

# Supply-Side Incentives for Medical Technology Adoption\*

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November 17, 2024

## Abstract

I provide novel evidence that physicians respond to changes in insurance reimbursement for in-office treatments, though responses vary and can be unexpected. To estimate physician elasticity to private insurance reimbursement, I exploit a plausibly exogenous regulatory change in Medicare payment. Specifically, I document how private reimbursement typically follows Medicare reimbursement (Clemens and Gottlieb, 2016; Chan and Dickstein, 2019) and use the estimated payer-specific relationship between the two prices to construct a valid instrument. My findings show that supply generally exhibits a positive slope—lower reimbursement reduces treatment provision. However, for certain treatments, e.g. flu vaccines, the supply curve is negatively sloped. I provide suggestive evidence that physicians compensate for reduced reimbursement by increasing provision of these and related treatments that can be easily combined in single patient visits.

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\*Preliminary version. First draft: March 2022. I am grateful to Michael J. Dickstein for his guidance and advice, and to all participants at the NYU Stern IO seminar and research group for their insightful comments.

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## Introduction

In the last few years, there has been a growing debate about how health insurers and other payers should properly design incentives to providers. The major trade-off is between cost-reducing mechanisms (e.g. capitation) and rating systems that reward quality of care. A key empirical question is how providers respond to these incentive schemes and, as a result, how to achieve the adoption of the most valuable medical technologies.

Several papers in healthcare and health services research have examined this question, focusing mostly on the context of hospitals (Ho and Pakes, 2014; Johnson and Rehavi, 2016; Gross et al., 2021) and long-term care (Einav et al., 2018; Hackmann et al., 2021). However, a particularly understudied setting is the one of providers as agents for treatments they administer directly in office visits. These treatments include, for example, oncology products, kidney dialysis, and vaccines; together, these treatments accounted for about \$37 billion in healthcare spending in 2019 in Medicare alone.<sup>1</sup> The case of physician-administered treatments (hereafter, PATs) differs substantially from the case of typical prescription drugs because of the central role played by providers. While for prescription drugs providers operate solely as prescribers, leaving to pharmacists the burden of purchasing and selling medical products to consumers, for PATs the so-called “buy-and-bill” system is in place (Figure 1). Under this system, providers purchase medical products from manufacturers, store and administer them usually within the office setting, and receive reimbursements directly from insurers and from patients’ copay or coinsurance (if any). In other words, in the case of PATs, providers unilaterally control the choice of medicines they administer. As a result, economic incentives—rather than solely clinical factors—can influence prescribing decisions.

In this work, I focus on the specific setting of vaccine administration, as a relevant example within the broader class of PATs. The market for vaccines is important for several reasons. First, vaccines are among the most frequently billed procedures in outpatient claims (Figure 2). Second, as I will detail in Section 1a, the existing incentive structure proves relatively complex in this context, since there may be multiple supply-side incentives in place: reimbursement to providers for providing a given vaccine product, reimbursement for vaccine administration, and bonuses paid to providers conditional on the achievement of immunization targets. In addition, more than in other contexts, the role of physician counseling and support is essential for vaccine uptake: despite a large number of vaccines being required to access school or highly recommended in the US, nonmedical exemptions are still broadly accepted as a valid justification to avoid immunizations. Because vaccines serve primarily to prevent and not to treat diseases, physicians may also perceive a lower reputational cost of responding to supply-side incentives (Chan et al., 2020). Finally, the well-known clinical externality generated by vaccines is an

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<sup>1</sup>Source: Kaiser Family Foundation’s analysis (04/2021), based on CMS Medicare B Drug Spending Dashboards.

important welfare motivation for studying how incentives operate in this market.

In my work, I address the following questions: What is the prevalence of competing incentives providers face when choosing to administer vaccines? To what extent do the quantity, composition, and value of treatment delivery vary, in response to a change in providers' incentives? How does this supply response differ across incentive environments, providers' characteristics, patient groups, and treatment categories? The ultimate goal of this work is to explore how to re-design incentive schemes for providers, to achieve the most cost-effective level of uptake. While focusing on the specific example of vaccines in this paper, my purpose is to provide insights and mechanisms that could be generalized to different types of PATs.

To begin my analysis, I document a plausibly exogenous variation in supply-side incentives which is specific to vaccines and that may help to identify providers' responses. Specifically, at the end of 2017, Medicare adjusted the regulatory "allowed amount" payable to providers for reimbursing vaccine administration. In New Hampshire, for example, Medicare reimbursement dropped by 20% (i.e. \$5) in 2018, and kept declining in subsequent years, reaching in 2020 its lowest level since 2010. Given that private insurers' price setting behavior is partially interconnected with Medicare's (Clemens and Gottlieb, 2016), it is not surprising that commercial plans' prices experienced a similar trajectory. Thus, I exploit Medicare regulatory change to construct a valid instrument for the *observed* private insurers' reimbursements for vaccine administration. Specifically, I document the extent to which private pricing follows Medicare's reimbursement amount over the entire sample (2012-20), and I use the estimated relationship between the two to construct an instrument, i.e. the *predicted* change in private pricing following the 2017 Medicare reform. As a result, in my 2SLS setting, those providers whose observed private reimbursement tracks more closely the predicted one serve as the compliers. My findings show that, for most vaccine types, a 20% *drop* (i.e. \$5) in average private reimbursement in a given year - once appropriately instrumented - is followed by a 10% *reduction* in the number of per provider vaccines administered to patients covered by a given insurer. I control - among others - for the number of total yearly visits per provider. However, some types of vaccines seem to respond differently to financial incentives: specifically, for vaccines against flu and pneumococcal diseases, a similar 20% *drop* in average yearly private reimbursement is associated to a 16% *increase* of supply. Future steps in my research involve reconciling these possibly contrasting results: a unified framework, generalizable to multiple PATs, may shed light on the mechanisms driving providers' treatment choice and their response to income shocks, given their characteristics (e.g. insurer and patient mix), and the type of disease they are treating or preventing. In addition, a deeper understanding of the propagation of Medicare pricing shocks to private insurers seems key to highlight the particular interaction between expected private payments and providers' characteristics. My analysis shows that, for example, the price-following mechanism is less pronounced among larger providers across all types of insurances, consistent with the idea that

price-following is decreasing in providers' bargaining power (Clemens and Gottlieb, 2016).

Furthermore, preliminary results suggest that, after the 2017 reform, providers increased the number of non-vaccine-related services billed per visit, when the visit contained at least one vaccine administration. This provides suggestive evidence that providers may try to compensate the declining revenues per vaccine administration by billing additional treatments that they perceive as complements within the same office visit. As a result, I plan to devote further attention to possible mechanisms such as spillover effects, complementarity (or substitutability) among medical treatments within the same office visit, which may play a role in explaining providers' response to financial incentives.

From a policy perspective, this project informs the optimal design of providers' incentive schemes, to achieve the most cost-effective level of medical treatment uptake. In particular, understanding supply-side levers targeting vaccine uptake can help policy-makers to design market interventions aimed at achieving national immunization targets. In turn, such improvements in incentive design would reduce the heavy burden on society, both in terms of incidence of vaccine-preventable diseases and costs for care. Insurance companies may benefit as well, since tailoring providers' incentives (e.g. through higher reimbursement per administered vaccine) may be costly in the short-term but overall profitable in the long-term: a recent analysis conducted by Avalere Health found that Medicare incurred \$106.4 billion in 2016-2018 treating vaccine-preventable diseases.

**Related Literature.** My work contributes to several strands of the literature. First, it contributes to the large body of literature on the relevance of incentives for health care utilization. Aron-Dine et al. (2013) and Chandra et al. (2012) provide a rich set of examples of demand-side incentives, supply-side drivers and "situational" factors which may shape treatment choices in medical care. Among the most recent works on the supply side, Chan et al. (2020) study how pneumonia diagnosis rates vary widely among radiologists, with heterogeneity in skills -and, thus, in the cost borne for an incorrect diagnosis- explaining a large percentage of this variation; Grennan et al. (2021) estimate a significant impact of the widespread habit of pharmaceutical companies providing meals and informal payments to physicians on prescribing; Currie and MacLeod (2017) explore the impact of requiring hospitals to publish their own Cesarean section rates on the reduction of C-sections and on the welfare effects on high and low-risk women. My paper analyzes the simplest type of supply-side lever, namely financial incentives deriving from insurers' reimbursements to providers.

Second, as already mentioned, most of the literature on supply-side incentives focuses on hospital settings or long-term care. On the contrary, there is limited evidence on how financial incentives operate within office-based care: Iizuka (2012) provides interesting insights which are specific to the Japanese healthcare market; Clemens and Gottlieb (2014) develop a model

of physicians’ joint supply and investment decision in the US, exploiting the 1997 geographic adjustment to provider outpatient reimbursement in the Medicare program; Jacobson et al. (2017) study how a change to Medicare fees caused physicians to increase their provision of chemotherapy. I provide new evidence with a specific focus on vaccine administration. Up to now, vaccines have received large attention especially when it comes to R&D dynamics (Finkelstein, 2004), optimal mechanisms of redistribution to developing countries (Kremer et al., 2020) or demand-side incentives (Oster, 2018; Gardenghi, 2020). Little is known about how supply-side levers operate in this context.

Third, this project contributes to the discussion on physicians’ agency and on providers’ supply elasticity with respect to reimbursement rates. Focusing on an aggregate measure of outpatients care for Medicare patients, Clemens and Gottlieb (2014)<sup>2</sup> find that the elasticity is positive—around 1.5—with elective procedures such as cataract surgery responding more strongly than less discretionary services. More recently, Xiang (2021) and Cabral et al. (2021) point towards a positive response of treatment supply to prices, when it comes to surgical treatment of cervical spondylosis and evaluation and management (E&M) services to low-income elderly individuals, respectively. On the contrary, Jacobson et al. (2017)<sup>3</sup> find that providers increase administration of chemotherapy to their Medicare patients in response to a reduction in reimbursement rates. Reconciling these possibly opposing views within a unified framework is among the scope of my research, as I detail in Section 4. Moreover, while most of the previous works quantifies the response of care provided to Medicare patients to prices, my analysis sheds light on the response of treatments supplied to private insurers’ patients.

Finally, my analysis contributes to the understanding of the *price-following* mechanism between Medicare and private pricing. Clemens and Gottlieb (2016) sketch a theoretical framework in which private insurers’ pricing is the result of a Nash bargaining process between commercial insurers and provider groups. In their setting, Medicare pricing may (or may not) affect providers’ outside option. In line with their theory, I find that private reimbursement to larger providers responds less to shocks to Medicare pricing, when it comes to vaccine administration: equivalently, price following is weaker for larger providers. This is consistent with the idea that larger providers (and, thus, more concentrated providers’ markets) have more bargaining power against private insurers. Moreover, my results show a substantial degree of heterogeneity across private insurances in the way in which they use Medicare pricing as a benchmark.

**Outline.** The remaining part of the paper proceeds as follows. In Section 1, I describe the market for physician-administered treatments and, specifically, the peculiarities of the market for vaccines. I illustrate the data in Section 2. In Section 3, I present some empirical facts and

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<sup>2</sup>As well as older works by Gruber et al. (1999), Hurley and Labelle (1995).

<sup>3</sup>Similarly, Rice (1983) and Yip (1998) support a negatively sloped supply curve.

the 2SLS analysis: the latter employs the plausibly exogenous regulatory change in Medicare pricing to estimate providers' elasticity to private reimbursement rates for vaccine administration. In Section 4, I outline next steps, with a specific focus on how I expect the nature of treatments and providers' characteristics to be the key determinants in explaining providers' elasticity of supply. Section 5 concludes.

## 1 Institutional setting

This section describes the key institutional details characterizing vaccine demand and supply in the US. Also, I outline the specificities of the key procedure codes used by providers and insurers to bill vaccines and vaccine administration. I then present the 2017 reform of Medicare regulatory reimbursement for vaccine administration, which is used as exogenous variation in my empirical strategy.

### 1.1 The market for vaccines

Physician-administered treatments are infusions or injections administered by providers within outpatient settings, e.g. doctors' offices. Some examples of these treatments are chemotherapy, dialysis, medications for arthritis and osteoporosis, vaccines. Together, these treatments accounted for about \$37 billion in healthcare spending in 2019 in Medicare alone<sup>4</sup>, with around \$2 billion spent on vaccines. These treatments are covered by either Medicare Part B and private insurances.

When it comes to the market for vaccines, demand and supply are heavily regulated in the US. On the demand side, the CDC plays a key role in making vaccine recommendations for children and adults. In most US states, some vaccines are compulsory for children in order to access school: however, often states accept exemptions, motivated by either medical conditions or personal reasons. On the supply side, vaccines are usually administered by primary care providers, pediatricians or nurses during office visits or at the pharmacy. When computing reimbursements to providers, insurance companies treat vaccine products and vaccine administration separately. For example, an average provider administering Fluzone Quadrivalent - a typical flu vaccine - to her Medicare patient in 2017 billed \$9.5 for the product, plus an extra \$23 for the administration. While the reimbursement for vaccine products varies heavily across vaccine types<sup>5</sup>, the reimbursement for vaccine administration is characterized by an important geographic and time variation within the US, while it is mostly constant across vaccine types. Crucially, both types of reimbursement differ across insurance companies. Moreover, there is

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<sup>4</sup>Source: Kaiser Family Foundation's analysis (04/2021), based on CMS Medicare B Drug Spending Dashboards.

<sup>5</sup>Under Medicare Part B, the regulatory reimbursement for any flu vaccine product is equal to 95% of its Average Wholesale Price; for most of the other vaccines, it is 106% of their Average Sale Price.

heterogeneity across insurers in the out-of-pocket cost faced by patients, although this amount is usually negligible.<sup>6</sup>

To further improve vaccine uptake, several quality measurements and value-based payments have been introduced over time: one of the most substantial is Medicare Advantage Star Rating.<sup>7</sup> Since 2008, and on an yearly basis, CMS has assigned up to five stars to any Medicare Advantage plan, based on how plans perform relatively to each other during the year on several dimensions: annual rates of flu and pneumococcal vaccines are among those dimensions (Figure 3). Plans with four or more stars are eligible for bonus payments: thus, plans are likely to reward those in-network providers who meet some given annual targets. Moreover, stars are posted publicly on Medicare Plan Finder to guide patients' plan selection during the annual open enrollment period, so this implicitly creates reputational rewards for a plan from winning more stars.

When providing vaccines to patients, providers' costs include mainly the cost of buying vaccines from manufacturers and the costs of storage, paying personnel, learning and monitoring adverse reactions, counseling and tracking patients. The cost of buying vaccines varies across insurance types: for example, providers receive vaccines for free under the Vaccine-for-Children program.<sup>8</sup> Under alternative insurance schemes instead, providers (or groups of providers) bargain with manufacturers over the purchase price. Data on actual prices and discounts are not publicly available<sup>9</sup>: however, the costs borne by providers are likely to be a function of observables such as providers' years of experience, practice size and market concentration.

Overall, the institutional context described so far motivates the interest in studying the market for vaccines: the existing incentive structure proves relatively complex and the crucial role played by providers in the administration choice leaves opportunity for those incentives to operate.

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<sup>6</sup>For Medicare Part B, the coinsurance rate is 20% for all covered diseases after meeting the deductible, with the exception of influenza and pneumococcal disease that have no coinsurance and no deductible. In addition to flu, pneumococcal disease and hepatitis B, Medicare Part B covers vaccines related to treatment of an injury or to direct exposure to the disease, e.g. tetanus, rabies, etc. Source: <https://www.aafp.org/family-physician/practice-and-career/getting-paid/coding/medicare-vaccine-coverage.html>

<sup>7</sup>Another relevant value-based payment program for Medicare providers is the so-called MIPS (Merit-Based Incentive Payment System), see: <http://www.physiciansadvocacyinstitute.org/Portals/0/assets/docs/MIPS-Pathway/MIPS%20Overview.pdf>. MIPS is a budget neutral CMS program, measuring eligible clinicians' performance and comparing it with their peers. In other words, clinicians receiving a positive Medicare payment adjustments are funded by those receiving negative payment adjustments.

<sup>8</sup>Children are eligible for the VFC program if younger than 19 and if one of the following applies: Medicaid-eligible, uninsured, underinsured, American Indian or Alaska Native.

<sup>9</sup>Although precise data on the bargained pricing agreement between manufacturers and providers is not publicly available, the CDC provides reliable lower and upper bounds for those amounts, for each year and for each NDC code: <https://www.cdc.gov/vaccines/programs/vfc/awardees/vaccine-management/price-list/index.html>

## 1.2 Relevant procedure codes for vaccine administration

As previously mentioned, providers and insurers treat vaccine products and vaccine administration separately: specifically, while procedure codes assigned to vaccine products are specific to each vaccine type<sup>10</sup>, the majority of codes used for vaccine administration are common to multiple vaccine types. Moreover, while the procedure codes used to bill vaccine products are common to both Medicare and private insurance billing systems, procedure codes for vaccine administration present some minor but worth mentioning degrees of heterogeneity between the public and private systems. In what follows, I detail the procedure codes used to bill vaccine administration, since they are the focus of the 2017 Medicare reform.

When it comes to private insurers, they usually employ a specific set of codes to bill vaccine administration. The difference among those codes is based mainly on patient’s age, route of administration, the presence of any counseling by the provider, the vaccine being the first (or the first component in a multicomponent vaccine) or any subsequent vaccine administered during the same visit. In Appendix (a), I provide a list of the procedure codes used and of their specific meaning.<sup>11</sup>

On the contrary, Medicare billing system prescribes to use G-codes to bill the administration of flu vaccines (G0008), vaccines against pneumococcal disease (G0009), and hepatitis B for people at risk (G0010). G-codes are rarely used among private insurers, although in the data I find a relatively consistent group of providers employing codes G0008 and G0009 also among private insurers.<sup>12</sup> Moreover, Medicare accepts the codes employed by the private system for all vaccine types other than the three vaccines associated to a G-code.<sup>13</sup> For example, a Medicare patient receiving a flu vaccine and a tetanus vaccine during the same office visit is billed G0008 and 90471 for administration, where the former stands for flu vaccine administration and the latter for tetanus vaccine administration.

## 1.3 The 2017 Medicare reform

Since 1992, Medicare has paid outpatient providers through a system of centrally administered prices, based on a national fee schedule. The fee schedule assigns a fixed “relative value” to each health care service, including vaccine administration. This value is the so-called Medicare “allowed amount” and is computed as the weighted average of a national conversion factor (CF), some geographic adjustment factors (GPCIs), and some measurements of resources required to provide the service (RVUs). Specifically, for service  $x$  supplied in payment area  $a$  in year  $t$ ,

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<sup>10</sup>A vaccine type is a combination of disease, brand and composition.

<sup>11</sup>Sources: <https://www.physicianspractice.com/view/correct-coding-vaccine-administration>, <https://www.aafp.org/family-physician/practice-and-career/getting-paid/coding/vaccine-administration.html>

<sup>12</sup>This is likely due to mistakes, since the same provider often serves either Medicare and non-Medicare patients.

<sup>13</sup>Source: <https://www.americanmedicalcoding.com/vaccine-administration-g-codes/>



Medicare allowed amount is computed as:

$$\begin{aligned} AllowedAmount_{x,t,a} = CF_t \times [ & RVU_x^{work} \times GPCI_a^{work} + \\ & RVU_x^{malpractice} \times GPCI_a^{malpractice} + \\ & RVU_x^{practiceexpense} \times GPCI_a^{practiceexpense}] \end{aligned} \quad (1)$$

Among the public measures introduced to contain healthcare costs at the federal level, at the end of 2017 Medicare adjusted the regulatory “allowed amount” payable to providers for reimbursing vaccine administration. In particular, the regulatory change under study consisted in an unprecedented drop of Practice Expense RVU, i.e. a measure of the costs of maintaining a practice.

The decline of Medicare allowed amount propagated heterogeneously across payment areas (see equation (1)) and continued to some extent in the following years. As shown in Figure 4 and further detailed in section 3a, the reform induced a 20% drop (i.e. \$5) in Medicare reimbursement in 2018 relative to 2017 for the most relevant CPT codes used to bill vaccine administration (CPT 90460, 90471, 90473). Moreover, the regulatory reimbursement for those codes kept dropping up to 2020, when the reimbursement amount was around equal to 50% of the original one in 2017 (US average). In my empirical analysis, I exploit this plausibly exogenous variation in Medicare reimbursement, together with the price following mechanism between Medicare and private insurers (Clemens and Gottlieb, 2016), to study the response of providers’ vaccine supply to private reimbursements.

## 2 Data

To conduct the analyses presented in this work, I use two publicly accessible data sources, namely the Medicare FFS provider utilization and payment aggregate dataset, and the New Hampshire commercial claims dataset (NH CHIS).

The Medicare FFS dataset contains the aggregate supply of services provided to US Medicare patients, together with the average associated reimbursement, for each provider, year and specific service. The time span included is the 2012-18 period. I restrict the dataset to providers operating in New Hampshire, for the purpose of comparability with the NH CHIS data. Table 1 provides some key summary statistics about those providers administering at least one vaccine during the available time-span. Clearly, due to the aggregate nature of the data, I cannot observe the content of each single medical visit and I cannot map each provider to her specific patients.

The NH CHIS dataset contains all commercial claims (including Medicare Advantage, but excluding Medicare and Medicaid patients) for New Hampshire, from 2012 to 2020. Each claim

captures what happens during a given visit, e.g. all treatments provided, all payments charged and the ones actually paid<sup>14</sup>, the place of service, patients' insurer types. Table 2 provides an overview of the sample of providers administering at least one vaccine to private insurance patients during the available time-span.

A few observations arise by comparing the summary statistics in Tables 1 and 2. First, the number of Medicare providers administering at least one vaccine during the available time-span is less than half the number of providers administering at least one vaccine to private insurance patients. Second, although the number of unique procedure codes used to bill vaccine administration is smaller under Medicare - partially driven by the fact that Medicare covers a limited number of vaccines -, the number of vaccine administrations per provider in a given year is larger under Medicare (mean, 2017: 132.47) than under private insurance (mean, 2017: 72.35). Finally, the total reimbursement per provider for vaccine administration in a given year is similar in Tables 1 and 2, if expressed in \$ terms; however, when expressing it as a percentage of the total yearly reimbursements for non-facility medical services per provider, Medicare yearly reimbursement for vaccine administration per provider is larger.

Although informative for conducting preliminary analyses, the above-mentioned publicly accessible datasets present some downsides. For example, I cannot track the same patient over time and I have only limited information about patients' characteristics (available only in NH CHIS). Moreover, insurers are grouped by broad type (e.g. HMO, PPO) and not by plan identifier, thus preventing me from keeping track of the more precise level of heterogeneity across insurers and from matching Medicare Advantage plans to their quality ratings. In addition, I cannot link the two datasets since Medicare aggregate data identifies providers through NPIs, while NH CHIS data uses different identifiers: thus, I am not able to observe the same provider when serving publicly insured patients and privately insured ones.

I plan to overcome the downsides of the publicly available datasets used so far by employing the recently purchased Colorado All Payer Claims Database.

### 3 Empirical analysis

In this section, I present some empirical facts emerging from the exploration of the data described in the previous section. Moreover, I outline the 2SLS estimation procedure, which employs the 2017 Medicare regulatory change to quantify the elasticity of vaccine supply to changes in private insurance prices. Finally, I describe some preliminary evidence of spillover effects after the 2017 reform, leading providers to increase the amount of non-vaccine related treatments billed in a vaccine-related visit. I conclude with a discussion of my results.

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<sup>14</sup>Specifically, I observe the overall payment charged, the actual payment of the insurer and the out-of-pocket cost for the beneficiary.

### 3.1 Descriptive facts

As mentioned in Section 1c and observed in Figure 4, Medicare changed its regulatory “allowed amount” payable to providers for vaccine administration at the end of 2017. Specifically, the reform induced a 20% drop (i.e. \$5) in reimbursement in 2018 relative to 2017 for the most relevant CPT codes used to bill vaccine administration (CPT 90460, 90471, 90473). Moreover, the regulatory reimbursement for those codes kept dropping up to 2020, when the reimbursement amount was equal to around 50% of the original one in 2017 (US average). While reimbursements for those codes experienced a significant drop, the payment associated to minor CPT codes used for vaccine administration (e.g. the codes used to bill injections other than the first one for each given visit - CPT 90461, 90472, 90474) remained pretty stable over time. A natural question is whether this drop in Medicare reimbursement was followed by a drop in private insurers’ pricing. To this end, Figure 5 shows estimates obtained from regressing average private prices at the provider-insurer-year level in New Hampshire on year fixed effects<sup>15</sup>, for each CPT code separately and after residualizing by provider and insurer fixed effects. Observed private prices in New Hampshire decreased by up to \$5 for those CPT codes for which Medicare reform prescribed a reduction of reimbursement after 2017 (i.e. 90460, 90471, 90473). G-codes followed a similar - and even cleaner - trend. Observed private prices were stable or - if anything - slightly increasing after 2017 for the remaining CPT codes. This first fact points towards a propagation of Medicare reimbursement shock to private insurance pricing.

To further investigate the relationship between Medicare and private insurers’ price setting strategies, I use the entire 2012-20 NH sample to see how the two relate independently from the specificities of the 2017 Medicare reform. Specifically, in Figure 6 I plot the distribution of the difference between observed private prices and Medicare allowed amount, at the provider-insurer-year level and for each CPT code, after residualizing by provider and year fixed effects. As expected, private insurers tend to set a reimbursement level above the one prescribed by Medicare; moreover, within each CPT code, there is heterogeneity among insurers. Not surprisingly, reimbursements for G-codes are closer to the ones prescribed by Medicare and display lower variance than the other CPT codes.

I quantify the price following mechanism between Medicare and private insurers in Tables 3 and 4. In Table 3, I regress log private prices in year  $t$  on log Medicare prices in year  $t$ , for all years available in NH data, after aggregating those variables at the insurer-CPT-year level.<sup>16</sup> Columns (1) and (3) show the cross-sectional price following coefficients, while columns (2) and (4) display the within-procedure price following relationship, as I additionally control

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<sup>15</sup>I restrict to individual providers for ease of exposition. In appendix, Figure 9 shows the outcome of the analysis replicated for different types of providers, e.g. individual vs retail providers.

<sup>16</sup>Given the presence of different types of providers in my sample, e.g. individuals and retailers, with potentially different bargained private prices, I construct aggregate prices at the insurer-CPT-year level by weighting provider types based on their frequency in the data.

for CPT fixed effects. Standard errors are clustered at the insurer level. In line with Chan and Dickstein (2019), the estimated coefficients highlight a positive relationship between Medicare and private insurers' pricing: a 1 percent increase in Medicare pricing is associated to a 0.38-0.54 (approximately) percent increase in private pricing. Moreover, there is heterogeneity across insurance types, e.g. Medicare Advantage plans seem to be the most responsive to Medicare pricing shocks. In appendix<sup>17</sup>, I show the outcomes of the same analysis when allowing for lagged transmission of Medicare pricing to private insurers. Following Chan and Dickstein (2019), I regress log private prices in year  $t$  on log Medicare prices in year  $\tau$ , where  $\tau$  is the Medicare year whose log price change is the closest to the log price change experienced by private insurers at time  $t$ .<sup>18</sup> In Table 4, I focus on individual providers only to leverage on another important dimension which may affect the price following mechanism, i.e. providers' size. According to Clemens and Gottlieb (2016)'s theoretical predictions, price following should be decreasing in providers' bargaining power. Thus, I expect the relationship between Medicare and private pricing to be decreasing in providers' size. Table 4 confirms this prediction: the price following coefficients are larger for small providers (quartiles q3 and q4), as proxied by the average yearly number of visits in the 2015-17 time span, than for large providers (quartiles q1 and q2). However, this relationship is not perfectly monotonic. I use the coefficients estimated in this section to construct my instrument, as I detail next.

## 3.2 2SLS analysis

### 3.2.1 Baseline specification

A simple regression of vaccine supply on reimbursements of private insurers to providers would suffer from standard endogeneity concerns. For example, I may be worried about simultaneity: not only vaccine supply may be the result of financial incentives received by providers, but also reimbursement levels may be a function of the amount of vaccines provided as per contractual details between providers and insurers. In addition, there may be several omitted variables that could bias my results, including: providers' unobservable characteristics (e.g. sensitivity towards prevention) correlated to higher payments, unobservable contractual details between providers and insurers leveraging on non-financial incentives (or informal financial incentives) to promote vaccines, and correlated to higher payments.<sup>19</sup>

To limit the endogeneity concerns, I exploit the 2017 Medicare reform to estimate the

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<sup>17</sup>See Tables 7 and 8.

<sup>18</sup>Specifically:  $\tau = \operatorname{argmin}_{t' \in \{t, t-1, t-2\}} |\Delta \operatorname{LogComm}P_{htl} - \Delta \operatorname{LogMedicare}P_{ht'l}|$ , where  $\Delta \operatorname{LogComm}P_{htl} = \operatorname{LogComm}P_{htl} - \Delta \operatorname{LogComm}P_{h(t-1)l}$  is the temporal change in log private prices for a given procedure  $h$  and insurer  $l$ , and similarly for the temporal change in log Medicare prices  $\Delta \operatorname{LogMedicare}P_{ht'l}$ .

<sup>19</sup>The first example of omitted variable could be mitigated by observing vaccine supply of the same provider when serving similar patients covered by different private insurers. This is because I expect (at least some of) providers' unobservables to be constant across patients covered by different insurers. On the other hand, concerns related to the second example of omitted variable cannot be addressed in this way.

following baseline 2SLS specification, in the spirit of Clemens and Gottlieb (2016). I run this specification for each CPT  $h$  separately (thus, subscript  $h$  is omitted from the following equations for ease of exposition):

$$P_{jtl} = \pi \text{PredChange}_{ql} * \text{PostReform}_t + \delta_t + \eta_l + \mu_j + X_{jtl} + e_{jtl} \quad (2)$$

$$Q_{jtl} = \beta \hat{P}_{jtl} + \delta_t + \eta_l + \mu_j + X_{jtl} + \epsilon_{jtl} \quad (3)$$

$P_{jtl}$  is the *observed* (potentially endogenous) private price for vaccine administration, reimbursed to provider  $j$  by insurer  $l$  in year  $t$ :  $\hat{P}_{jtl}$  is the same variable once instrumented.  $Q_{jtl}$  is the outcome variable of interest, i.e. the natural logarithm of the cumulative number of vaccine administrations (billed as CPT  $h$ ) supplied by provider  $j$  in year  $t$  to those patients covered by insurer  $l$ .  $\text{PredChange}_{ql} * \text{PostReform}_t$  is my instrument for the observed private prices, which can be interpreted as the one-year *predicted* change of private prices paid by insurer  $l$  to a provider whose size belongs to quartile  $q$ , after the 2017 Medicare regulatory change. More details about the construction of the instrument are provided in the following section.  $\delta_t$ ,  $\eta_l$ ,  $\mu_j$  are respectively year fixed effects, insurer-type fixed effects, and provider fixed effects (specifically, I present mutually exclusive specifications including provider-type fixed effects<sup>20</sup>, provider size -in quartiles- fixed effects<sup>21</sup>, provider fixed effects). Controlling for provider fixed effects (or for their alternative variations) is motivated by the concern that providers may differ in the possibility of over- or under-supplying vaccines, as well as other medical treatments, based on their own characteristics (e.g. insurance mix, patient mix). Finally,  $X_{jtl}$  is a vector of time-varying provider characteristics (e.g. provider size, as approximated by the number of yearly visits - linearly and squared) and of provider-insurer fixed effects (depending on the type of provider fixed effects used).

Overall, the first equation is the first-stage, explaining how a \$1 predicted private price change flows into the observed private payment; the second equation is the IV-structural equation, which measures how vaccine supply responds to a \$1 change in actual private payment (as manipulated by the Medicare change through the predicted private payment). Identification arises from variation of observed private prices and of vaccine supply over time, for the same provider-insurer-CPT. Standard errors are clustered at the provider size level (in quartiles), since I construct the instrument such that this is the dimension along which the payment shock varies.

Results for both the first stage and the IV regressions are presented in Table 5 and discussed in details section 3d. Columns (1) and (2) show the specification including provider-type fixed effects, columns (3) and (4) include provider size fixed effects, while columns (5) and (6) display

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<sup>20</sup>E.g. individuals vs retailers.

<sup>21</sup>As proxied by the average number of yearly visits in the period preceeding the 2017 reform. Thus, it is a time-invariant variable.

the coefficients associated to the most granular fixed effects, i.e. provider fixed effects. For each of these three different specifications, the second column includes also provider-insurer fixed effects (with provider fixed effects being defined differently in the three cases).

### 3.2.2 Instrument construction and identifying assumptions

As explained in the previous section, I instrument the *observed* private price for vaccine administration, reimbursed to provider  $j$  by private insurer  $l$  in year  $t$ , with the *predicted* private payment change for the same CPT, provider, and insurer, after the 2017 Medicare reform. Specifically, I define the following elements composing my instrument (again, I omit subscript  $h$ , indicating each CPT code related to vaccine administration, for ease of exposition):

- $\Delta M = (M_{2018} - M_{2017})/M_{2017}$  is the % variation in Medicare allowed amount for a given CPT code between year 2018 and 2017, in New Hampshire.<sup>22</sup>
- $c_l$  is the insurance  $l$ -specific price following relationship between Medicare and private insurers, estimated in section 3a over the entire New Hampshire sample (see Table 3). In appendix<sup>23</sup>, I present the results from an alternative specification using the coefficients  $c_{l,q}$  estimated in Table 4: those coefficients account not only for insurer  $l$ -specific differences in the price following mechanism, but also for differences across providers whose size belongs to different quartiles  $q$ .
- $f(\Delta M, c_l)$  is the predicted % change in private prices after the 2017 reform. Clearly, it depends on Medicare allowed amount % variation and on the estimated insurance-specific correction term.
- $P_{q,l,prereform}$  is the average reimbursement paid by private insurer  $l$  in the years immediately before the reform (2015-17), for a given CPT code, to providers whose size is in quartile  $q$ .
- As a result,  $PredChange_{q,l} = f(\Delta M, c_l) * P_{q,l,prereform}$  is the predicted private price change (in \$ terms) for providers in quartile  $q$  and for insurer  $l$ , implied by the Medicare reform. This definition assumes a precise estimated relationship between the % change in Medicare pricing and the associated % change in private pricing. In the previous section, we show that this relationship exists in the data when looking at the entire New Hampshire sample.
- $PredChange_{ql} * PostReform_t$  is my instrument, where  $PostReform_t$  is a dummy equal

<sup>22</sup>Source: CMS Medicare look-up tool, available online at: <https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PFSlookup>. There is no geographic variation within New Hampshire in the regulatory amount prescribed by Medicare for non-facility services. I also consider alternative definitions of  $\Delta M$  where I account for the % variation of each year - following 2017 - wrt 2017, given that the price shock is persistent over time.

<sup>23</sup>See Table 9.

to 1 in the post-reform period (i.e. after 2017) and to 0 otherwise.

Given the definition of my instrument, compliers are those providers whose observed variation in private pricing (in \$) tracks more closely the predicted variation (in \$), which is a function of Medicare % variation induced by the 2017 reform.

The instrument constructed above is valid under the standard set of assumptions. First, the instrument should be relevant, i.e. the predicted private price change after the reform should be reflected in the actual private price. Second,  $\text{Cov}(\epsilon_{jtl}, \text{PredChange}_{ql} * \text{PostReform}_t) = 0$  should hold, i.e. Medicare pricing shock in 2017 must be conditionally independent of other sources of change in vaccine supply. While a key measure of relevance is the magnitude of the F-statistic in the first stage, control variables and fixed effects help mitigate concerns regarding the violation of the second assumption. Table 5 displays a pretty high F-statistic across all specifications, which reassures about the strength of my instrument.

### 3.2.3 Event study

To further strengthen my quantification of providers' response to financial incentives in the case of vaccines, I run a fully parametric event study, to check for the existence of pretrends in the endogenous variable (i.e. observed private prices) correlating with the instrument:

$$P_{jtl} = \sum_{t \neq 2017} \alpha_t \text{PredChange}_{ql} * I_t + \delta_t + \eta_l + \mu_j + X_{jtl} + u_{jtl} \quad (4)$$

Differently from the first-stage in the 2SLS baseline specification,  $I_t$  is a dummy equal to 1 in year  $t$  (I choose 2017 as the benchmark year). Estimates of coefficients  $\alpha_{2018}$ ,  $\alpha_{2019}$ ,  $\alpha_{2020}$  track the dynamic relationship between predicted private price changes and observed private prices. Estimates of the remaining coefficients ( $\alpha_t$ , with  $t < 2017$ ), if close to zero, provide evidence of the absence of any pre-trend.

The estimated coefficients are displayed in Figure 7: overall, I find evidence of a positive relationship between the predicted private price change and the observed private prices, following the 2017 Medicare reform: also, I do not observe any significant pretrend in this relationship for the time-period before 2017.

### 3.3 Evidence of spillovers

Finally, I document some preliminary evidences of spillover effects. Specifically, a natural question is whether, after the 2017 Medicare reform and the consequent transmission of the shock to private insurers' prices, providers may have reacted in ways other than the mere under- (or over-) provision of vaccines.

As a preliminary evidence of this trend, in Table 6 I plot the number of medical services

over time, as well as the corresponding monetary reimbursement obtained by providers, splitting between vaccine-related services (product vs administration) and vaccine-unrelated services. I include only those visits where there was at least one administration of a flu shot, for a single insurer type. First, I observe that the average reimbursement for vaccine administration drops after 2017 - as expected, due to Medicare reform. Secondly, I see that the average reimbursement for vaccine products administered during a visit remains pretty stable - thus, it does not compensate the negative income shock for administration. Finally, the administration of vaccine-unrelated medical care seems to increase after the 2017 reform, both in terms of supplied units and in monetary terms.

This is consistent with the idea that, on average, providers may have tried to compensate the income shock following the drop in vaccine administration reimbursement by billing additional services unrelated to vaccines during the same visit. Further steps for a more systematic investigation of spillover effects are discussed in Section 4.

### 3.4 Discussion of results

The results provided so far highlight how financial incentives can shape providers' treatment choices along multiple complex dimensions. Firstly, a 20% (i.e. \$5) drop in private insurers' reimbursement in the New Hampshire context, when instrumented with Medicare regulatory price change in 2017, is followed by a 10% decrease in vaccine administrations for most vaccine types. This is equivalent to a 0.5 elasticity. However, for particular types of vaccines (e.g. flu), the supply curve is negatively sloped: a similar 20% drop in private reimbursement is associated to a 16% increase of supply. The event-study analysis finds no evidence of significant pretrends in the pre-reform period.

In terms of the sign of supply elasticity to financial incentives, these results speak to the conflicting literature aiming at finding empirical support for whether medical care supply is negatively or positively sloped. As already anticipated, Clemens and Gottlieb (2014) find that the elasticity is positive, when focusing on an aggregate measure of patient care (i.e. RVUs); on the contrary, Jacobson et al. (2017) find that providers increase administration of chemotherapy among Medicare patients in response to an exogenous reduction of reimbursement rates.

In terms of magnitude of supply elasticity, my results are consistent with the range of elasticity values found in the previous literature: for example, Clemens and Gottlieb (2014) estimate an elasticity around 0.8 in the short-run and around 1.5 in the long-run, with elective procedures such as cataract surgery responding more strongly (elasticity around 4) than less discretionary services (elasticity around 1). In a similar fashion, Xiang (2021) estimates a 0.5 to 1.5 elasticity of surgery for cervical spondylosis (in terms of RVUs<sup>24</sup>) to charge differen-

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<sup>24</sup>Differently from Clemens and Gottlieb (2014) and Xiang (2021), I should be careful in measuring the elasticity of supply to reimbursement in terms of RVUs: the 2017 reform prescribed a change in the number of RVUs



tials between surgical and non-surgical treatment. Cabral et al. (2021) find a 1.3 elasticity of Evaluation and Management (E&M) services provided to low-income elderly individuals to a federally-mandated payment increase for those services.

Furthermore, my results point towards a strong and significant price following mechanism linking Medicare regulatory reimbursements to private insurers' pricing strategy, in line with Chan and Dickstein (2019). I stress the relevance of this mechanism by either: (i) looking at this relationship with a purely descriptive approach using a broad time-span (2012-20), as I did in Section 3a; and (ii) estimating this relationship as the first stage within a 2SLS setting, as I did in Section 3b. Specifically, the F-statistic of the first stage confirms that this relationship is strong. Moreover, a first stage coefficient equal to 1 would stand for a perfect overlap between the *predicted* private insurers' price shock in 2017, following Medicare reform, and the *observed* private insurers' price change. My estimated first stage coefficients range from 0.7 to 1.5 (with the exception of CPT code G0009, for which the coefficient is above 2), highlighting some degree of measurement error. This error can be motivated by either: (i) 2017 being an outlier in the price following relationship between Medicare and private insurers' pricing. As a matter of fact, I use the entire time-span 2012-20 to estimate the average price-following coefficients, while my first stage estimates leverage specifically on the 2017 reform; and/or (ii) the limited granularity of the data, which does not allow to construct plan-specific price following coefficients, since I can only observe broad insurer-types rather than plan identifiers.

Finally, my results suggest preliminary evidence of spillover effects following the 2017 reform: not only providers may have tried to compensate the negative income shock by adjusting vaccine supply; they may have also modified the treatment mix during vaccine-related visits.

## 4 Theoretical predictions

In the previous sections, I present some empirical evidences shedding lights on providers' response to private insurers' reimbursement, when it comes to vaccine administration. My results are in line with the literature, in the sense that they seem to confirm that the relationship between price changes and volume supplied is a priori ambiguous. The theoretical literature on physician-induced demand explains this ambiguity by leveraging on the relative magnitude of the income (IE) and substitution effects (SE): when SE dominates over IE, providers are expected to reduce the volume of services supplied as reimbursement decreases; on the contrary, if IE dominates over SE, providers' supply curve is negatively sloped. From a welfare point of view, the extent to which one situation is preferable to the other depends on the degree of

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allocated to vaccine administration, thus I expect at least part of the change in total RVUs per provider-insurer-year to follow by construction. However, if using supply measured in RVU terms to make my results comparable to the above-mentioned works, I should disentangle the change in total RVUs due to the fall in regulatory RVUs per vaccine administration, and the one due to the increased or decreased number of vaccine administrations.

provider agency. Specifically, it depends on whether, before receiving any income shock, the provider was providing excessive care or was rationing care below the first best amount<sup>25</sup>.

Given the conflicting empirical findings observed in the literature for physician-administered treatments, and confirmed in my analysis for vaccines, a natural question is whether there exist some key observable features predicting the prevalence of a positively-sloped supply curve in some situations and of a negatively-sloped supply curve in some others. Both the literature and my findings point towards the nature of the disease and some providers' characteristics being key predictors in this sense. In terms of nature of the disease, for example, I expect discretionary treatments (e.g. cataract removal, rather than chemotherapy) to be more easily avoided or substituted with high rewarding treatments once a negative shock to reimbursement occurs, thus suggesting a positively-sloped supply (*treatment discretionality and substitutability*). Also, I expect some treatments to be easier to bundle together with additional, previously unrelated, services in a given visit: thus, a negative income shock to providers for a given service may be seen as an opportunity for increasing their revenues by introducing a higher degree of bundling (*treatment complementarity*). Treatments also differ in how easily they can be administered to patients without urgent need: in this sense, preventive services are a good example of treatments that can be easily overprovided without serious health implications or reputational concerns, if the provider is willing to do so (*base enlargement potential*). In addition, even treatment with the same base enlargement potential may differ in the *sunk costs* paid by providers, thus affecting providers' willingness to increase or decrease supply after a price shock. In terms of providers' characteristics, their *patient mix* seems relevant: the extent to which a provider can decide to overprovide (underprovide) care in response to decreasing financial incentives may depend on whether a substantial (limited) fraction of her patients is likely to tolerate additional treatments. This is true both on the extensive margin (e.g. more patients receiving the same treatment) or on the intensive margin (e.g. the same patients receiving more treatment). Similarly, providers' *insurance mix* may matter: the heterogeneous compensations received from different insurers for a given medical service, as well as the extent to which a shock to Medicare pricing propagates to private insurers, determine the expected magnitude of any income shock to providers. As a result, having a richer (rather than poorer) pool of patients in terms of insurance mix can affect providers' response to reimbursement changes. A careful modeling of the provider-patient interaction may help highlight the role of all these determinants in explaining providers' elasticity of supply.

Finally, the previous discussion on the validity of my instrumental variable highlights the relevance of the price following mechanism between Medicare and private insurers. As pointed out in the empirical analysis, the degree of price following seems to be heterogeneous in the

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<sup>25</sup>Usually, the physician-induced demand literature employs the amount of care chosen by a fully informed patient as the first best amount of care. See McGuire (2000) and Johnson (2014) for an overview of the physician agency and physician-induced demand literatures.

identity of the insurer and in the bargaining power of the provider. While previous research focuses extensively on the bargaining process between private insurers and providers, the role of Medicare in this process deserves further attention, especially when it comes to study potential private price re-adjustments following sudden shocks to Medicare pricing.

## 5 Conclusion

This paper sheds light on the extent to which providers respond to supply-side incentives in the context of physician-administered treatments. By construction, the “buy-and-bill” system regulating the distribution and reimbursement of these treatments gives providers more discretion in choosing whether and which treatments to administer, thus leaving opportunity for various incentives to operate.

I exploit the 2017 regulatory change in Medicare “allowed amount” payable to providers for reimbursing vaccine administration as an instrument for the observed price paid to providers by private insurers. A 2SLS regression framework shows that a 20% drop in private insurers’ reimbursement is followed by a 10% reduction in vaccine uptake among patients covered by private insurers, for most types of vaccines. However, for particular types of vaccines (e.g. flu), the supply curve is negatively sloped: a similar 20% drop in private reimbursement is associated to a 16% increase of supply. I consider demand-side financial incentives as negligible in the context of vaccine administration, given that copay and copayments, when different from zero, are pretty small. Moreover, preliminary evidence points toward the presence of spillover effects in providers’ behavior: on average, providers try to compensate the negative income shock experienced after the 2017 reform by billing additional services unrelated to vaccines, during vaccine-related visits.

Importantly, this paper also contributes to the formalization of the price following mechanism linking Medicare prices to private insurers’ pricing. In particular, it sheds light on the extent to which a Medicare price shock affecting a particular category of medical services, i.e. vaccine administration, propagates to private insurers and affects their already established contractual relationship with providers. I find that the price following relationship is heterogeneous across private insurer types, and that small providers respond more strongly to Medicare price adjustments, which is consistent with the price following mechanism being decreasing in providers’ bargaining power.

My analysis informs the debate on how to design optimal incentives schemes for providers, with the objective of achieving the adoption of the most cost-effective medical technologies. A natural direction for future research includes the investigation of the cost implications for insurance companies of adopting optimal incentive schemes, in the context of physician-administered drugs. This is particularly relevant given the recent FDA approval of Aducanumab for Alzheimer’s

disease, for example, and the related debate about to what extent Medicare should cover this expensive drug. A proper analysis would model demand for the treatment and compute the change in insurer costs following the coverage of the new drug. With a supply model, one could then allow insurers to re-price premiums and consumers to reallocate to health plans based on the new equilibrium market outcome (Tebaldi et al., 2021; Polyakova and Ryan, 2019).

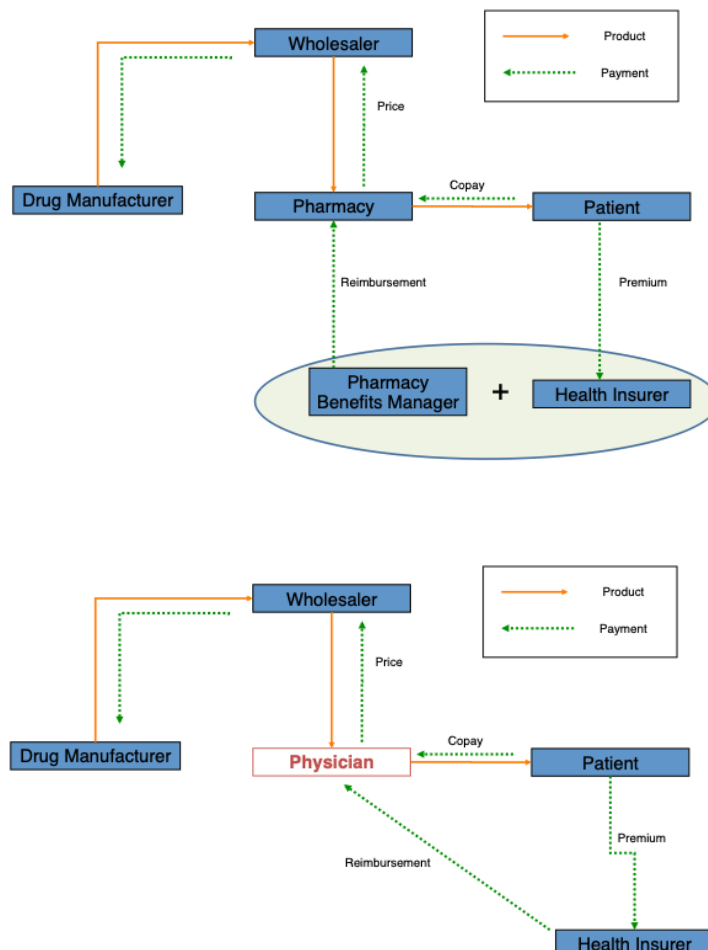
## References

- [1] Aron-Dine, A., L. Einav and A. Finkelstein (2013). The RAND Health Insurance Experiment, Three Decades Later. *Journal of Economic Perspectives* 27(1): 197–222.
- [2] Cabral, M., C. Carey and S. Miller (2021). The Impact of Provider Payments on Health Care Utilization: Evidence from Medicare and Medicaid. NBER Working Paper.
- [3] Chan, D.C., M. Dickstein (2019). Industry Input in Policymaking: Evidence from Medicare. *The Quarterly Journal of Economics*, 134(3): 1299–1342.
- [4] Chan, D.C., M. Gentzkow and C. Yu (2020). Selection with Variation in Diagnostic Skill: Evidence from Radiologists. *The Quarterly Journal of Economics*, conditionally accepted.
- [5] Chandra, A., D. Cutler, Z. Song (2012). Who Ordered That? The Economics of Treatment Choices in Medical Care. *The Handbook of Health Economics*, 2: 397-432.
- [6] Clemens, J. and J. D. Gottlieb (2016). In the Shadow of a Giant: Medicare’s Influence on Private Physician Payments. *Journal of Political Economy*, 125(1): 1-39.
- [7] Clemens, J. and J. D. Gottlieb (2014). Do Physicians’ Financial Incentives Affect Medical Treatment and Patient Health? *American Economic Review*, 104(4): 1320-1349.
- [8] Currie, J. and B. MacLeod (2017). Diagnosing Expertise: Human Capital, Decision Making and Performance Among Physicians. *Journal of Labor Economics*, 35(1):1-43.
- [9] Einav, L., A. Finkelstein, and N. Mahoney (2018). Provider Incentives and Healthcare Costs: Evidence from Long-Term Care Hospitals. *Econometrica*, 86(6): 2161-2219.
- [10] Finkelstein, A. (2004). Static and Dynamic Effects of Health Policy: Evidence from the Vaccine Industry. *The Quarterly Journal of Economics*, 119(2):527–564.
- [11] Gardenghi, C. (2020). Sick of Italian politics: partisan media campaigns and immunization choices. Working Paper.
- [12] Grennan, M., K. Myers, A. Swanson, and A. Chatterji (2021). No Free Lunch? Welfare Analysis of Firms Selling Through Expert Intermediaries. *Review of Economic Studies*, R&R.
- [13] Gross, T., M. S. Sacarny, and D. Silver (2021). Regulated Revenues and Hospital Behavior: Evidence from a Medicare Overhaul. NBER Working Paper 29023.
- [14] Gruber, J., J. Kim, and D. Mayzlin (1999). Physician Fees and Procedure Intensity: The Case of Cesarean Delivery. *Journal of Health Economics* 18:473–490.
- [15] Hackmann, M. B., V. Pohl and N. Ziebarth (2021). Patient Versus Provider Incentives in Long Term Care. *AEJ: Applied, R&R*.
- [16] Ho, K. and A. Pakes (2014). Hospital Choices, Hospital Prices and Financial Incentives to Physicians. *American Economic Review*, 2014, 104(12): 3841-84.
- [17] Hurley, J., and R. Labelle (1995). Relative fees and the utilization of physicians’ services in Canada. *Health Economics* 4:419–438.

- [18] Iizuka, Toshiaki (2012). Physician Agency and Adoption of Generic Pharmaceuticals. *American Economic Review*, 102 (6): 2826-58.
- [19] Jacobson M.G., T.Y. Chang, C. Earle, and J. Newhouse (2017). Physician Agency and Patient Survival. *Journal of Economic Behavior & Organization*, 134: 27-47.
- [20] Johnson E. (2014). Physician-Induced Demand. *Encyclopedia of Health Economics*, Volume 3.
- [21] Johnson E. and M. Rehavi (2016). Physicians Treating Physicians: Information and Incentives in Childbirth. *American Economic Journal: Economic Policy*, 8(1): 115-141.
- [22] Kremer, M., J. Levin, and C. Snyder (2020). Advance Market Commitments: Insights from Theory and Experience. *AEA Papers and Proceedings*, 110: 269-73.
- [23] McGuire (2000). Physician Agency. *Handbook of Health Economics*, Volume 1.
- [24] Oster, E. (2018). Does Disease Cause Vaccination? Disease Outbreaks and Vaccination Response. *Journal of Health Economics*, 57 (1): 90-101.
- [25] Polyakova, M. and S. P. Ryan (2019). Subsidy targeting with market power. NBER Working Paper 26367.
- [26] Rice, T. (1983). The impact of changing Medicare reimbursement rates on physician-induced demand. *Medical Care* 21, 803-815.
- [27] Tebaldi, P., A. Torgovitsky and H. Yang (2021). Nonparametric Estimates of Demand in the California Health Insurance Exchange. *Econometrica*, resubmitted.
- [28] Xiang, J. (2021). Physicians as Persuaders: Evidence from Hospitals in China. *Econometrica*, R&R.
- [29] Yip, W. (1998). Physician Responses to Medical Fee Reductions: Changes in the Volume and Intensity of Supply of Coronary Artery Bypass Graft (CABG) Surgeries in the Medicare and Private Sectors. *Journal of Health Economics* 17, 675-700.

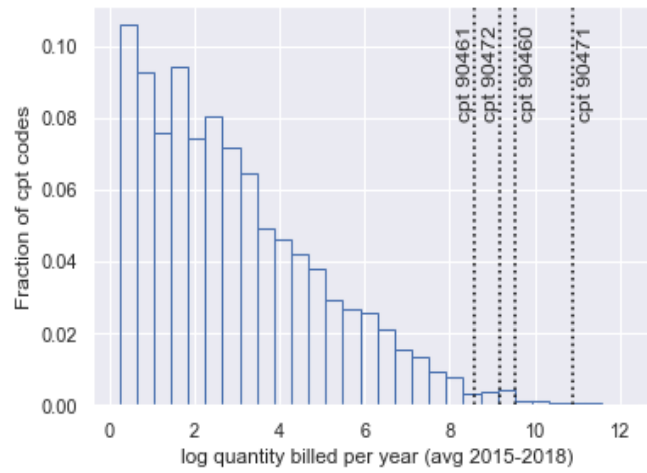
## Figures and tables

Figure 1: Typical prescription drug vs “buy-and-bill” system for PATs.



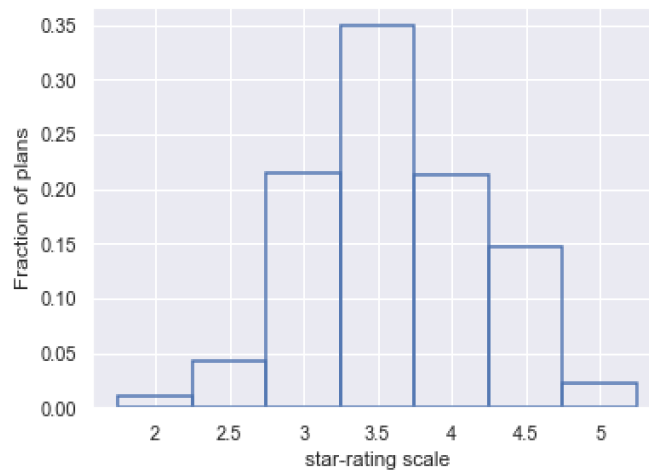
NOTE: These figures summarize the system for distribution and reimbursement for two major categories of medical products: typical prescription drugs (on top) vs physician-administered treatments, i.e. PATs (on bottom). While for prescription drugs providers operate solely as prescribers, for PATs providers play a crucial role by choosing which treatments to administer and by getting the related reimbursements directly. As a result, economic incentives are likely to influence prescribing decisions for PATs.

Figure 2: Quantity of outpatient services billed per year, by procedure code.



NOTE: For each procedural code included in outpatient claims, this figure shows the natural logarithm of the annual quantity billed (average between years 2015 to 2018). I focus on a single insurance type (HMO), but the trend is similar for all other insurance types. The vertical dotted lines highlight the key procedural codes used for vaccine administration. Here, for example, CPT 90471 is the 7th most billed procedural code. Source: New Hampshire commercial claims data.

Figure 3: Distribution of health insurance plans, based on 2018 star rating.



NOTE: This histogram displays the distribution of Medicare Advantage health insurance plans based on their 2018 star rating, given their performances in the previous year. Flu vaccine administration rate in the covered population is among the criteria used to assign stars. Source: CMS.



Table 1: Summary statistics: Medicare FFS aggregate data, New Hampshire only.<sup>26</sup>

	<i>Obs</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
N Provider-Year obs	4639.00				
N Providers	1074.00				
N Procedure codes (vaccine-related)	5.00				
N Proc codes per provider (vaccine-related)	1074.00	1.70	0.57	1.00	4.00
N Vaccine administrations per provider (2017)	681.00	132.47	126.95	11.00	1137.00
Tot \$ reimb. for vaccine admin per provider (2017)	681.00	2924.35	2670.95	31.35	28122.20
Tot \$ reimbursement per provider (2017)	681.00	46846.96	48920.51	371.46	492649.00

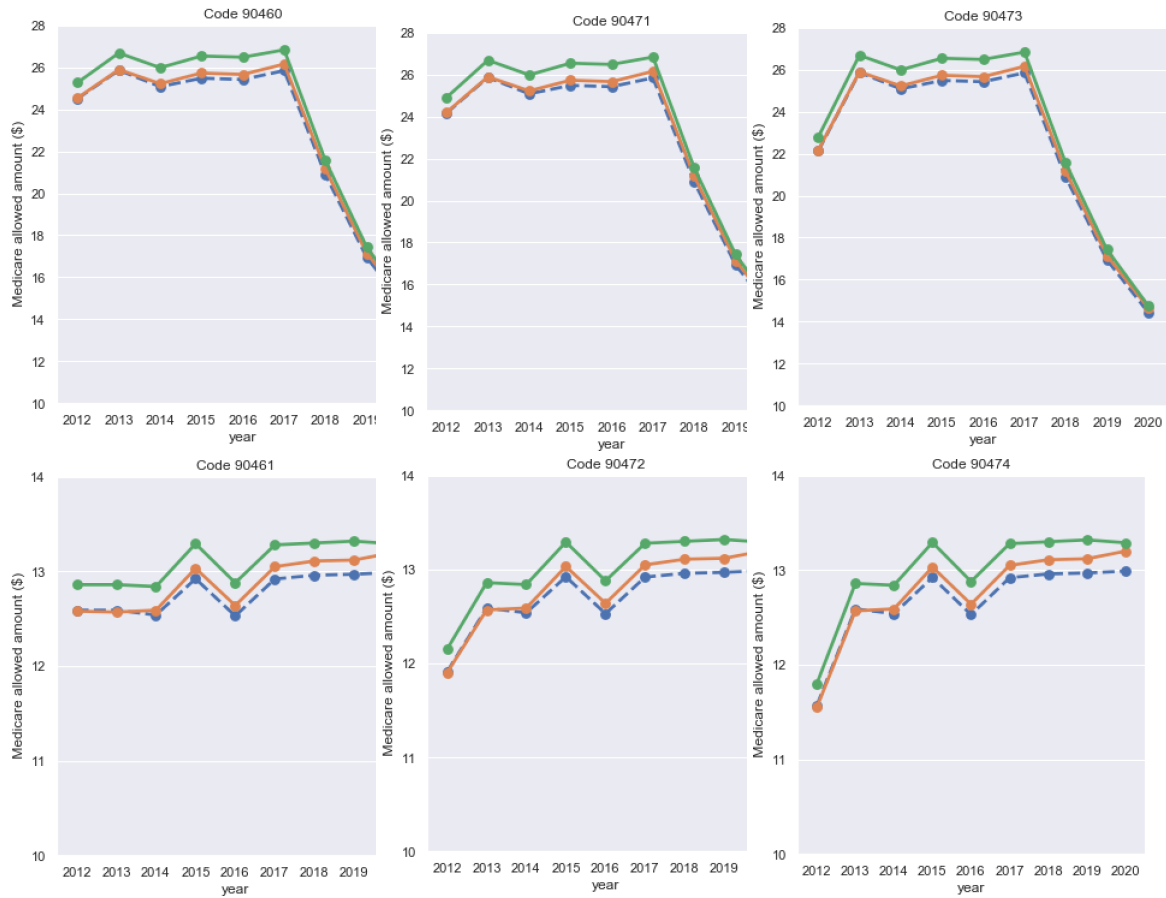
Table 2: Summary statistics: New Hampshire commercial claims data.<sup>27</sup>

	<i>Obs</i>	<i>Mean</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
N Provider-Year-Insurer obs	30158.00				
N Provider-Year obs	12451.00				
N Providers	2818.00				
N Procedure codes (vaccine-related)	9.00				
N Proc codes per provider (vaccine-related)	2818.00	2.75	1.70	1.00	8.00
N Private insurers	6.00				
N Private insurers per provider	2818.00	3.05	1.50	1.00	6.00
N Vaccine administrations per provider (2017)	1692.00	72.35	87.84	2.00	569.00
Tot \$ reimb. for vaccine admin per provider (2017)	1692.00	2372.10	3408.61	3.57	26401.59
Tot \$ reimbursement per provider (2017)	1692.00	96457.19	140195.60	168.87	2004120.00

<sup>26</sup>This table refers to the sample of providers administering at least one vaccine during the available time-span (2012-18). Vaccine-related procedure codes refer to those codes indicating vaccine administration only, so I am excluding codes indicating vaccine products. As a consequence, total reimbursement for vaccine administration in 2017 refers to administration per se, and does not include the reimbursement for any vaccine product provided to patients. Total reimbursement in 2017 is the cumulative reimbursement obtained by Medicare for all those services administered in 2017 in non-facility settings, for those providers administering at least one vaccine during the available time-span. Overall, i.e. without these restrictions, the dataset includes around 4,000 Medicare providers operating in non-facility settings in New Hampshire, in the available time-span (2012-18).

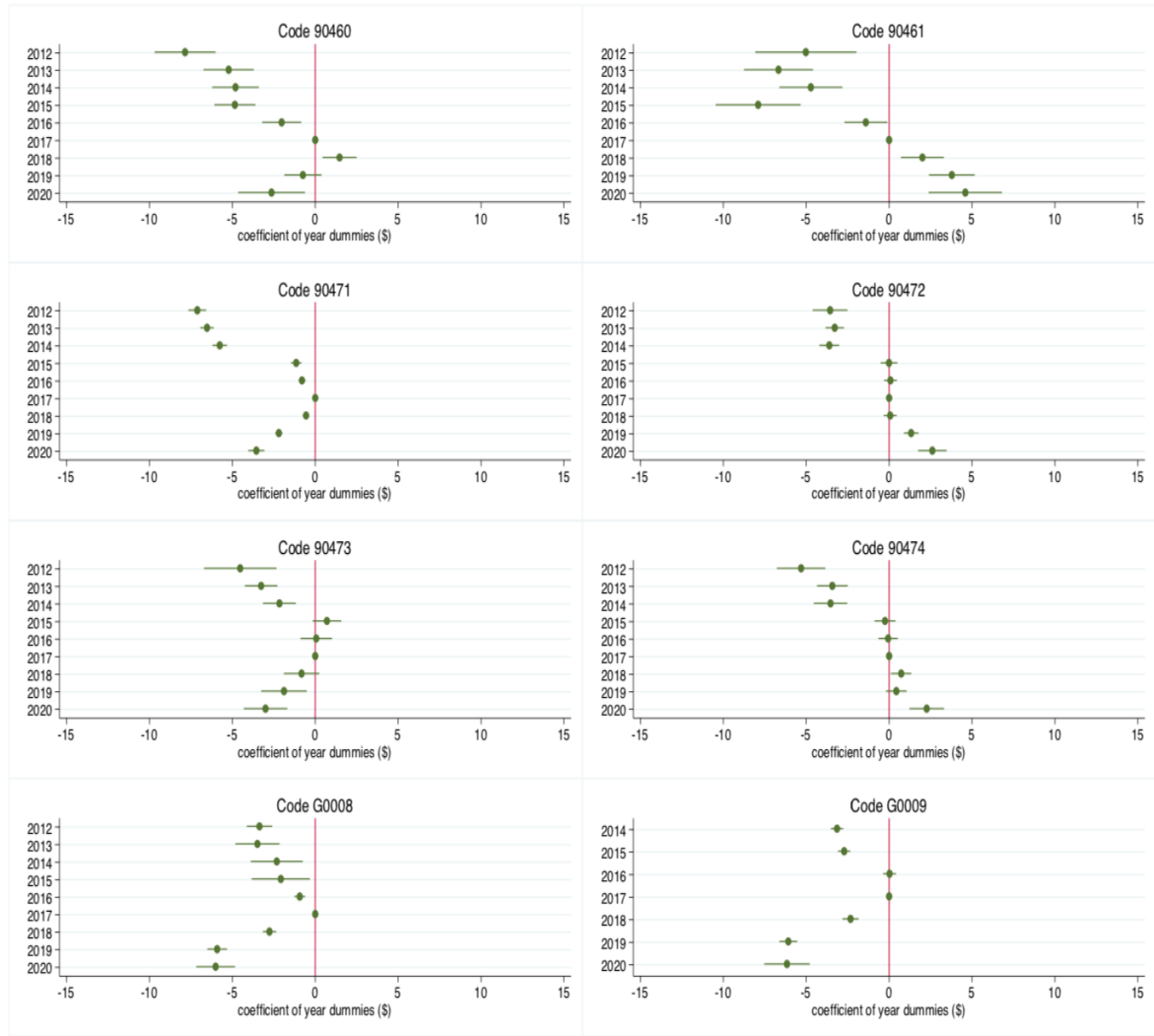
<sup>27</sup>This table refers to the sample of providers administering at least one vaccine during the available time-span (2012-20). Vaccine-related procedure codes refer to those codes indicating vaccine administration only, so I am excluding codes indicating vaccine products. As a consequence, total reimbursement for vaccine administration in 2017 refers to administration per se, and does not include the reimbursement for any vaccine product provided to patients. Total reimbursement in 2017 is the cumulative reimbursement obtained by private insurers for all those services administered in 2017 in office settings, for those providers administering at least one vaccine during the available time-span. Overall, i.e. without these restrictions, the dataset includes around 35,000 providers operating in office settings in New Hampshire and treating private insurance patients, in the available time-span (2012-20).

Figure 4: Change in Medicare’s regulatory amount for vaccine administration.



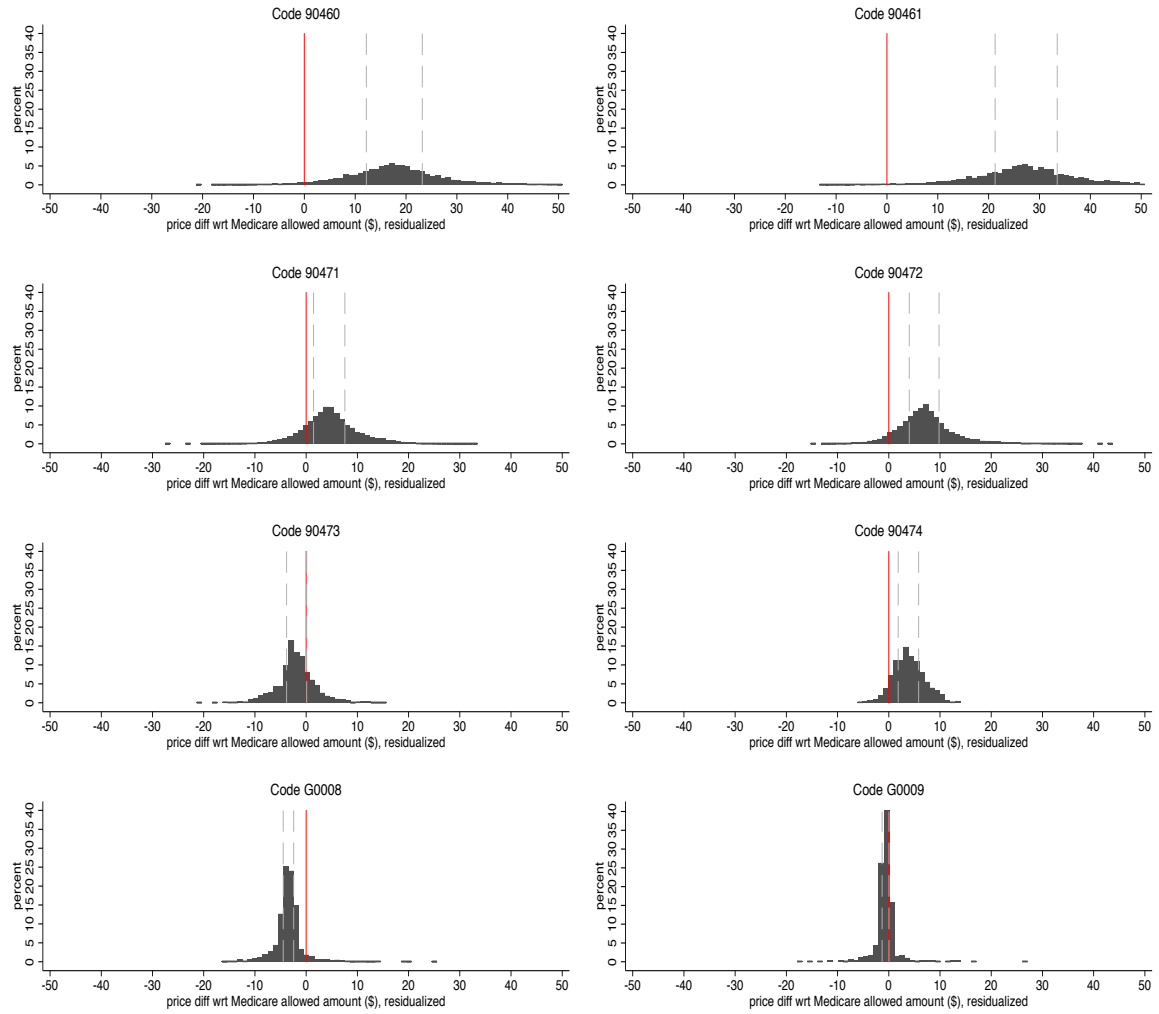
NOTE: These figures show the time-trend of Medicare allowed amount for a set of CPT codes used to bill vaccine administration, between 2012 and 2020. The allowed amounts displayed refer to non-facility settings only. The blue dotted line represents the US average, while the green and orange solid lines refer to New Hampshire and Colorado, respectively. In the latter two cases, there is no geographic variation within each state, as per Medicare’s geographic segmentation. Overall, the figures document a pronounced drop of reimbursement to providers for vaccine administration starting from 2018, when it comes to CPT codes 90460, 90471, 90473. I observe a 20% drop (i.e. \$5) in reimbursement for vaccine administration in 2018 relative to 2017 and a drop of almost 50% by 2020 relative to 2017 (US average). On the contrary, the reimbursement associated to CPT codes 90461, 90472, 90474 is stable. Source: Medicare FFS provider utilization and payment aggregate data.

Figure 5: Observed variation of private insurance reimbursement amounts.



NOTE: These figures show the variation of observed average prices among private insurers over years, for each single CPT separately. I restrict the focus on individual providers only (see appendix for heterogeneity across provider types). The reference point is 2017, i.e. the year right before Medicare allowed amount reform. Average prices are residualized by regressing them on provider FE and insurer FE. For each CPT, estimates are obtained from regressing residualized average prices at the provider-year level on time fixed effects. For interpretation purposes, unconditional means are added back. The figures show that observed prices decrease for those CPT codes for which Medicare reform prescribes a reduction of reimbursement after 2017 (i.e. 90460, 90471, 90473). G-codes follow this trend as well: according to the regulation<sup>28</sup>, Medicare allowed amount for G-codes is anchored to the one of CPT code 90471. Observed prices are stable or slightly increasing after 2017 for the remaining CPT codes. Source: New Hampshire commercial claims data.

Figure 6: Deviation of private insurers' reimbursements from Medicare regulatory prices.



NOTE: For each CPT code, the figures above depict the distribution of the difference between observed private prices and Medicare allowed amount, after residualization (dashed lines represent the 25 and 75 percentiles). Specifically, I residualize the price difference by regressing it on provider FE and year FE. Unconditional means are added back for interpretation purposes. These figures reveal that, for most of the vaccine-related CPT codes, private insurers tend to set a reimbursement level above the one prescribed by Medicare; moreover, within each CPT code, there is heterogeneity among insurers. Not surprisingly, reimbursements for G-codes<sup>29</sup> are pretty close to the ones prescribed by Medicare and are characterized by a smaller variance. Source: New Hampshire commercial claims data.

Table 3: Price transmission to commercial insurers (entire sample).

	(1)	(2)	(3)	(4)
Log private price				
Log Medicare price	0.381*** (0.0896)	0.543** (0.141)		
x EPO			-0.0465 (0.0528)	0.0920 (0.109)
x HMO			0.511*** (0.0551)	0.656*** (0.0489)
x MA HMO			0.861*** (0.0811)	1.003*** (0.0406)
x POS			0.408*** (0.0542)	0.551*** (0.0620)
x PPO			0.416*** (0.0577)	0.559*** (0.0564)
x Suppl			0.314*** (0.0706)	0.398*** (0.0459)
Obs	385	385	385	385
Adj R-sq	0.375	0.564	0.391	0.583
Year FEs	Yes	Yes	Yes	Yes
Insurer FEs	Yes	Yes	Yes	Yes
Procedure FEs	No	Yes	No	Yes
Clusters	Insurer	Insurer	Insurer	Insurer

Robust standard errors in parentheses (\*\*\*)  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ )

Table 4: Price transmission to commercial insurers (individuals only).

	(1)	(2)	(3)	(4)	(5)	(6)
Log private price						
Log Medicare price	0.284*** (0.0544)	0.368** (0.120)				
x EPO			0.140*** (0.0270)	0.0804 (0.0617)		
x HMO			0.343*** (0.0299)	0.362*** (0.0668)		
x MA HMO			1.179*** (0.0744)	1.244*** (0.112)		
x POS			0.118** (0.0297)	0.125 (0.0674)		
x PPO			0.311*** (0.0282)	0.327*** (0.0676)		
x EPO x q1					0.141** (0.0372)	0.0874 (0.0615)
x EPO x q2					0.0288 (0.0507)	0.00315 (0.0738)
x EPO x q3					0.214** (0.0516)	0.160 (0.0848)
x EPO x q4					0.276* (0.103)	0.177* (0.0676)
x HMO x q1					0.330*** (0.0464)	0.361*** (0.0673)
x HMO x q2					0.231** (0.0596)	0.287** (0.0818)
x HMO x q3					0.397*** (0.0581)	0.428** (0.0942)
x HMO x q4					0.445*** (0.0938)	0.402*** (0.0643)
x MA HMO x q1					1.187*** (0.0750)	1.239*** (0.107)
x MA HMO x q2					1.109*** (0.0878)	1.189*** (0.119)
x MA HMO x q3					1.247*** (0.0916)	1.309*** (0.131)
x MA HMO x q4					1.326*** (0.0986)	1.359*** (0.0920)
x POS x q1					0.0860 (0.0448)	0.110 (0.0685)
x POS x q2					0.0188 (0.0577)	0.0723 (0.0817)
x POS x q3					0.179** (0.0574)	0.194 (0.0943)
x POS x q4					0.244* (0.0944)	0.191** (0.0635)
x PPO x q1					0.273*** (0.0483)	0.309** (0.0717)
x PPO x q2					0.201** (0.0625)	0.258** (0.0867)
x PPO x q3					0.388*** (0.0614)	0.409** (0.0992)
x PPO x q4					0.439*** (0.0910)	0.417*** (0.0613)

Table 5: Supply response to reimbursement change.

	(1)	(2)	(3)	(4)	(5)	(6)
Log(number vaccines administered)						
CPT 90460						
Private price (instrumented)	0.0615** (0.0250)	0.0585** (0.0236)	0.0490** (0.0217)	0.0503** (0.0215)	0.0243*** (0.00768)	0.0200*** (0.00724)
1st stage coefficient	0.715*** (0.198)	0.755*** (0.201)	0.762*** (0.198)	0.779*** (0.200)	1.107*** (0.134)	1.164*** (0.142)
Obs	5,595	5,595	5,595	5,595	5,469	5,082
F stat 1st stage	13.07	14.12	14.80	15.22	68.50	67.58
CPT 90471						
Private price (instrumented)	0.0312*** (0.00609)	0.0308*** (0.00611)	0.0322*** (0.00644)	0.0319*** (0.00631)	0.0332*** (0.00304)	0.0387*** (0.00362)
1st stage coefficient	1.119*** (0.0669)	1.127*** (0.0676)	1.059*** (0.0670)	1.084*** (0.0674)	1.493*** (0.0432)	1.296*** (0.0416)
Obs	24,700	24,700	24,700	24,700	24,521	23,407
F stat 1st stage	280	277.4	249.7	258.7	1191	970.8
CPT G0008						
Private price (instrumented)	-0.0720*** (0.0153)	-0.0911*** (0.0152)	-0.0820*** (0.0247)	-0.0932*** (0.0270)	-0.102*** (0.0130)	-0.0871*** (0.0123)
1st stage coefficient	1.473*** (0.127)	1.549*** (0.125)	0.861*** (0.127)	0.801*** (0.126)	1.539*** (0.101)	1.488*** (0.0832)
Obs	2,120	2,120	2,120	2,119	1,883	1,712
F stat 1st stage	134.6	153.3	46.10	40.57	232.4	319.8
CPT G0009						
Private price (instrumented)	-0.00511 (0.0131)	-0.00704 (0.0127)	-0.0124 (0.0128)	-0.0175 (0.0142)	-0.0322** (0.0149)	-0.0271 (0.0253)
1st stage coefficient	2.639*** (0.284)	2.825*** (0.288)	2.571*** (0.270)	2.446*** (0.278)	2.745*** (0.263)	2.707*** (0.316)
Obs	845	843	845	843	676	640
F stat 1st stage	86.30	96.38	90.75	77.34	109.1	73.14
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FEs	Yes	Yes	Yes	Yes	Yes	Yes
ProvType FEs	Yes	Yes	No	No	No	No
Ins-ProvType FEs	No	Yes	No	No	No	No
ProvSize	No	No	Yes	Yes	No	No
Ins-ProvSize	No	No	No	Yes	No	No
Prov FEs	No	No	No	No	Yes	Yes
Ins-Prov FEs	No	No	No	No	No	Yes
Clusters (prov size quartile)	Yes	Yes	Yes	Yes	Yes	Yes
Control n claims (lin & sq)	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses (\*\*\*) p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1)

Figure 7: Private prices' pretrends: event study.

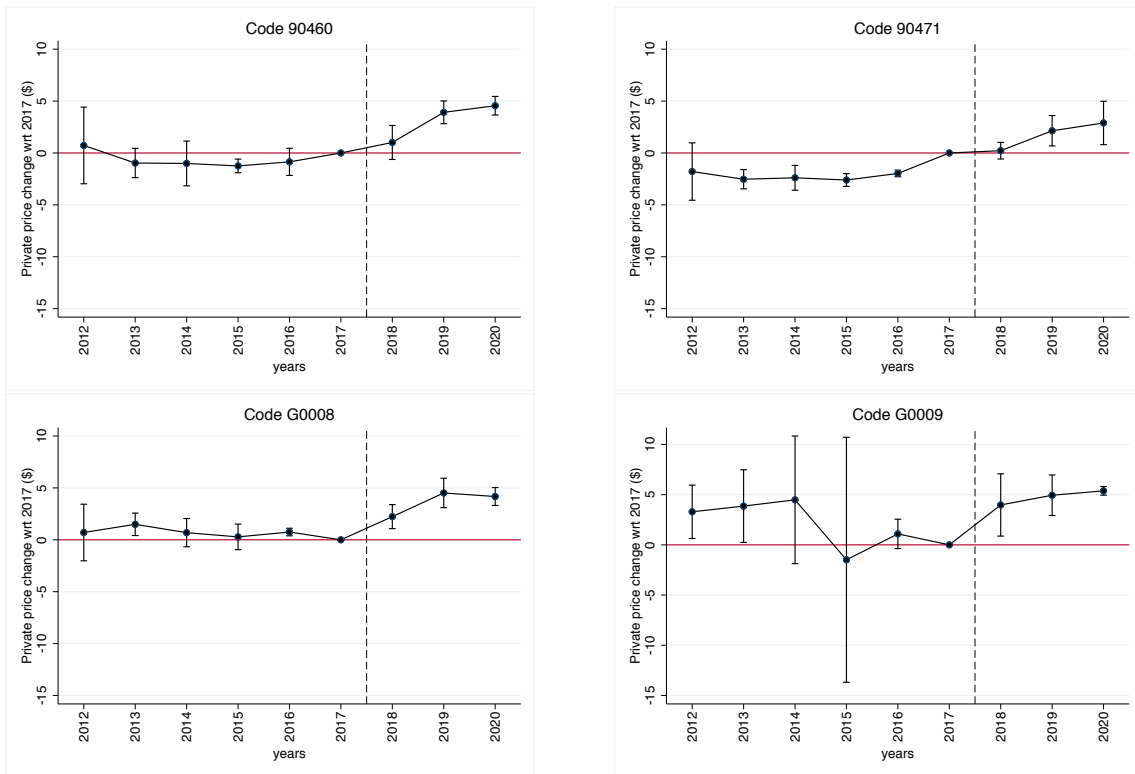




Table 6: Preliminary evidence of spillover effects.

year	\$ vaccine admin	\$ vaccine-product	\$ unrelated to vaccines	# unrelated to vaccines
2012	27	19	152	1.9
2013	25	13	284	4.1
2014	26	20	227	4.0
2015	29	29	138	2.2
2016	30	48	125	1.5
2017	30	50	142	1.6
2018	24	49	156	1.8
2019	18	53	164	1.8
2020	16	52	376	5.4

NOTE: For a single insurer type (Medicare Advantage), this figure shows the number of services and the related amounts reimbursed on average in each year, focusing on the 100K visits where at least one flu vaccine is provided. The table highlights that, for those visits in which at least one flu vaccine is administered, (a) the average reimbursement for vaccine administration drops after 2017 (as expected, due to Medicare reform); (b) the average reimbursement for vaccine-products administered during the visit remains pretty stable - thus, it does not compensate (a); (c) the number of vaccine-unrelated services seems to increase after the 2017 reform and, consequently, also the average total amount reimbursed for these services. The outliers reported for years 2013, 2014 and 2020 can be explained in light of the exceptional circumstances affecting US in those years (swine flu in 2013-14, Covid pandemic in 2020). Source: New Hampshire commercial claims data.

# Appendix

## 5.1 List of procedure codes used for vaccine administration

In what follows, I detail the main procedure codes used by private insurers to bill vaccine administrations. The different meaning of the following codes is driven by patient's age, route of administration, the presence of any counseling by the provider, the vaccine being the first (or the first component in a multicomponent vaccine) or any subsequent vaccine administered during a given visit.<sup>30</sup>

- 90460: Immunization administration through 18 years of age, via any route of administration, with counseling by physician or other qualified health care professional; first or only component of each vaccine administered (e.g. for Tdap, tetanus is the first component, no matter whether Tdap is the first vaccine administered during the visit).
- 90461: Immunization administration through 18 years of age via any route of administration, with counseling by physician or other qualified health care professional; each additional vaccine component administered, different from the first one.
- 90471: Immunization administration for whatever age (percutaneous, intradermal, subcutaneous, or intramuscular injections); no counseling; first or only vaccine (no matter if single or combination of components), e.g. Tdap is billed as a single vaccine.
- 90472: Immunization administration for whatever age (percutaneous, intradermal, subcutaneous, or intramuscular injections); no counseling; each additional vaccine (single or combination).
- 90473: Immunization administration by intranasal or oral route; no counseling; first or only vaccine (no matter if single or combination of components).
- 90474: Immunization administration by intranasal or oral route; no counseling; each additional vaccine (single or combination).

Formally, Medicare G-codes are not used among private insurers, although in the data I find a relatively consistent group of providers employing codes G0008 and G0009 also among private insurers.<sup>31</sup> On the other hand, Medicare accepts private insurers' codes for all those additional covered vaccine types<sup>32</sup> that are not billed through G-codes (flu shot -G0008-, vaccine for pneumococcal disease -G0009-, hepatitis B vaccine for people at risk -G0010-).

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<sup>30</sup>Sources: <https://www.physicianspractice.com/view/correct-coding-vaccine-administration> , <https://www.aafp.org/family-physician/practice-and-career/getting-paid/coding/vaccine-administration.html>

<sup>31</sup>This is likely due to mistakes, given that the same provider often serves either Medicare and non-Medicare patients.

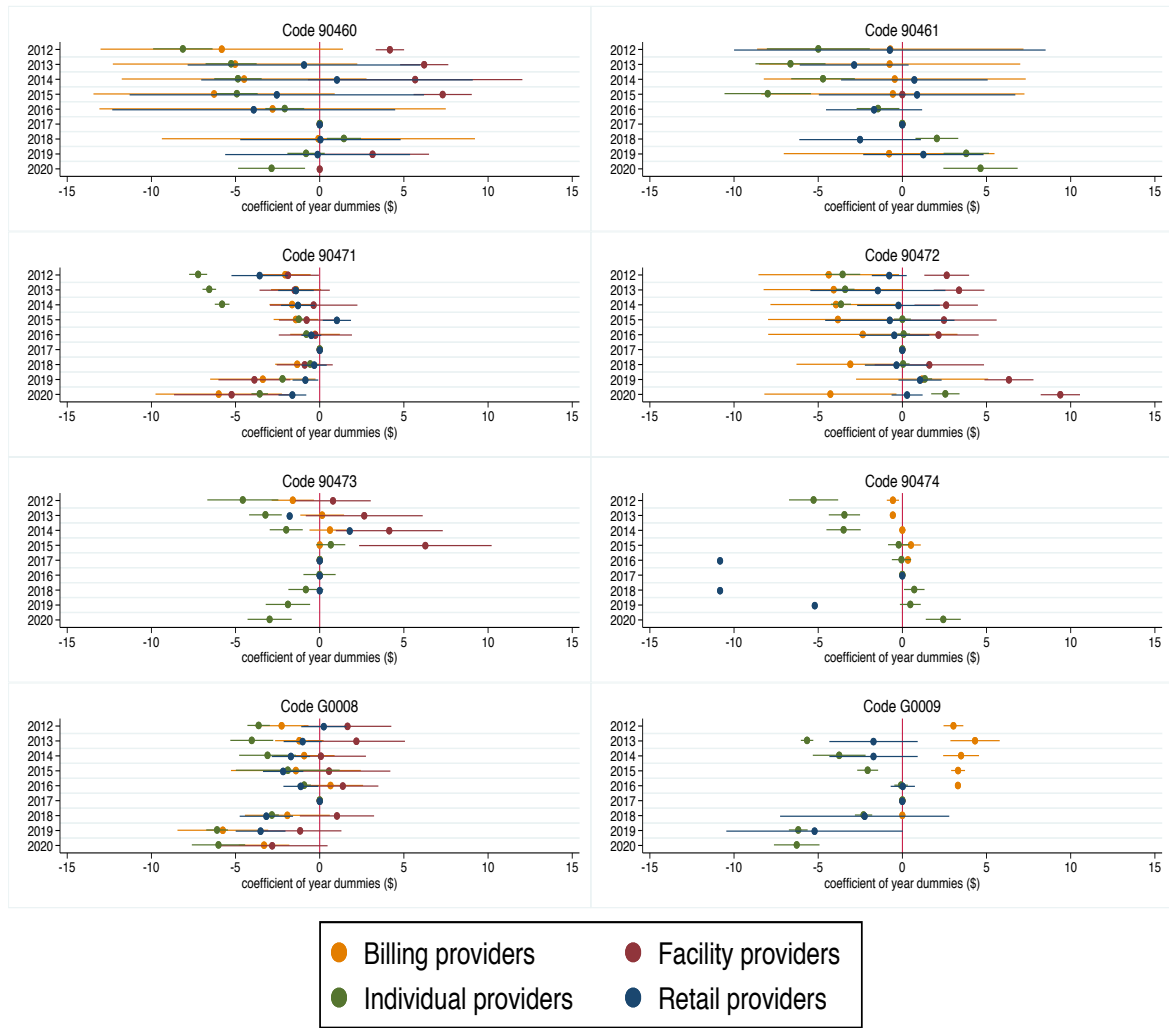
<sup>32</sup>In addition to flu, pneumococcal disease and hepatitis B, Medicare Part B covers vaccines related to treatment of an injury or to direct exposure to the disease, e.g. tetanus, rabies, etc. Medicare Part D covers all the remaining commercially available vaccines not covered by Medicare part B: usually, these vaccines are administered more frequently within the non-Medicare population than in the Medicare population.

## 5.2 Additional figures and tables

Figure 8: New Hampshire: map of counties and main cities



Figure 9: Observed variation of private insurances' reimbursement amounts.



NOTE: These figures show the variation of observed average prices over years, for each single CPT separately and for each type of provider. The reference point is 2017, i.e. the year right before Medicare allowed amount reform. Average prices are residualized by regressing them on provider FE and insurer FE. For each CPT and provider type, estimates are obtained from regressing residualized average prices at the provider-year level on time fixed effects. For interpretation purposes, unconditional means are added back. The figures show that observed prices decrease for those CPT codes for which Medicare reform prescribes a reduction of reimbursement after 2017 (i.e. 90460, 90471, 90473), especially for individual providers. G-codes follow this trend as well: according to several sources, Medicare allowed amount for G-codes is anchored to the one for CPT code 90471. Observed prices are stable or slightly increasing after 2017 for the remaining CPT codes. Source: New Hampshire commercial claims data.

Table 7: (Lagged) Price transmission to commercial insurers (all sample).

	(1)	(2)	(3)	(4)	(5)	(6)
Log private price						
Log Medicare price	0.323** (0.0820)	0.312** (0.0886)	0.461 (0.508)			
x EPO				0.0525 (0.0322)	0.0132 (0.0440)	0.00616 (0.610)
x HMO				0.414*** (0.0243)	0.410*** (0.0225)	0.423 (0.490)
x MA HMO				0.787*** (0.0716)	0.799*** (0.0730)	0.764 (0.559)
x POS				0.354*** (0.0205)	0.344*** (0.0261)	0.329 (0.525)
x PPO				0.385*** (0.0472)	0.368*** (0.0546)	0.351 (0.552)
x Suppl				-0.0818* (0.0362)	-0.107** (0.0267)	-0.183 (0.603)
Obs	385	385	385	385	385	385
Adj R-sq	0.369	0.395	0.570	0.381	0.410	0.588
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FEs	Yes	Yes	Yes	Yes	Yes	Yes
Medicare Year lagged	No	Yes	Yes	No	Yes	Yes
Procedure FEs	No	No	Yes	No	No	Yes
Clusters	Insurer	Insurer	Insurer	Insurer	Insurer	Insurer

Robust standard errors in parentheses (\*\*\*)  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 8: (Lagged) Price transmission to commercial insurers (individuals only).

	(1)	(2)	(3)	(4)	(5)	(6)
Log private price						
Log Medicare price	0.284*** (0.0494)	0.460** (0.138)				
x EPO			0.192*** (0.0170)	0.201** (0.0692)		
x HMO			0.312*** (0.0172)	0.405*** (0.0676)		
x MA HMO			1.136*** (0.0736)	1.286*** (0.121)		
x POS			0.147*** (0.0168)	0.221** (0.0685)		
x PPO			0.294*** (0.0184)	0.382*** (0.0706)		
x EPO x q1					0.193*** (0.0264)	0.210** (0.0661)
x EPO x q2					0.0824* (0.0372)	0.123 (0.0827)
x EPO x q3					0.252*** (0.0496)	0.264* (0.104)
x EPO x q4					0.340** (0.0875)	0.299*** (0.0498)
x HMO x q1					0.298*** (0.0317)	0.409*** (0.0654)
x HMO x q2					0.201*** (0.0418)	0.331** (0.0829)
x HMO x q3					0.353*** (0.0520)	0.457** (0.105)
x HMO x q4					0.429*** (0.0833)	0.450*** (0.0417)
x MA HMO x q1					1.142*** (0.0734)	1.279*** (0.116)
x MA HMO x q2					1.066*** (0.0836)	1.226*** (0.130)
x MA HMO x q3					1.195*** (0.0976)	1.337*** (0.150)
x MA HMO x q4					1.295*** (0.0849)	1.399*** (0.0890)
x POS x q1					0.117** (0.0296)	0.211** (0.0660)
x POS x q2					0.0510 (0.0396)	0.170 (0.0827)
x POS x q3					0.195** (0.0506)	0.274* (0.105)
x POS x q4					0.289** (0.0841)	0.293*** (0.0427)
x PPO x q1					0.253*** (0.0358)	0.366*** (0.0720)
x PPO x q2					0.183** (0.0474)	0.312** (0.0903)
x PPO x q3					0.352*** (0.0567)	0.443** (0.111)
x PPO x q4					0.434*** (0.0791)	0.473*** (0.0409)

Table 9: Supply response to reimbursement change.

	(1)	(2)	(3)	(4)
Log(number vaccines administered)				
CPT 90460				
Private price (instrumented)	0.0354*** (0.0131)	0.0378*** (0.0131)	0.0150** (0.00661)	0.00951 (0.00675)
1st stage coefficient	1.460*** (0.250)	1.493*** (0.253)	1.523*** (0.173)	1.431*** (0.176)
Obs	5,059	5,059	4,949	4,604
F stat 1st stage	34.18	34.73	77.86	66.42
CPT 90471				
Private price (instrumented)	0.0274*** (0.00618)	0.0313*** (0.00632)	0.0350*** (0.00372)	0.0314*** (0.00394)
1st stage coefficient	1.094*** (0.0692)	1.089*** (0.0697)	1.226*** (0.0456)	1.176*** (0.0436)
Obs	21,938	21,938	21,820	20,883
F stat 1st stage	250.1	244.5	723.7	726.7
CPT G0008				
Private price (instrumented)	-0.0514*** (0.0129)	-0.0320** (0.0136)	-0.0618*** (0.00961)	-0.0343*** (0.00979)
1st stage coefficient	1.095*** (0.0773)	1.056*** (0.0796)	1.255*** (0.0583)	1.366*** (0.0589)
Obs	1,498	1,497	1,328	1,211
F stat 1st stage	200.8	176	463.3	538.1
CPT G0009				
Private price (instrumented)	-0.0124 (0.0135)	-0.0196 (0.0143)	-0.0260* (0.0137)	-0.0697* (0.0386)
1st stage coefficient	1.513*** (0.125)	1.534*** (0.127)	1.456*** (0.0937)	0.941*** (0.138)
Obs	744	743	602	574
F stat 1st stage	147.5	146.8	241.1	46.60
Year FEs	Yes	Yes	Yes	Yes
Insurer FEs	Yes	Yes	Yes	Yes
ProvSize	Yes	Yes	No	No
Ins-ProvSize	No	Yes	No	No
Prov FEs	No	No	Yes	Yes
Ins-Prov FEs	No	No	No	Yes
Clusters (prov size quartile)	Yes	Yes	Yes	Yes
Control n claims (lin & sq)	Yes	Yes	Yes	Yes

Standard errors in parentheses (\*\*\*)  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$