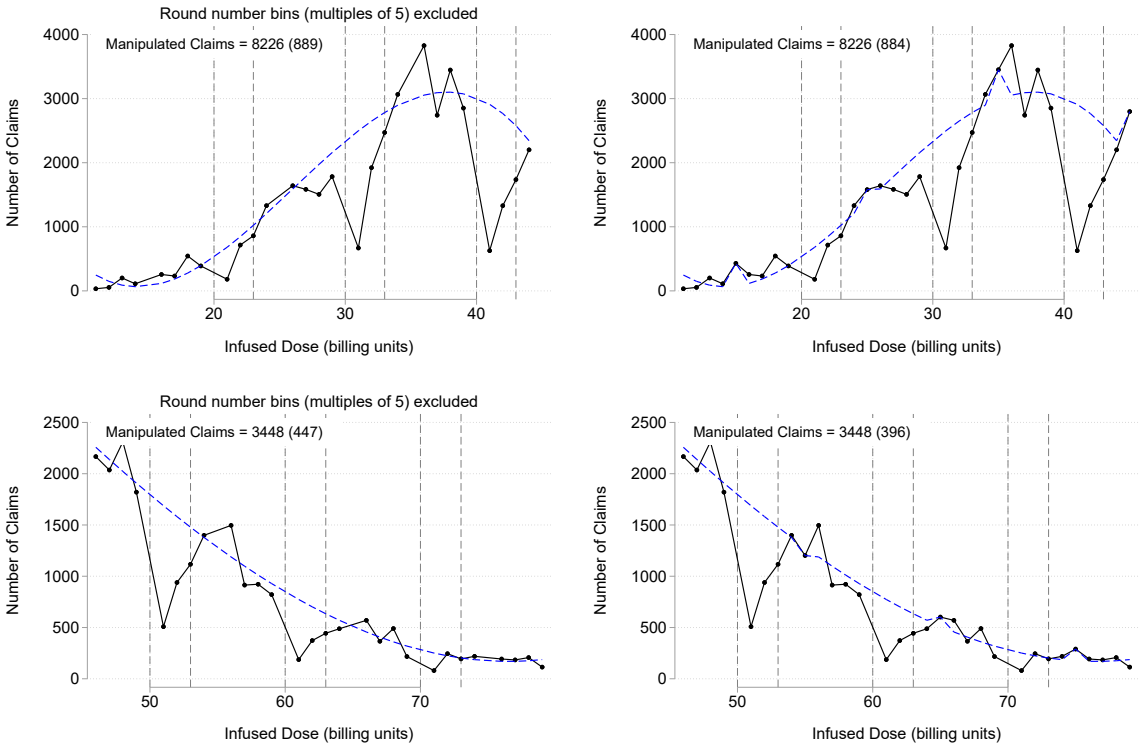
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.25: Provider Manipulation of Truxima Doses



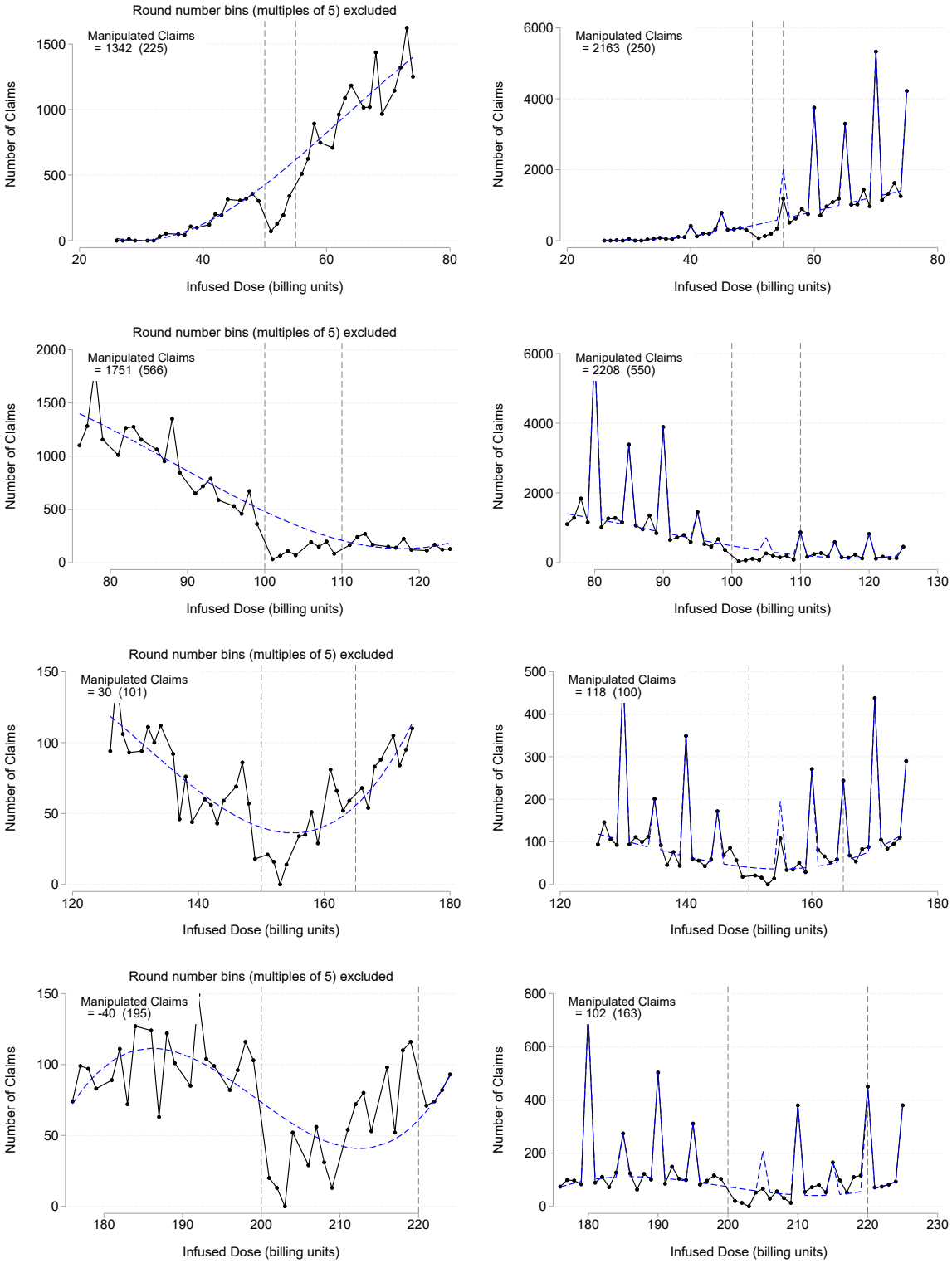
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.26: Provider Manipulation of Vectibix Doses



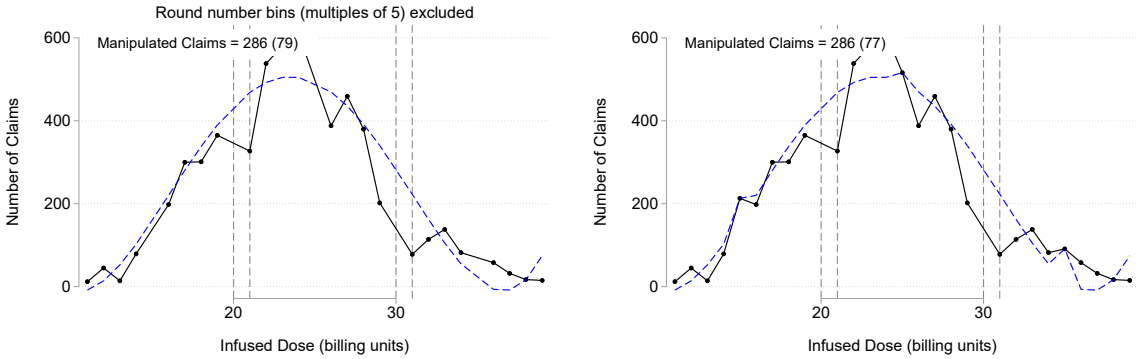
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.27: Provider Manipulation of Yervoy Doses



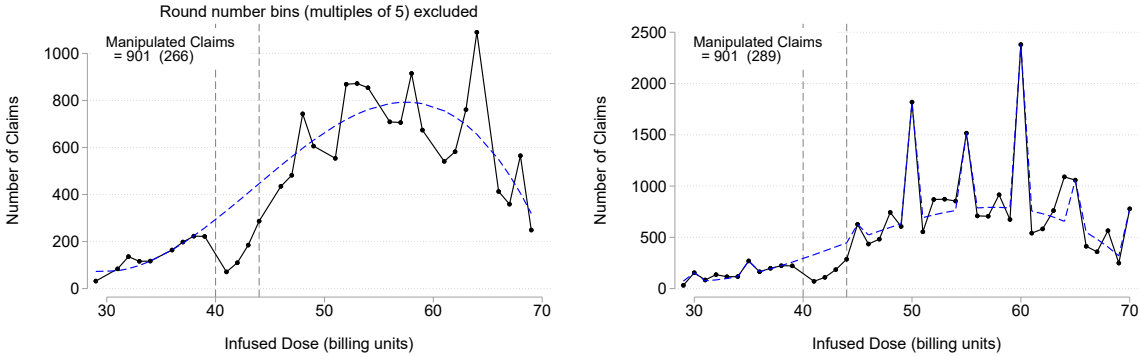
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.28: Provider Manipulation of Yondelis Doses



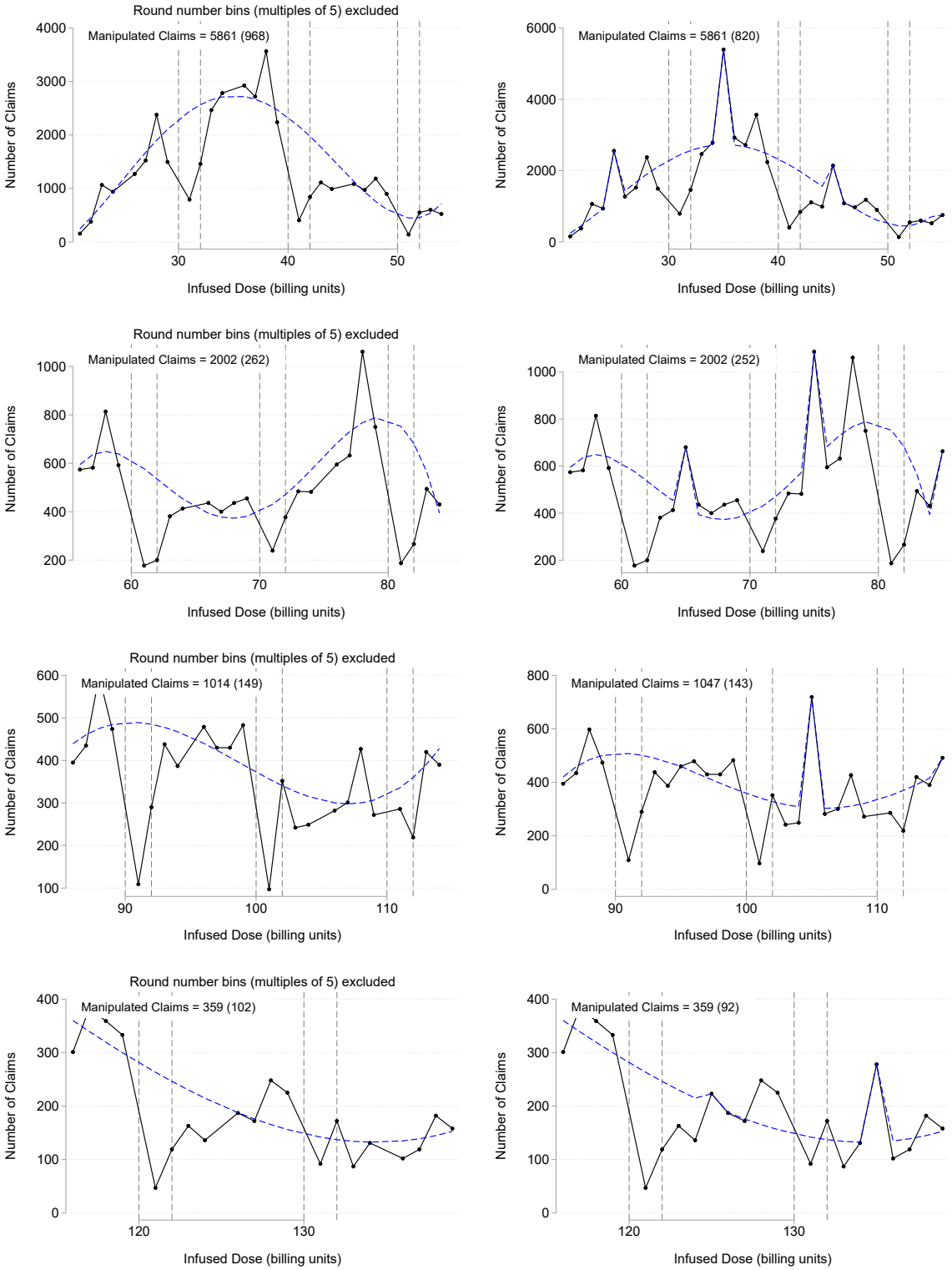
Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.29: Provider Manipulation of Zepzelca Doses



Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

Figure A.30: Provider Manipulation of Zirabev Doses



Notes: Blue = counterfactual distribution estimated as described in Section 4.1. Black = actual dose distributions. First vertical line is the dose at which an additional vial is required. Doses in round number bins (multiples of 5) are removed from the left panel for clarity (heaping is due to rounding in the reporting of these doses by providers).

B Break-even demand elasticity for dose manipulation

A provider earns a constant profit margin $m > 0$ per vial used, and the patient pays a fixed coinsurance per vial. The patient's body-size implies a dose of v_H vials, and the provider considers manipulating the dose down to $v_L = v_H - 1$ vials.

Profit and price per claim. Profit per claim is proportional to the number of vials administered:

$$\pi_0 = v_H m,$$
$$\pi_1 = v_L m.$$

Patient out-of-pocket price per claim is also proportional to the number of vials. If the pre-rounding price is P_0, then after rounding it is

$$P_1 = \frac{v_L}{v_H} P_0.$$

Let Q_0 and Q_1 denote the number of claims before and after rounding. Total profit before and after rounding are therefore

$$\Pi_0 = v_H m Q_0,$$
$$\Pi_1 = v_L m Q_1.$$

Break-even condition. Break-even requires that total profit be unchanged by rounding:

$$v_L m Q_1 = v_H m Q_0.$$

Cancelling terms yields

$$Q_1 = \frac{v_H}{v_L} Q_0.$$

Thus, utilization must increase by a factor of v_H/v_L for the provider to break even.

Midpoint elasticity at the break-even point. Because rounding induces a discrete and often large price change, we summarize demand responsiveness using a midpoint elasticity.

Quantity increases from Q_0 to $(v_H/v_L)Q_0$. The midpoint percentage change in quantity is

$$\frac{\Delta Q}{\bar{Q}} = \frac{(v_H/v_L - 1)Q_0}{(Q_0 + (v_H/v_L)Q_0)/2} = \frac{2(v_H - v_L)}{v_H + v_L}.$$

Price falls from P_0 to $(v_L/v_H)P_0$. The midpoint percentage change in price is

$$\frac{\Delta P}{\bar{P}} = \frac{(v_L/v_H - 1)P_0}{(P_0 + (v_L/v_H)P_0)/2} = -\frac{2(v_H - v_L)}{v_H + v_L}.$$

The midpoint elasticity of demand at the break-even point is therefore

$$\varepsilon^* = \frac{\Delta Q/\bar{Q}}{\Delta P/\bar{P}} = -1.$$

Any demand response less elastic than this benchmark implies that dose rounding of this form reduces provider profit.