Innovations and Inequities in Access to Medical Services*

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Abstract

Improving returns on health spending requires balancing tradeoffs between promoting innovative treatments and equitable care access. Introducing innovative treatments can negatively impact adjacent services by straining specialist capacity or degrading physician skills, creating spillover effects that reduce overall access to care while exacerbating inequities and inefficiencies. I propose a model of physician specialization to study these effects. When innovations compete with other procedures for inputs, total treatment rates may decline, leaving some patients to forego care. I apply the model to aortic valve replacements, showing adoption reduced overall intervention volumes in interventional cardiology. This was driven by capacity constraints and declining operator skill, resulting in worse average outcomes for patients receiving non-innovated interventions. These reductions disproportionately affected historically marginalized populations, worsening inequities and inefficiencies in patient allocation and outcomes.

Keywords: Innovation Diffusion, Health Inequities, Capacity Constraints, Physician Skill, Allocative Efficiency

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1 Introduction

Improving the quality of medical treatments has immense economic and social value, through returns from improved health and insurance value from reduced population risk (Murphy and Topel, 2006; Lakdawalla et al., 2017). Developing and disseminating novel medical technologies is a promising way to improve the return on high levels of health spending in developed countries (Cutler et al., 2007). However, novel technologies may exacerbate health inequities, which have affected marginalized individuals across socioeconomic status, race, and ethnicity—among others—for over two centuries (Adler and Rehkopf, 2008).

Novel interventions are typically high cost, meaning there may be financial barriers to accessing them (Hoagland and Kipping, 2024; Arcaya and Figueroa, 2017). However, innovations may also have indirect effects affecting access to other, already existing technologies. These effects vary by the characteristics of the innovating technology. Some innovations may expand access to earlier, now cheaper, generations of a technology; for example, innovation in durable goods markets such as MRI machines may reduce the price of older models (Gowrisankaran and Rysman, 2012). Other innovations such as surgical procedures, meanwhile, compete with existing interventions for scarce inputs, such as capacity-constrained physician or operating room time (Gandhi, 2023), or physician learning and skill development (Chandra and Staiger, 2007; Gong, 2018).

In the case where innovations and existing medical interventions compete for surgical time or skill, an innovation's overall impact on access to medical services is an open question. Total intervention volume might decrease—restricting access to care—if capacity constraints mean that adopting a more time-intensive intervention leaves less availability for other, existing procedures (Kleiner, 2019; Harris et al., 2020). These declines may be further impacted by changes in operator skill post-adoption. On the one hand, adoption may leave operators with less time to perform the older technique, spurring a loss of skill; on the other, innovations may generate positive skill spillovers across techniques. Understanding an innovation's impact on the allocation of patients to procedures—including the efficiency of those allocations or their implications for health equity—requires carefully considering these indirect effects.

I present a model of physician decision-making characterizing these effects. In the model, physicians select one of three treatments for patients: two interventions of different intensity (in the empirical setting, a high-intensity aortic valve *replacement* or a lower-intensity aortic valve *support* procedure), and standard maintenance care. The model incorporates technological spillovers—meaning treatment returns increase with volume (Chandra and Staiger, 2007, 2016)—and waiting costs arising from constraints on the total availability of interventions. Innovations that increase returns to high-intensity procedures change decision-making

along two margins. First, some intermediate-risk patients are sorted into higher-intensity interventions, decreasing the use of lower-intensity procedures and corresponding returns for inframarginal patients continuing to receive them. Second—and more surprising—reduced returns result in some high-risk patients no longer receive any intervention at all.

The model's central insight is that these extensive margin changes may inequitably affect some patient groups and exacerbate allocative inefficiencies in who receives care. Inequitable crowd-out may arise directly—because different groups have different surgical appropriateness—or indirectly—because risk is imperfectly observed across groups. When this crowd-out is more pronounced in markets that already have a low probability of treating patients conditional on their risk, these inequitable losses may further exacerbate allocative inefficiencies, resulting in underprovision of care to certain patient groups.

The model I present captures responses to a broad class of innovations competing with adjacent interventions for intensive skill or capital. This includes, for example, many recent developments in minimally-invasive or robotic surgeries, which have unique requirements for surgical training, skill development, and facility space or capital. Training in using these devices may crowd-out traditional surgical skill development and affect both quality and volume for patients who do not meet criteria for robotic procedures. Other relevant examples of possible model applications include specialized stroke interventions (e.g., mechanical thrombectomy), novel cancer therapies (CAR-T, proton therapy), and minimally invasive orthopedic procedures (arthroscopy), all of which require similar modifications to capacity and operator training that may disrupt availability of existing, lower-intensity services.[1]

I use the U.S. dissemination of transcatheter aortic valve replacements (TAVR) as a case study to test the model's predictions. TAVR is a minimally-invasive and cost-effective alternative to open surgical aortic valve replacements (SAVRs); importantly, TAVR is appropriate for patients deemed too high-risk for SAVR. I use TAVR's adoption in a local market as the innovating shock in the model and study its impact on overall access to interventional cardiology. Previous work has used TAVR to study physician learning and centralized access to innovations (Yang, 2023) and adoption decisions (Huckman and Stern, 2022; League, 2023).

TAVR's adoption occurred primarily by interventional cardiologists, who typically performed valve support procedures such as catheterization prior to adoption. To estimate how TAVR's adoption affected the availability of lower-intensity procedures, I therefore study its

[1]In addition, the core finding that an innovation in one product may affect the availability of adjacent products generalizes to a broader set of innovations outside of medical technologies, such as developments in education (Biasi and Ma, 2022). For example, recent work considers detrimental effects of broadband internet in primary schools (Belo et al., 2014), noting that technology is not equitably accessible (Supovitz and Manghani, 2022). If innovations in classrooms directly compete for resources such as teacher attention, expanded internet-based learning may inequitably disrupt student learning.

impact on these valve support interventions (also called percutaneous coronary interventions, or PCIs). Although adjacent to—not replaced by—TAVR, I observe the provision of PCIs falls dramatically following adoption, causing *total* procedural volume to decline by 8%.

I show that both physician skill degradation and capacity constraints are important mechanisms driving this decline. First, TAVR's adoption resulted in worse average patient outcomes for PCIs. I use an instrumental variables approach, leveraging a patient's differential distance to PCI operators and average TAVR adoption rates within a market to instrument for an individual PCI operator's adoption of TAVR. I find that TAVR's adoption led to a 8% increase in surgical complications, an 18% increase in readmission rates, and a 12% increase in mortality. Second, I show capacity constraints—primarily the use of the catheterization lab—also affected patient access. After TAVR's adoption, fewer individual patients receive care in catheterization labs, despite total lab output remaining constant.

The model predicts these volume declines may be inequitably distributed across patients. I show that TAVR's adoption reduced volume the most for markets with greater material deprivation or a greater share of nonwhite patients; even within a market, patients from more disadvantaged regions are more likely to lose access to care. Finally, patients most likely to lose access to PCIs post-adoption also resided in markets with lower risk-adjusted treatment thresholds, meaning they were the least likely patients to receive interventions even *prior* to TAVR's adoption. This suggests these spillover effects may exacerbate allocative inefficiencies, rather than reallocating resources away from unnecessary or low-return PCIs.

The model and empirical findings fit into a discussion of the potentially unequal impact of technological change (Skinner and Staiger, 2015; Gans, 2024). Although much of this discussion studies skilled-biased innovations in the factor market (Violante, 2008; Acemoglu and Restrepo, 2020), recent work explores innovation's impacts on product markets, arguing the endogenous direction of innovation results in products aimed at higher-income households (Faber and Fally, 2022; Jaravel, 2019). This directed technological change is also prevalent in healthcare, where market size and patient incomes drive entry decisions for pharmaceuticals, medical devices, and clinical trial funding (Acemoglu and Linn, 2004; Moradpour and Hollis, 2020; Ji and Rogers, 2024). The flow of health innovations is also sensitive to market features such as insurance coverage (Agha et al., 2022), procurement environments (Clemens and Rogers, 2020), and tax incentives (Gamba et al., 2021; Yin, 2008).

My work highlights previously overlooked spillover effects of innovation, including the effects of skill degradation and capacity constraints on allocative inefficiencies and health inequities. These effects arise because economies of scale cause an innovation shock in one sector to affect technological returns in another, reducing patient welfare in possibly unequal ways. Recent work has studied how innovations may change incentives and endogenous

behaviors, such as the decision to join a waiting list for an organ transplant post-innovation (Callison et al., 2023). In contrast, my work identifies how the features of innovations and the supply thereof may affect returns to care, exacerbating inefficient allocations of resources and disparities in accessing treatment. Finally, my work is related to a broader discussion on how physicians respond to medical innovation (DeCicca et al., 2024; Barrenho et al., 2024).

I also present the first theoretical framework for considering equity impacts of health innovations, building on previous work exploring health inequities (Fleurbaey and Schokkaert, 2011). Recent work has explored policies to equitably improve access to high-value services through physician payments (Kaarboe and Siciliani, 2023) or to limit geographic variation in service provision (Chandra et al., 2022). I argue technological advancement contributes to these disparities, modeling responses to susceptible innovations. These disparities in access to healthcare have been shown to cascade into other forms of inequality, including educational and income inequality and allocative inefficiencies (Chandra and Staiger, 2016; Kotschy, 2022). I examine how my observed innovation spillover effects are related to typical measures of allocative efficiency, such as estimating market-specific value added in healthcare (Einav et al., 2022; Olenski and Sacher, 2024) and education (Abdulkadiroğlu et al., 2020).

Health disparities have increased in recent years, with some patients even experiencing disproportionate decreases in life expectancy (Case and Deaton, 2015; Olshansky et al., 2012). I find procedural innovations are not guaranteed to improve efficient or equitable access; this is related to previous work studying the spillover effects of health events (Fadlon et al., 2025; Hoagland, 2025) and differences in policy outcomes across patient groups (Singh and Venkataramani, 2024). Policymakers aiming to improve equitable access to innovative care may widen their focus beyond accessing innovations alone, considering broader protections to limit unintended spillovers. Rather than reducing or regulating the flow of welfare-improving innovations, policies supporting appropriate infrastructure to scale up an innovation without skill degradation or crowding out older procedures may limit these effects.

2 Model

Suppose there is a continuum of patients seeking care from a physician. Patients and physicians—acting jointly—can select from three possible treatments, indexed by $s \in \{0, 1, 2\}$: preventive maintenance ($s = 0$), low-intensity surgical interventions ($s = 1$), and high-intensity surgical interventions ($s = 2$). Empirically, $s = 2$ corresponds to valve replacements (SAVR/TAVR) while $s = 1$ corresponds to valve supports (PCIs).[2]

[2]The mapping of this model to my empirical setting is discussed in Section 3 below.

2.1 Patient Utility

First, consider patient utility from each of the three possible procedures. Utility depends on three components: their own surgical risk and expected benefit; productivity spillovers from physician specialization; and the time patients wait for an intervention, capturing capacity constraints. Specifically, the expected utility of a procedure s is given by

$$U_{is} = \beta_s \theta_{is} + \alpha_s P_s - c_s(P_1, P_2) + \varepsilon_{is}, s \in \{0, 1, 2\}. \tag{1}$$

A procedure's appropriateness for a given patient depends first on a risk index θ_{is}, where increasing θ_{is} indicates higher levels of predicted surgical risk net of expected benefit.[3] Hence, individuals with lower levels of θ_{is} receive more intensive treatment.

The second and third terms of Equation 1 indicate market-specific spillovers affecting utility. P_s represents the fraction of a patient's market receiving treatment s, incorporating productivity spillovers in the style of Chandra and Staiger (2007). When $\alpha_s > 0$, increased local use of s improves average outcomes regardless of θ_{is}.

The third term indicates disutility from waiting to obtain a procedure. Specifically, suppose that a market's total capacity for interventions is fixed at k, and that high-intensity interventions consume more resources than low-intensity ones by a factor of δ so that a market's total resource utilization is $P_1 + (1 + \delta)P_2$.[4] Then, we can define an individual's expected cost from waiting for a specific procedure as

$$c_{is}(P_1, P_2) = c_s \cdot [P_1 + (1 + \delta)P_2 - k], \tag{2}$$

where $c_s > 0$ indicates how waiting affects procedure-specific utility.[5]

The model includes market spillovers via both productivity spillovers and capacity constraints. Although these mechanisms operate in similar ways, including both operationalizes the model for a broad class of innovations, rather than limiting it to only interventional

[3]For example, suppose $\theta_{is} = R_{is} - \gamma B_{is}$, where R_{is} indicates expected risk from s and B_{is} is expected survival benefit. The parameter γ allows for risk and benefit to enter the utility with distinct magnitudes. Innovations may increase B_{is}, decrease R_{is}, or both; in all cases, equilibrium implications will be the same, differing only in the magnitude of the resulting shift. Given this, I focus on a single metric, θ_{is}, throughout. In practice, θ_{is} is not perfectly observed, but may be proxied by observable characteristics Z_{is}.

[4]One can suppose k applies to $s \in \{1, 2\}$ and is fixed in the short run, for example due to limited operating space (Section 6). The model does not inherently assume that these constraints are binding, nor are results changed substantively if constraints include the outside option.

[5]The c_s terms capture both disutility from waiting as well as utility benefits from interventions with low demand. In the empirical setting, one could assume that $c_1 > c_2$, as SAVR provides an outside surgical option unavailable to those waiting for PCI. A useful normalization is $c_0 = 0$ for the outside option; while this may not be strictly true in practice, the model only requires $c_0 < c_1$ for results to hold. This is a realistic assumption corresponding to greater waiting costs for surgery compared to office-based care.

cardiology. These two mechanisms also have distinct implications for how innovations disrupt equilibria, particularly with regards to the time horizon of their effects. While capacity constraints may bind in the short run, they can be relaxed over time; on the other hand, returns to specialization may materialize as productivity spillovers only in the long run.

Given this linear utility framework, patients' decisions can be characterized as two-way comparisons for any θ_{is}. To simplify comparisons, I make the natural assumption that optimal treatment intensity is perfectly distributed across θ_{is}; equivalently, I assume the marginal utility of treatment with respect to risk is greater (in absolute value) for more intensive interventions.[6] Patients then choose treatment only along two margins: a choice between valve replacement and valve supports, or a choice between supports and no intervention. This assumption allows me to represent risk as a single measure across treatments, θ_i.

A patient thus chooses the intensive treatment, $s = 2$, only if $U_{i2} > U_{i1}$, meaning that the expected utility for high-intensity treatment is greater than the expected utility for low-intensity treatment, given patient net risk θ_i and market specialization P_s. Over the distribution of the now univariate θ_i, this probability is given by:

$$\begin{aligned}\Pr\{s=2\} &= \Pr\{U_{i2} - U_{i1} > 0\} \\ &= \Pr\{(\beta_2 - \beta_1)\theta_i + \alpha_2 P_2 - \alpha_1 P_1 - (c_2 - c_1)((P_1 + (1+\delta)P_2) - k) > \varepsilon_{i1} - \varepsilon_{i2}\} \\ &= \Pr\{\beta_{21}\theta_i + \alpha_2 P_2 - \alpha_1 P_1 - c_{21}((P_1 + (1+\delta)P_2) - k) > \varepsilon_{i,12}\}, \end{aligned} \tag{3}$$

where I define $\beta_{21} = \beta_2 - \beta_1$, $c_{21} = c_2 - c_1$, and $\varepsilon_{i,12} = \varepsilon_{i1} - \varepsilon_{i2}$. Similarly, the probability that a patient chooses the intermediate treatment ($s = 1$) is:

$$\Pr\{U_{i1} - U_{i0} > 0\} = \Pr\{\beta_{10}\theta_i + (\alpha_1 + \alpha_0)P_1 + \alpha_0 P_2 - \alpha_0 - c_{10}((P_1 + (1+\delta)P_2) - k) > \varepsilon_{i,01}\}, \tag{4}$$

minus the probability that the patient chooses the most intensive intervention.

2.2 Market Equilibrium

The equilibrium at the market level is therefore defined as a fixed point that solves the system of equations:

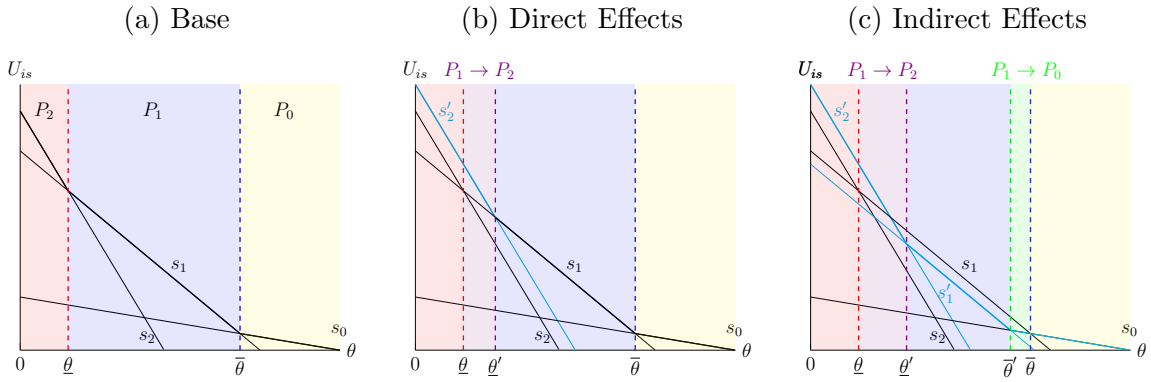
$$P_2 = \int_\theta \Pr\{\beta_{21}\theta + \alpha_2 P_2 - \alpha_1 P_1 - c_{21}((P_1 + (1+\delta)P_2) - k) > \varepsilon_{12}\} f(\theta) d\theta. \tag{5}$$

$$P_1 = \int_\theta \Pr\{\beta_{10}\theta + (\alpha_1 + \alpha_0)P_1 + \alpha_0 P_2 - \alpha_0 - c_{10}((P_1 + (1+\delta)P_2) - k) > \varepsilon_{10}\} f(\theta) d\theta - P_2 \tag{6}$$

[6] I assume $|\partial U_{i2}/\partial\theta_2| > |\partial U_{i1}/\partial\theta_1| > |\partial U_{i0}/\partial\theta_0|$. This implies steeper indifference curves for more intensive treatments, all things equal.

An equilibrium can be conceptualized in a single-crossing framework: any initial allocation generates utility benefits that induce marginal patients to switch between the three treatment options. These flows, in turn, affect the returns to each procedure, further shifting patients and returns until a stable equilibrium is reached.[7]

Figure 1. Treatment Decisions Based on Patient Risk



Notes: Graphical illustration of model equilibria pre- and post-innovation. Panel (a) presents treatment utilities given θ prior to innovation, which define treatment regions for s_2 (red, P_2); s_1 (blue, P_1); and s_0 (yellow, P_0). Panel (b) presents direct effects of innovation, which changes the threshold between high- and low-intensity interventions (captured in purple). Panel (c) highlights indirect effects, where spillover externalities result in movement from s_1 to s_0 (captured in green).

Figure 1 (a) plots $U_s(\theta_i)$ for each s, illustrating the allocation of patients to treatments. Overall, utility is declining in risk, with steeper declines for more intensive interventions by assumption. This creates three well-defined treatment regions: low-risk patients select s_2, moderate-risk patients select s_1, and high-risk patients choose no intervention (s_0). Denote the cutoff risk levels $\underline{\theta}$ and $\overline{\theta}$; combined with the distribution of θ, these define each treatment's market share, $\{\overline{P}_0, \overline{P}_1, \overline{P}_2\}$.

2.3 The Effect of Innovations

Consider an innovation—such as TAVR—in high-intensity treatments, s_2. TAVR's adoption can be characterized as a uniform cost reduction across θ without affecting survival utility (Section 3); hence suppose U_2 shifts by a fixed τ.[8]

The second and third panels of Figure 1 present the direct and indirect effects of this shift. In panel (b), the utility increase from s_2 to s_2' directly attracts patients who switch from s_1 (in purple). This flow changes the returns to s_1, lowering expected returns even for

[7] Appendix Section A.1 argues that such an equilibrium is guaranteed to exist, and is unique under relatively mild conditions.

[8] τ need not be constant for results to hold; alternative cases are discussed at the end of this section.

inframarginal patients who continue to receive low-intensity interventions.[9] It also affects total demand for resources, as patients shifting from low- to high-intensity interventions require more capacity based on the size of δ.

Importantly, these market spillovers may result in further increases in U_2 and decreases in U_1. Panel (c) shows these indirect effects as two separate flows out of s_1: some into s_2 ($P_1 \to P_2$, in purple) and others into s_0 ($P_1 \to P_0$, in green). The new equilibrium has updated risk thresholds $(\underline{\theta}', \overline{\theta}')$.

Notably, the shift in $\overline{\theta}$ defines a share of patients who now forego treatment. To quantify this crowd-out, note that the risk thresholds $\underline{\theta}$ and $\overline{\theta}$ are defined, in expectation over ε, by

$$\beta_{21}\underline{\theta} + (\alpha_1 + \alpha_2)F(\underline{\theta}) - c_{21}\left[F(\overline{\theta}) + \delta F(\underline{\theta}) - k\right] + \tau = \alpha_1 F(\overline{\theta}) \tag{7}$$

$$\beta_{10}\overline{\theta} + \alpha_1\left(F(\overline{\theta}) - F(\underline{\theta})\right) - c_1\left[F(\overline{\theta}) + \delta F(\underline{\theta}) - k\right] = \alpha_0\left(1 - F(\overline{\theta})\right), \tag{8}$$

where $\beta_{ij} = \beta_i - \beta_j$ for $i, j \in \{0, 1, 2\}$, and I have set $c_0 = 0$.[10]

This system of equations defines comparative statics measuring how risk thresholds change with an innovation's value τ:

$$\frac{\partial \underline{\theta}}{\partial \tau} = \frac{\beta_{10} + (\alpha_1 + \alpha_0 - c_1)\, f(\overline{\theta})}{(c_{21} + \alpha_1)(\alpha_1 + c_1\,\delta)\, f(\underline{\theta})\, f(\overline{\theta}) - \left[\beta_{21} + (\alpha_1 + \alpha_2 - c_{21}\,\delta)\, f(\underline{\theta})\right]\left[\beta_{10} + (\alpha_1 + \alpha_0 - c_1)\, f(\overline{\theta})\right]}$$

$$\frac{\partial \overline{\theta}}{\partial \tau} = \frac{(\,\alpha_1 + c_1\,\delta)\, f(\underline{\theta})}{(c_{21} + \alpha_1)(\alpha_1 + c_1\,\delta)\, f(\underline{\theta})\, f(\overline{\theta}) - \left[\beta_{21} + (\alpha_1 + \alpha_2 - c_{21}\,\delta)\, f(\underline{\theta})\right]\left[\beta_{10} + (\alpha_1 + \alpha_0 - c_1)\, f(\overline{\theta})\right]}.$$

A key insight from the model is that a market-expanding innovation in one sector can lead to a reduction in total volume, meaning that patients are crowded out from receiving treatment. Given that these share a denominator, whenever τ leads P_2 to expand (meaning $\frac{\partial \underline{\theta}}{\partial \tau} > 0$), the shift in the extensive margin ($\frac{\partial \overline{\theta}}{\partial \tau}$) will be non-positive if and only if the numerators are oppositely-signed:

$$\frac{(\alpha_1 + c_1\delta) f(\underline{\theta})}{\beta_{10} + (\alpha_0 + \alpha_1 - c_1) f(\overline{\theta})} \leq 0 \tag{9}$$

$$\Leftrightarrow \underbrace{-\alpha_0 f(\overline{\theta})}_{\partial P_0/\partial \theta} - \underbrace{\alpha_1[f(\overline{\theta}) - f(\underline{\theta})] + c_1(f(\overline{\theta}) + \delta f(\underline{\theta}))}_{\partial P_1/\partial \theta} \geq \beta_1 - \beta_0. \tag{10}$$

[9] An innovation might provide productivity benefits even for adjacent incumbent technologies; for example, performing TAVR might enhance surgical skill for other PCIs. In the empirical application, I show that this is not the case (Section 6). In general, as spillovers *across* interventions are likely smaller than spillovers *within* an intervention, these can be differenced out without loss of generality.

[10] Illustrating the changes in treatment thresholds in this way makes it clear that the model implications do not depend on this normalization, as discussed above.

The terms on the left side of the inequality represent post-innovation reductions in productivity spillovers for both s_0 and s_1, as well as any change in waiting costs associated with flows from s_1 to s_2 (scaled by the relative intensity parameter, δ). The right side captures differences in the marginal utility of seeking a low-intensity intervention compared to the outside option for a fixed level of net risk. Hence, crowd-out occurs when the marginal utility gains from receiving any surgical intervention (the switch from s_0 to s_1) are outweighed by the losses from diminished productivity spillovers or increased waiting times for s_1.

These crowd-out effects rest on the assumption that innovations compete with existing interventions for scarce inputs, including physician skill and hospital capital. This competition means that if a high-intensity intervention improves its average outcomes, the availability of lower-intensity procedures is reduced (Figure 1). Many medical innovations have this competitive feature, including robot-assisted surgery, specialized stroke interventions, and novel cancer therapies, among others. However, one could consider alternative models where innovations free up inputs rather than constrain them. If new technologies reduce procedure times or minimize recovery periods, total availability could expand rather than contract. Appendix Figure A1 illustrates an alternative model to consider these cases. Here, I focus on the context where innovations compete with adjacent technologies to highlight its unique implications, and directly test that this framework matches the case of TAVR's adoption.

2.4 Allocative Efficiency & Equitable Access

An innovation's spillover effect may simply indicate changes in productive efficiency or comparative advantage across procedures. Alternatively, however, these crowd-out effects may reflect allocative inefficiencies, where either some patients were receiving too much care prior to an innovation, or too few patients were receiving care after adoption. Identifying whether this is the case is important to understand the normative implications of these spillover effects, especially if the affected patients differ systematically from unaffected patients.

Identification of allocative efficiencies typically requires additional parametric assumptions (Chandra and Staiger, 2016). However, an informative test for the effect of an innovation on allocative inefficiencies uses the fact that an innovation's impact will be different across markets, as each market has a different pre-equilibrium allocation of patients to treatments. Fundamentally, an allocative inefficiency in this model arises if treatment decisions were made for patients based exclusively on risk ($\beta_s \theta_i$), without appropriately taking into

account market-level spillovers.[11] These inefficiencies would be further exacerbated if patient risk was assigned with systematic, non-random measurement error, discussed below.

I can therefore use this model to test whether innovations exacerbate or reduce any inefficiencies already present in treatment decisions. This is done by comparing how potential crowd-out effects correlate with market-specific treatment thresholds pre-innovation. This correlation identifies the *direction*—if not the level—of allocative inefficiencies. Formally, if patients prefer to select interventions based on the conditions in Equations 3 and 4, a patient in market CZ should receive any intervention if

$$\beta_{10}\theta_i + \underbrace{(\alpha_1 + \alpha_0)P_1 + \alpha_0 P_2 - \alpha_0 - c_1(P_{1,CZ} + (1+\delta)P_{2,CZ} - k)}_{\varphi_{CZ}} \geq \varepsilon_{10}. \tag{11}$$

That is, patients prefer to receive interventions based on a combination of their own clinical needs or underlying risk and market-specific factors dictating returns to treatment. Denote by φ_{CZ} the value of market-specific differences in treatment thresholds; these values represent risk-adjusted treatment rates after controlling for patient characteristics in θ_i, driven by productivity spillovers and market capacity. Then, considering only the extensive margin decision of receiving any intervention, the coefficients $\vec{\varphi}_{CZ}$ in Equation 12 indicate market-level differences in treatment propensity, conditional on patient characteristics:

$$\Pr(s_i \in \{1,2\}) = \Pr(\text{Any Treatment}_i = 1|\theta_i) = F(\beta\theta_i + \varphi_{CZ}). \tag{12}$$

In Equation 12, local markets with a higher treatment propensity conditional on patient risk would have a positive value for φ_{CZ}, while negative coefficients indicate lower treatment probabilities.[12] In the context of innovations, the correlation between crowd-out effects (Equation **??**) and φ_{CZ} is particularly informative: if the crowd out region is larger in markets with higher treatment propensities, innovation adoption may be reducing flat-of-the-curve over-utilization. If instead patients are more likely to be crowded out of care in markets with already low treatment propensities, an innovation's spillover effects may constitute nontrivial reductions in access, potentially exacerbating allocative inefficiencies.

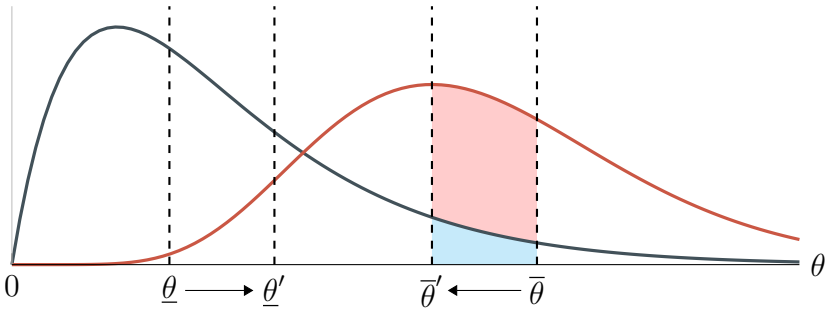
Inequalities and Inequities in Crowd-out. Any loss in efficient access to specialty care may be considered a market distortion. However, these losses may differ substantially

[11] Alternatively, an allocative inefficiency could include incorporating market-level spillovers when patients only care about $\beta_s\theta_i$ in deciding their treatment. This is less plausible given that patients generally care about productivity spillovers and waiting costs (Chandra and Staiger, 2007).

[12] This estimation is a simple version of value-added estimation methods identifying the value of healthcare facilities (e.g., SNFs, hospitals) or teachers (Hull, 2020; Einav et al., 2022). Previous work has expanded this framework to isolate levels of allocative inefficiencies across markets (Chandra and Staiger, 2016).

across patient groups, particularly if groups have heterogeneous risk; losses may be further exacerbated if some groups have systematically misperceived risks.

Figure 2. Inequities in Crowdout



Notes: Graph shows potential differences in which patients forego specialty care following an innovation. Patient pool is divided into two groups with heterogeneous risks; patient risk θ determines treatment status, denoted by $\{\underline{\theta}, \overline{\theta}\}$. Innovations shift these cutoff values, creating a crowd-out region (shaded).

Figure 2 presents the intuition for potential inequalities arising from the spillover effects of an innovation's adoption. The figure illustrates two hypothetical patient groups with different distributions of risk. The figure also shows the crowd-out region affected by an innovation (Figure 1). Even when risk is correctly measured, these groups have different likelihoods of losing access to specialty treatment, simply by virtue of having different underlying risk distributions. However, these inequalities may further correspond to *inequities* in access when risk distributions are imperfectly or incorrectly observed.[13]

2.5 Empirical Implications

The model predicts that innovations may generate spillover health inequities in two steps. First, innovations affect technological spillovers and create "crowd-out regions," shifting high-risk patients out of interventions. Second, these affected patients may be systematically different from the overall population, particularly if risk is incorrectly proxied. This loss in access, particularly in relationship to a market's propensity to treat patients conditional on their risk, may leave some patients differentially unable to access specialty care.

Four empirical implications arise from the model. First, I test for the direct and indirect effects of innovation, by assessing how adoption affects treatment decisions overall as well as by intervention type. Second, I identify the mechanisms contributing to this crowd-out, including losses in operator skill and capacity constraints. Third, I identify a crowd-out region by assessing *which* patients are affected based on their risk. Finally, I examine whether

[13] Appendix Section A formalizes these results. Imperfect proxying may arise from provider error or other factors, including patient beliefs or biased health measurements like risk scores (Obermeyer et al., 2019).

crowded-out patients are inequitably made up of different demographic groups, and what the implications of this crowd-out is for allocative efficiencies across markets.

While the model treats the market for medical treatments as static, in reality an innovation's diffusion over time affects both productivity spillovers and capacity constraints. For example, as TAVR adoption increases and new infrastructure is developed, specialization gains grow while capacity constraints ease. This may allow patients waiting for care to enjoy the benefits of provider skill accumulation. Although the core model is static, it can be interpreted as a flow equilibrium at any point; in Appendix Section A.4, I generalize it to allow patients to trade off waiting against accruing benefits. The dynamic extension preserves the static intuition while amplifying the volume-decline effect as an innovation diffuses. In general, these dynamics serve only to reinforce substitution toward the more intensive intervention, leading to further reductions in total intervention volume.[14]

3 Setting and Data

3.1 Interventional Cardiology and the Adoption of TAVR

Aortic stenosis is a serious condition affecting 1.5 million people in the US; untreated, its 5-year survival rate is roughly 20% (Rosalia et al., 2023). It is the most common heart valve condition and the third most common cardiovascular disease in the world after hypertension and coronary artery disease. Accordingly, more than 80,000 surgical aortic valve replacements (SAVRs) were performed annually in the US prior to TAVR's adoption in 2011. During SAVR, a cardiothoracic surgeon removes the damaged or diseased aortic valve in an open heart surgical procedure, and installs a new valve; this process typically requires a 5-7 day hospital stay and a prolonged recovery period.

TAVR is a minimally-invasive alternative to SAVR, relying on transfemoral placement of an expandable valve instead of open-heart surgery. Numerous randomized trials have indicated that TAVR is noninferior among patients at intermediate or high risk for mortality from SAVR (Leon et al., 2016) and, subsequently, low-risk patients (Mack et al., 2019). The first TAVR device (Edwards-SAPIEN) received approval from the Food and Drug Administration for high-risk patients in November 2011; over time, TAVR's use has expanded to include lower-risk patients, outpacing SAVR as the leading surgical approach in 2017 (D'Agostino et al., 2018). Conditional on risk, TAVR is considered a cost-effective alternative to SAVR (Baron et al., 2019). However, important access gaps persist, with fewer than half of patients needing a valve replacement receiving either intervention (Li et al., 2022).

[14] This is also what I observe in the empirical evidence, for example in Figure 3.

3.2 Procedure Selection

The adoption of TAVR is ideal for studying the potentially unequal impacts of innovation for two reasons. First, TAVR was market-expanding: the total number of valve replacements in the US increased by two-thirds between 2010 and 2017, with the number of operators nearly doubling (Appendix Figure B1). This increase in the total addressable market provided incentives for physicians to alter practice styles, similar to expansions of PCIs in the 1990s (Cutler and Huckman, 2003). Second, TAVR shifted patients across physician specialties. While SAVR can be performed only by cardiothoracic surgeons, TAVR leverages both surgeons and interventional cardiologists (Adams et al., 2014). These two specialists receive differentiated training and are hyper-specialized in different procedures. By 2017, 20% of TAVRs were performed by interventional cardiologists, highlighting the comparative advantages of the two interventions (Breg, 2022).

I therefore use TAVR's adoption as a case study to evaluate how a shock to a high-intensity procedure may have spill over effects on volume of other interventions. Following the model in Section 2, I assign valve replacements (both SAVR and TAVR) as the high-intensity intervention ($s = 2$) and consider major valve-based interventions performed by interventional cardiologists pre-adoption as low-intensity interventions ($s = 1$). Specifically, I include a broad set of valve support interventions—including PCIs such as angioplasty, stenting, and CABG procedures—in the set of adjacent services to study,[15] with outpatient cardiology care as the outside option ($s = 0$). Appendix Table B1 defines the relevant codes used to identify both valve replacements and valve supports.

Modeling valve replacement, valve supports, and outside cardiology care as competing technologies makes sense conceptually in the model framework, and also captures two of the key features of the model: productivity spillovers and capacity constraints. Interventional cardiology requires a unique skill set, and each of these procedures is highly dependent on physician skill development, primarily through learning-by-doing. For example, the proficiency standard for performing TAVR requires between 20 and 50 TAVR procedures for a learning operator (Salemi et al., 2019; Liu et al., 2020), and TAVR programs at the institutional level are required to perform 50 or more TAVRs annually to ensure adequate quality (Neuburger et al., 2019).[16] Additionally, these valve-based cardiac procedures, including both TAVR and PCIs, directly compete for time and space in catehterization labs, where the vast majority of these interventions are performed. As such, post-adoption, the shift of

[15] I will refer to this group of procedures throughout the paper as PCIs for brevity. This is because the vast majority of valve support procedures are PCIs, including angioplasty (also referred to as percutaneous transluminal coronary angioplasty, or PTCA) and cardiac catheterization.

[16] As they learn, TAVR operators receive on-site training via simulations and observing TAVRs performed by other interventional cardiologists. Operators may even participate in "mini-fellowships" (Jose et al., 2016).

patients from SAVR to TAVR may plausibly affect the capacity to perform valve support procedures (e.g., through reduced availability of catheterization labs) and operator skill (e.g., as they are required to learn a closely related, but distinct, intervention).

Although setting up the empirical exercise in this way captures the model intuition and the core features needed to study crowd out, the mapping of the model to an empirical setting is still imperfect. Two issues are particularly salient. First, not all patients will be candidates for full valve replacements. PCIs have been considered a suitable option for patients too high-risk for full (especially open) replacements (Goel et al., 2012). Hence, post-adoption, TAVR would have captured patients both from SAVR and PCI markets, following Figure 1. However, the vast majority of PCIs are performed on patients for whom a complete replacement is not necessary (e.g., θ is too large for high-intensity interventions). This should not be an issue when studying spillovers as changes to both capacity and operator skill from TAVR's adoption may well affect even patients who are not candidates for TAVR or SAVR.

Second, some "low-intensity" procedures included are similar to SAVR in that they require certain risk thresholds to be met. For example, CABG is not typically classified as a PCI and generally is performed on less risky patients. Here, I include CABG in the set of low-intensity interventions as I include all valve support procedures in an attempt to capture the full range of spillover effects across interventional cardiology. However, I also decompose these effects by intervention type to show that the results are not driven by outlier interventions such as CABG (which is only 1.3% of the set of PCIs). In this way, I avoid biasing my results based on cherry-picking a set of adjacent procedures. One should therefore consider the set of valve replacements as interventional cardiology procedures that compete—at a physician or facility level—with TAVR for operator skill and capacity, rather than each affected patient facing a perfect choice between any of the included procedures.[17]

3.3 Data

I use claims data for traditional Medicare patients from 2010 to 2017. Medicare enrollees are the primary market for interventional cardiology, constituting 85.2% of valve replacements for aortic valve disease and 46.5% of PCI operations, compared to 9.6% and 31.0% for patients with commercial insurance, respectively (Goldsweig, 2020; Lin et al., 2023).[18]

[17]Notably, only 146 ($< 0.01\%$) of patients receive more than one valve replacement, and 107,842 (8.68%) receive more than one valve support procedure. Only 15,896 (1.28%) patients receive both a valve replacement and a valve support procedure within the observation window. Hence, we need not be concerned that patients are receiving multiple procedures, particularly across areas of specialization.

[18]Note that during this period, roughly 70% of Medicare patients were on traditional Medicare. While exact data on TAVR receipt between TM and MA patients is not available, a rough ballpark is that 60% of all TAVRs were performed on TM patients.

I identify the receipt of SAVR, TAVR, and other interventional cardiology care using 100% of the Inpatient Encounters and 20% of the Outpatient and Carrier Encounters. I also use 100% of the Beneficiary Summary Files and the Medicare Data on Provider Practice and Specialty (MD-PPAS) files to obtain information on patients, their providers, and the local markets; this includes patient risk and demographic information including race, sex, dual eligibility, area-level disadvantage scores, and risk score (Ellis et al., 2022).[19]

Healthcare Market Definitions. I define local markets at the commuting zone (CZ) level. CZs are geographically contiguous groups of counties within which residents typically commute (for example, to work), and are constructed based on Census commuting flow data. I assign CZs based on patient residence to avoid problems of market definitions should patients travel to another market to receive a preferred procedure (Dingel et al., 2023).[20] There are roughly 700 CZs commuting zones in the 2020 definition; of these, 452 are included in my sample, as I require a market to perform at least 5 interventions annually. Similar work in this area has used commuting zones as reasonable definitions of local labor markets for hospitals and physicians (Prager and Schmitt, 2021; Rinz, 2018). Within each market, I define the timing of TAVR adoption based on the first documented procedure in the CZ.

Patient Definitions. I observe the full volume of patients receiving care in inpatient settings, but only 20% of outpatient procedures. Although TAVR, SAVR, and other PCIs were typically performed in inpatient settings between 2010–2017, more recent years have seen these procedures trending to outpatient settings. In part, this was intended to reduce the costs of these procedures, with initiatives such as the Recovery Audit Program and the 2-midnight rule providing incentives to switch these procedures to outpatient settings in conjunction with fee changes for PCIs (Blankenship and Marshall, 2013). However, it wasn't until after outcome differences were rigorously examined with the EXCEL trial—published in 2021, well after my analytical sample—that this change began in earnest (Gaba et al., 2021). To accommodate potential bias from excluding unobserved interventions, I conduct analysis at two levels: the market level using the universe of inpatient encounters, and the patient level across the entire 20% sample of Medicare beneficiaries.[21]

[19]Note that this data excludes individuals enrolled in Medicare Advantage plans. See Appendix Table B1 for the relevant procedure codes. Disadvantage scores are from the Neighborhood Atlas' Area Deprivation Index, which ranks zip codes by socioeconomic disadvantage given income, education, employment, and housing quality (Kind and Buckingham, 2018).

[20]Roughly 0.68% of procedures in my sample occur outside a patient's home CZ. Robustness checks accommodating shopping and migration are presented in Section 5. The average CZ for PCI provision is Bloomington, Indiana, which provides roughly 1200 PCIs annually, 200 of which are for TM patients.

[21]I observe no relationship between TAVR's adoption and shifts to outpatient settings, reassuring evidence that the parallel trends assumption is likely not violated. However, I report both market- and patient-level analysis as a robustness exercise. For market-level analysis, I restrict the relevant procedures to those

For patient level analysis, I use the full 20% subsample rather than limiting the denominator to only patients who are candidates for an intervention. Identifying medically-managed patients with aortic stenosis is difficult in claims data, as it is generally low acuity until just prior to surgery. Hence, patients may not have appropriate diagnostic information included on their claims, and even those with a diagnosis may not be realistically candidates for an intervention (Chiang et al., 2016; Hoagland et al., 2024). My results are robust to limiting patient-level analysis to those with a diagnosis prior to intervention. My main sample includes 10,874,161 patients, of whom 1,343,580 have an aortic stenosis diagnosis.[22]

Table 1 presents relevant summary information across valve replacements and some key valve supports.[23] Valve replacements are roughly four times costlier than valve supports, including both SAVR and TAVR. TAVR is performed on riskier patients than SAVR (a difference of 0.72 percentage points, or 15.8%), with the average risk of a TAVR patient more comparable to the average risk of a PCI recipient. TAVR is also performed on older patients (a 5.3% increase), but otherwise there are few observable differences in patient demographics during the year of adoption. Despite these differences in patient risk and age, TAVR achieves comparable outcomes to SAVR even in the first year of adoption. In general, patient demographics summarized here—including the racial breakdown of intervention recipients on Medicare—are consistent with prior work (McNeely et al., 2018).

4 Methods

I assess the effects of TAVR's adoption on access to valve replacements (SAVR and TAVR) and valve supports (PCIs) within a local market. This adoption may change patient and physician decision-making in response to treatment availability and the (potentially market-varying) estimated returns to each procedure.

4.1 Estimating Patient Risk

Cardiac surgery risk is typically estimated using models constructed by The Society of Thoracic Surgeons (STS), accounting for pre-operative factors that influence surgical outcomes (O'Brien et al., 2009). I use the STS Predicted Risk of Mortality (STS-PROM) model, a logistic regression of mortality on demographics and clinical information (Appendix Table B2).

performed by interventional cardiologists, in order to most closely match the predictions of the model; when performing analysis at the patient level, I include all procedures regardless of physician specialty.

[22] Aortic stenosis diagnoses are identified in the data using ICD-9 codes 395.0, 746.3, 396.2, and 424.1, and ICD-10 codes I06.0, I06.2, I35.0, and Q23.0. Note that this is a prevalence rate of about 12.4%, roughly in line with estimated AS prevalence (Osnabrugge et al., 2013).

[23] Specifically, I summarize all PCIs and the most common interventions (PTCA and cardiac catherization). I also summarize CABG to highlight its differences to other PCIs as discussed above.

	Valve Replacements			Valve Supports			
	All	SAVR	TAVR	All	PTCA	Cath.	CABG
Panel A: Procedure Costs and Risks							
Billed Cost	$62,460	$65,866	$59,888	$14,972	$16,871	$9,548	$41,708
	($562)	($968)	($654)	($ 31)	($ 41)	($ 33)	($441)
Patient Risk	5.01	4.60	5.32	5.75	5.50	5.90	4.58
	(0.076)	(0.108)	(0.104)	(0.013)	(0.019)	(0.025)	(0.076)
Readmission	20.55	20.18	20.84	13.79	15.29	16.41	12.00
	(0.792)	(1.199)	(1.055)	(0.078)	(0.131)	(0.150)	(0.633)
Mortality	4.92	4.82	4.99	4.80	2.92	3.40	3.91
	(0.424)	(0.640)	(0.565)	(0.048)	(0.061)	(0.073)	(0.378)
Panel B: Patient Demographics							
Age	81.0	78.6	82.8	73.0	72.5	71.5	71.9
	(0.17)	(0.27)	(0.20)	(0.02)	(0.04)	(0.04)	(0.15)
Female	0.43	0.41	0.45	0.44	0.39	0.49	0.29
	(0.010)	(0.015)	(0.013)	(0.001)	(0.002)	(0.002)	(0.009)
Black	0.03	0.03	0.02	0.10	0.07	0.12	0.06
	(0.003)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)	(0.004)
Hispanic	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Dual Eligible	0.12	0.10	0.13	0.23	0.20	0.26	0.12
	(0.006)	(0.009)	(0.009)	(0.001)	(0.001)	(0.002)	(0.006)
Total Volume, Adoption Year	2,603	1,120	1,483	196,120	75,386	60,751	2,633
Total Volume, Full Period	42,063	5,107	36,956	1,439,163	536,356	501,307	18,804

Notes: Table summarizes cardiology procedures in the year of TAVR adoption. Listed procedures are a subset of all procedures, with some omitted for brevity (see Appendix Table B1 for a complete list). Cath. refers to cardiac catheterization. Patient risk is predicted using the 30-day STS-PROM model; readmission and mortality rates are also reported at 30 days.

Table 1. Summary Statistics: Procedures

The model classifies patients into low risk (score $\leq 3\%$), moderate risk (score between 3% and 8%), and high risk (score $\geq 8\%$). Traditionally, SAVR is limited to low-risk patients, while PCIs can be done on higher-risk patients. The empirical distribution of predicted risk in my sample closely matches population STS-PROM predictions: I estimate an average (median) risk of 3.6% (4.8%), with 40% of patients identified as low-risk, 44% as intermediate-risk, and 15% as high-risk (Appendix Figure B2).

4.2 Effect of Innovations

To estimate the causal impact of TAVR's adoption on treatment decisions, I use a local projections difference in differences (LP-DID) estimator (Dube et al., 2023), a "stacked" dynamic estimator that is unaffected by potential bias arising from heterogeneous treatment effects (Roth et al., 2023). The regression uses local projections methods to restrict the estimation sample so that previously-treated observations are not included in the control group. This specification performs similarly to other recent approaches including weighted stacked DID regressions and imputation estimators. Formally, for h periods pre- and post-treatment, I estimate the equation

$$y_{CZ,t+h} - y_{CZ,t-1} = \beta_h^{\text{LP-DID}} \Delta D_{CZ,t} + \alpha_{CZ} + \tau_t + \varepsilon_{CZ,t}^h, \tag{13}$$

where the sample is restricted to newly treated ($\Delta D_{it} = 1$) or clean controls ($\Delta D_{i,t+h} = 0$). Outcomes include intervention volumes at the market CZ level and treatment decisions for patients i, with periods separated into quarters t. I cluster standard errors at the CZ level, and report pooled estimates of post-treatment effects with each regression.[24]

Throughout, the identifying assumption is that the timing of TAVR's adoption within a local market is exogenous for PCI operators, in the sense that there are parallel trends and no anticipatory changes in valve *support* procedures. That is, my approach requires the assumption that interventional cardiologists did not adopt TAVR due to underlying changes in the expected volume of patients seeking PCIs, or change PCI volumes preemptively anticipating adoption. While hospitals certainly made strategic decisions about TAVR adoption based on anticipated valve replacement volume, there is little reason to suspect that anticipation affected PCI volumes prior to TAVR's adoption. This assumption can also be examined directly by assessing differential pre-trends between adopting and non-adopting markets.

[24]Effects were estimated using the LPDID package in Stata (Busch and Girardi, 2023); this also allows for using an average of pre-treatment observations as the baseline reference period to avoid the inefficiencies associated with using a single pre-treatment period as the baseline, as discussed in Dube et al. (2023). Throughout, the analysis uses a balanced sample of geographies in order to ensure that results are not contaminated by potential compositional changes in the sample.

This assumption may be violated if contemporaneous changes to physician practice affected PCI volumes close to the time of TAVR adoption. For example, facilities may have changed their scheduling of PCIs in anticipation of future demand for procedures occurring in a catheterization lab. I examine this directly in the data and do not observe such anticipatory behavior, either for a market's first adopters or those that adopt later (Appendix Figure B3). Another possibility is that PCI use may have declined contemporaneously with—but independently of—TAVR. For example, a 2007 randomized control trial (the COURAGE trial) indicated PCIs did not meaningfully reduce mortality or cardiovascular risk for patients with stable coronary artery disease, leading to declines in PCI use (Boden et al., 2007; Almarzooq et al., 2021). If reductions occurred in tandem with TAVR's adoption, regression estimates could be biased. This is unlikely to be true, however, for several reasons. First, the COURAGE trial led to immediate shifts in practice, with the bulk of changes occurring prior to the start of my analytical window in 2010. Given the staggered adoption design, bias could only arise if most markets were simultaneously late responders to the COURAGE trial and early TAVR adopters. Finally, my results are robust to excluding patients with stable coronary artery disease, the patient population affected by this change.

Finally, one might be concerned that a scarcity of highly skilled operators compromises the identifying assumption. For example, when one hospital adopts TAVR in a region, it either trains its interventional cardiologists or recruits new operators with the required expertise. This means that if interventional cardiology labor is in short supply, early-adopting hospitals may attract most of the skilled operators and potentially delay TAVR adoption at neighboring hospitals. There are two reasons this is unlikely to drive my results. This is unlikely to be true, as previous work has argued that the supply of interventional cardiologists is sufficiently large—particularly relative to the capacity constraints imposed by capital, such as operating space—as to not constrain on hospital labor supply (Kumar et al., 2021). It is therefore unlikely that a single market could capture enough of the TAVR operator market as to influence its neighbors' adoption decisions. Even if this were true, however, this would only serve to attenuate my estimated treatment effects unless this led to neighboring markets increasing their total intervention volume. This is particularly unlikely as it would mean that patients would need to travel away from the market with cutting-edge care to seek treatment.

4.3 Heterogeneity & Inequities in Post-Innovation Access

After assessing TAVR's spillover effects on volume, I examine how treatment effects vary across three dimensions: geography, socioeconomic status, and race and ethnicity. I use the Area Deprivation Index (ADI) score for 9-digit zip codes to define differences in geo-

graphic vulnerability both across and within markets. I also measure how many enrollees are dually-eligible for Medicaid to proxy for socioeconomic status, and measure racial diversity in a market as the fraction of nonwhite enrollees in a region. To identify heterogeneous treatment effects, I bin markets and estimate pooled effects adjusted for multiple inferences using sharpened false discovery rate control methods (Anderson, 2008). Where applicable, I smooth these results using weighted local nonlinear regressions.

5 Effects of TAVR's Adoption on Volume

Figure 3 presents the dynamic effects of TAVR adoption on interventional cardiology procedures at the commuting zone and patient levels. Prior to adoption, I observe no meaningful variation in procedure volumes: the pre-treatment pooled LP-DID estimate at the CZ level is 0.558, with a 95% confidence interval of $[-0.576, 1.692]$. Following adoption, I observe a marked decline in total intervention volume, with average volume dropping by 3.87 interventions quarterly in a market, or 14.8 interventions annually. This is roughly 8.2% (21.5%) of the total volume of the average (median) commuting zone, which performs 47.3 (18) procedures per quarter. These effects are first observed one year after TAVR's adoption and become more pronounced with time.

I observe similar effects at the patient level: overall interventional cardiology procedure rates in a given quarter decline by 0.87 per 1,000 patients from an average (median) baseline of 4.53 (2.65) per 1,000. This is roughly an 19.2% decline from the average, comparable to the market-level results. The patient-level analysis includes outpatient procedures as well as inpatient interventions, suggesting that the observed results are not driven by unobserved shifts of PCIs to being performed in outpatient settings during my analytic period.

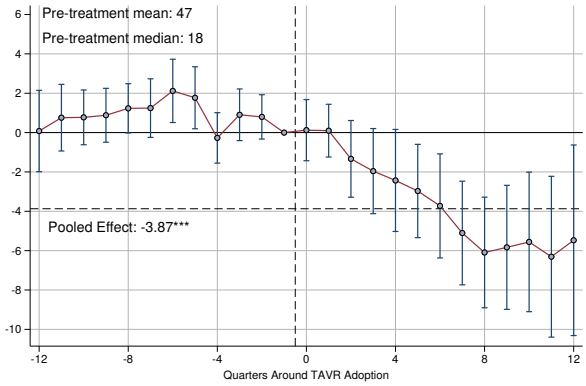
Overall changes in volume conflate both increases in valve replacements post-TAVR and changes in PCI availability. In Appendix Figures B4, I disaggregate these effects by interventions at the market level. Valve replacement takeup increased by 1.48 valve replacements quarterly on average. This increase includes both the conversion of some SAVRs into TAVRs as well as an expanded market for valve replacements, in keeping with Figure 1. In line with the model, TAVR also lowered the risk threshold for valve replacements, reaching patients that were 4.1 years older and 7.7% higher-risk in the year of adoption (Appendix Figure B5).

On the other hand, TAVR's adoption led to declines in the volumes of other interventions ultimately outpacing TAVR uptake. I observe average reductions of 5.6 PTCAs and 3.3 other PCIs quarterly, with transitory for cardiac catherization. This implies that roughly 6 valve supports were eliminated for each TAVR procedure adopted by the average CZ, roughly consistent with the cost differential between TAVR and PTCA or cardiac catheterization.[25]

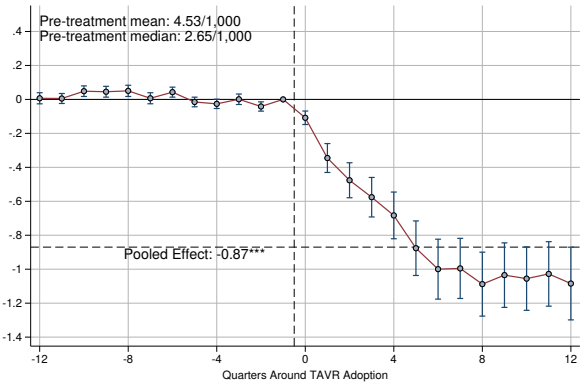
[25]The 95% confidence interval is 3.8 to 8.2 PCIs per TAVR adopted, in line with Figure 3.

Figure 3. Effect of TAVR Adoption on Total Intervention Volumes, Commuting Zone Level

(a) Market Level (# of Inpatient Procedures)



(b) Patient Level (Rate/1,000 patients)



Notes: Estimated impact of TAVR adoption on (a) total volume of intervention interventions in a local market and (b) the rate of any valve intervention per 1,000 patients (Equation 13). Both outcomes include all valve interventions performed including valve replacements (SAVR/TAVR) and valve supports (PCIs). Markets performing fewer than 5 inpatient procedures quarterly are dropped from estimation. Rates in panel (b) are calculated using the full population from the 20% subsample of Medicare beneficiaries as the denominator. Standard errors are clustered by CZ.

5.1 Robustness and Identification Concerns

One potential concern is that these declines represent idiosyncratic changes in volume across all of cardiology care, rather than in interventional cardiology alone. Appendix Figure B6 tests this by examining volume for procedures typical to cardiothoracic surgery. In contrast to the results in Figure 3, I do not observe any changes in the volume of these other procedures. If anything, in fact, the point estimates suggest that cardiothoracic surgery volumes may have increased post-adoption. Taken together, this suggests my results are not driven to industry-level changes in how cardiology care is provided.

Another concern is that a few hospitals or geographic regions may drive my results, or that TAVR's adoption affected either patient or physician migration when seeking care. For example, if patients begin flocking to early-adopting regions to receive TAVR, these regions may experience total volume declines in excess of the model's predictions; on the other hand, if interventional cardiologists move their practice to take advantage of TAVR, their home market may experience short-run declines in surgical availability.

I first show in Appendix Figure B7 that my results are not driven only by a few markets with exceptionally large volumes prior to adoption. I stratify my sample based on pre-adoption volumes and show that estimated declines appear in both high- and low-volume markets. Second, I consider differential patient and physician migration. In Appendix Figure B8, I document a strong negative relationship between a CZ's TAVR volume post-

adoption and changes in total intervention volume over time. This suggests that TAVR's effects are concentrated in the market where it was adopted—with limited spillovers across geographies—and that CZs which invested more heavily in TAVR experienced larger declines in volume.[26] In Appendix Table B3, I further estimate how TAVR's adoption affects patient or operator migration between markets and the probability a patient will receive interventional cardiology outside of their home market. I do not observe TAVR's adoption affecting any of these measures, which already occur infrequently even prior to adoption.[27]

Another possible interpretation is that these results constitute only transitional, short-run effects. Initial declines in volume could represent time spent building up capacity to accommodate both TAVR and PCI patients, after which declines would dissipate. Short-run effects are important in their own right, particularly if they exacerbate inequitable health outcomes and impose life-cycle impacts on access to care. However, long-run equilibria—which may change as factors such as market entry and patent expiry evolve over time—should be carefully considered in future research. In Appendix Figure B9, I show that my results do not return to baseline prior to the end of my available data. I also consider how service prices evolve over time to investigate this concern further. Short-tun transitional effects driven by limited capacity for TAVR would be expected to affect prices for other interventional cardiology services, driving them up in the short run for patients with more elastic demand (Anderson et al., 2024). I show that prices for these services do not change post-adoption even for commercially-insured patients.[28]

These results are robust to multiple alternative specifications. First, I report regression estimates using Poisson regression to examine whether results are driven by markets with excessive pre-TAVR volume (Appendix Table B4). Second, I consider the possible effects of changes in PCI provision following the COURAGE trial discussed above. In Appendix Figure B11, I show removing PCI patients affected by this trial does not change the main results.[29] Finally, one might be concerned that the dynamic effects presented in Figure 3 may be endogenous to market characteristics, with some markets potentially adopting TAVR earlier

[26] I observe these reductions even for CZs with low TAVR takeup rates, further suggesting that my results are not attributable only to a subset of markets.

[27] Table B3 suggests a possible effect where treated operators are more likely to stay in their home market ($p = 0.06$). This effect runs in the opposite direction from a potentially concerning result, as it shows estimated volume declines are not driven by operators leaving a market.

[28] I use the Merative data on commercially-insured patients across the US to obtain commercial PCI prices (measured as the sum of insurer and enrollee payments). Average Medicare payments are based on the relevant DRGs for each procedure. Once adjusted for linear increases over time, neither commercial nor Medicare prices change meaningfully over the post-adoption period, particularly in the short run.

[29] The COURAGE trial led to reductions in the availability of elective PCI for patients with stable angina or stable coronary artery disease. These patients are identified based on diagnosis codes (ICD-9-CM: 413.9; ICD-10-CM: I20.8, I20.9) anywhere in the first ten diagnoses; this is likely a conservative approach, as this also removes patients with medical histories of stable angina.

than others in anticipation of potentially time-varying returns from investment. In general, this is unlikely to be a critical issue as over 50% of adoption occurred within the first year and 75% within two years. However, as a robustness check, in Appendix Figure B12 I report results from a dynamic difference-in-differences specification that does not leverage variation in adoption timing across markets, but rather compares intervention volumes between ever-adopting and never-adopting markets relative to TAVR's FDA approval in the last quarter of 2011. I observe similar declines in total intervention volume—particularly after the first two years of approval—even using this design.[30]

Finally, I test how TAVR's adoption affected patient-physician interactions and heterogeneity across patient severity. I highlight two facts in the Appendix. First, Appendix Figure B13 shows that cardiologists are roughly 72.5% more likely to screen patients for valve replacement appropriateness post-adoption, suggesting physicians adapt diagnostic screenings to available interventions (Mullainathan and Obermeyer, 2021) or to information about treatment options (Hoagland et al., 2024). Second, I also show that while TAVR reduced the overall availability of PCIs, urgent PCIs—including angiography for patients immediately following a heart attack—were not delayed (Appendix Figure B14).

6 Mechanisms & Equity Implications

My results suggest TAVR reduced overall access to valve supports and interventional cardiology. These reductions may be driven by innovation competition with adjacent technologies for scarce inputs, including physician skill and operating room capacity. They may also have important distributional effects with implications for health equity and allocative efficiency.

6.1 Physician Skill Degradation

First, I examine changes in PCI outcomes following TAVR's adoption. There are two reasons why TAVR's adoption could affect the outcomes of adjacent procedures including PCIs. On the one hand, as operators increase the time dedicated to learning a new procedure (TAVR), they may lose skill in performing PCI. On the other, it could be that the highest skilled operators choose to take up TAVR in addition to PCIs. This would result in less PCI availability only for the highest-skill PCI operators, lowering the average operator skill.

[30] I also examine whether effects may be driven by MA patients who do not appear in the data. If adopting CZs also experienced the largest growth in MA enrollment, observed declines could arise mechanically. Using Medicare Enrollment Dashboard data, I find weak *negative* relationships between MA enrollment growth and TAVR's adoption; after conditioning on controls including the fraction of beneficiaries with aortic stenosis, average intervention volumes in the pre-period, and patient and provider demographics (including risk), these relationships are statistically insignificant.

Immediately following TAVR's adoption, I observe that interventional cardiologists adapt by hyper-specializing in either TAVR or PCI provision (Appendix Figure B15). While TAVR's adoption leads to reductions in the average number of PCIs per operator by 0.66 PCIs (13.2%), operators who continue to perform PCI increase their volume by 3.44 procedures quarterly, or nearly 50%. In part, this is likely due to minimum-volume rules requiring a certain number of either TAVR or PCI procedures annually, providing an incentive for specialization (Yang, 2023; Rashid et al., 2016). However, this strong response indicates significant changes in the pool of operators performing PCIs, and may lead to differences in PCI outcomes and quality for these two groups of operators (Kleiner, 2019).

One might be concerned that a simple regression estimating the effect of TAVR's adoption by an operator on their other patient's outcomes may conflate various endogenous mechanisms besides underlying changes in operator skill. First, patients sorting into the innovative valve replacement intervention may cause compositional changes in patients receiving PCIs, affecting their underlying risk. However, this can be tested directly: while TAVR's adoption shifted lower-risk patients away from PCIs, Figure B4 shows that the extensive margin changes among higher-risk patients swamps this shift, canceling out any increase in average patient risk. Appendix Figure B16 further shows that the predicted risk for patients receiving PCI did not increase on average following TAVR's adoption; if anything, PCI patients are slightly less risky on average post-adoption.

Another potential concern is that in addition to changes in operator skill, the match quality between patients and operators may have changed post adoption. For example, an operator who adopted TAVR may become more selective in which PCI cases they take on due to their limited time. These PCI cases may be riskier on average, whether due to billing incentives on the operator's part or patient shopping for operators. These changes may bias a naive regression toward overstating TAVR's effect on PCI complications.

To adjust for this, I use an instrumental variables (IV) design exploiting exogenous variation in the diffusion pattern of TAVR across both patients and operators. I use two instruments: a patient's differential distance between a PCI operator who has adopted TAVR (compared to one who has not), and a measure of average TAVR adoption in an operator's market.[31] The first instrument captures patient incentives to sort across operators, exploiting quasi-random variation in the extra patient costs associated with seeking out a

[31] Specifically, the differential distance is calculated in miles between zip code centroids for both the patient and PCI operators. I construct a measure $DiffDist_{it} = \min(Dist_{it}|TAVR = 1) - \min(Dist_{it}|TAVR = 0)$ for patient i in time t across all PCI operators. A positive value indicates that a patient must travel further to receive their PCI from an operator who has adopted TAVR. I measure average adoption as the leave-one-out average of TAVR adoption among PCI operators in an operator's commuting zone. Both instruments are strong, relevant instruments on their own, and pass all over-identification tests when used together.

TAVR-adopting PCI operator (Yang, 2023). The second instrument captures network effects in the timing of TAVR's adoption within a local market. Both instruments are strong predictors of a patient's receiving their PCI from a TAVR-adopting operator. Additionally, these IVs likely satisfy the exclusion restriction, as the outcomes from a patient's PCI are likely unaffected by how far the patient travels for care or how many of their operator's neighbors have adopted TAVR. The only way these measures affect patient-operator PCI outcomes is through the match to a TAVR-adopting operator.

Table 2 presents estimates of how TAVR's adoption affects patient outcomes from PCIs. These include surgical complications, readmissions, failures leading to emergency restenosis, and mortality. I estimate both OLS and 2SLS regressions using a pooled DD specification for consistency across columns.[32] The regressions adjust for operator and time fixed effects as well as a suite of time-varying controls including patient demographics and risk and procedure fixed effects. I report coefficients as percentage changes relative to baseline means to facilitate comparison across outcomes.

Overall, I observe consistently worse PCI outcomes after TAVR's adoption, particularly for surgical complications, readmissions, and patient mortality. The rate of surgical complications increases by 4% post-adoption; after instrumenting for potential selection in the patient-operator match, this increases to 8.2%. Complications are largely driven by increased rates of intracranial hemorrhage and thrombosis, conditions that can arise either when a stent is improperly placed or expanded, or after inappropriate use of anticoagulation therapy or dual antiplatelet therapy. I also observe large increases in readmission rates after instrumenting, a 17.6% increase from an already high baseline. This corresponds to an additional 82 readmissions per 1,000 PCI recipients within 30 days. Finally, 90-day PCI mortality increases by 12% following TAVR adoption, or an additional 8.3 PCI deaths per 1,000 recipients.[33] Interestingly, I observe a significant decline in the need for emergency revascularization; however, this may be in part due to increased patient mortality.

These instrumental variables estimates identify a local average treatment effect (LATE) for patients whose exposure to a TAVR-adopting PCI operator is driven by differential geographic proximity or local adoption patterns. Importantly, this may explain why the 2SLS regression coefficients are large relative to the OLS coefficients, for two reasons. First, compliers may be those who are either more medically complex or are receiving care in lower-resource settings. For example, patients for whom distance is particularly salient may

[32] Appendix Figure B17 shows the relevant figures using the LP-DID specification, done after averaging over patients within an operator.

[33] The baseline rates I report are well within the typical reported range for surgical complications, readmission rates, and mortality. (Tran et al., 2019; Hannan et al., 2023; Shanmugam et al., 2015). Previous estimates for PCI mortality rates among the elderly range between 1.6% and 17.9% (Kwok et al., 2015).

	Baseline rate	OLS			IV
	per 1,000	(1)	(2)	(3)	(4)
Panel A: Surgical Complications (1-30 days)					
Any	164.88	0.109***	0.059***	0.040***	0.082*
		(0.0142)	(0.0133)	(0.0121)	(0.0382)
Arterial embolism	4.88	0.222***	0.104	0.105	0.090
		(0.0458)	(0.0655)	(0.0650)	(0.2301)
Bleeding requiring transfusion	114.96	0.061***	0.071***	0.042*	0.014
		(0.0186)	(0.0178)	(0.0168)	(0.0491)
Cardiac tamponade	2.08	0.481***	0.215^{+}	0.217^{+}	0.661^{+}
		(0.0793)	(0.1160)	(0.1132)	(0.3918)
Cardiogenic shock	40.14	0.296***	0.012	0.017	0.139^{+}
		(0.0287)	(0.0241)	(0.0215)	(0.0814)
Intracranial hemorrhage	15.68	0.172***	0.042	0.042	0.286*
		(0.0262)	(0.0359)	(0.0352)	(0.1251)
Thrombosis	15.50	0.188***	0.075*	0.074*	0.249*
		(0.0431)	(0.0348)	(0.0344)	(0.1257)
Panel B: Readmissions (1-30 days)					
Any	462.11	0.128***	0.017**	0.003	0.176***
		(0.0085)	(0.0056)	(0.0053)	(0.0218)
Readmission with heart failure	270.50	0.277***	0.072***	0.040***	0.240***
		(0.0125)	(0.0091)	(0.0081)	(0.0312)
Readmission with myocardial infarction	259.12	0.090***	-0.035***	-0.037***	0.280***
		(0.0100)	(0.0099)	(0.0090)	(0.0377)
Panel C: Repeat Vessel Intervention (31-365 days)					
Any	51.15	-0.202***	-0.028	-0.007	-0.304***
		(0.0306)	(0.0246)	(0.0213)	(0.0732)
Panel D: Mortality (1-90 days)					
Any	69.72	0.189***	0.629***	0.037*	0.120*
		(0.0188)	(0.0179)	(0.0176)	(0.0577)
First Stage F Statistic		–	–	–	7,122
Operator and Time Fixed Effects			X	X	X
Patient Covariates				X	X

Notes: Table presents pooled DD and DDIV estimates of how TAVR's adoption affected a PCI operator's outcomes for inpatient procedures. Table B5 contains codes used to define outcomes; Appendix Figure B17 estimates dynamic versions at the operator level. The coefficient of interest indicates whether the operator had already adopted TAVR at the time of the PCI; it is scaled relative to baseline means for comparability. Covariates include operator and year fixed effects in column (2); in columns (3) and (4) they also include: indicators for patient risk score, age, chronic conditions, ADI, sex, race, income, dual eligibility status, and whether the patient received a PCI outside of their home CBSA; operator volume; and procedure code fixed effects. Column (4) instruments for the post-adoption dummy with measures of average adoption in an operator's CZ as well as the differential distance between the patient and a TAVR-adopting operator vs a non-adopting operator. Standard errors are clustered at the CZ level. $^{+}p < 0.1$,$^{*}p < 0.05$,$^{**}p < 0.01$,$^{***}p < 0.001$

Table 2. Effect of TAVR's Adoption on PCI Outcomes

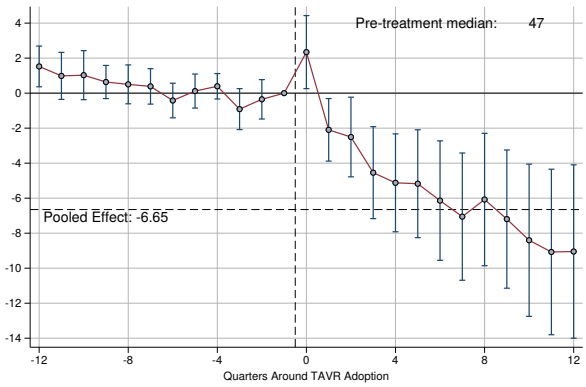
be disproportionately affected by changes in operator skill or congestion in a catheterization lab. Second, these estimates may reflect both the direct effects of skill decay as well as resulting physician specialization post-adoption whereby higher-skill operators reallocate towards TAVR, leaving PCI procedures to operators with lower baseline volume or weaker historical performance (Appendix Figure B15). Hence, the IV regressions may conflate each of these important channels affecting PCI outcomes. Overall, however, both the OLS and IV estimates suggest average PCI outcomes declined following TAVR adoption.

6.2 Physical Capacity Constraints

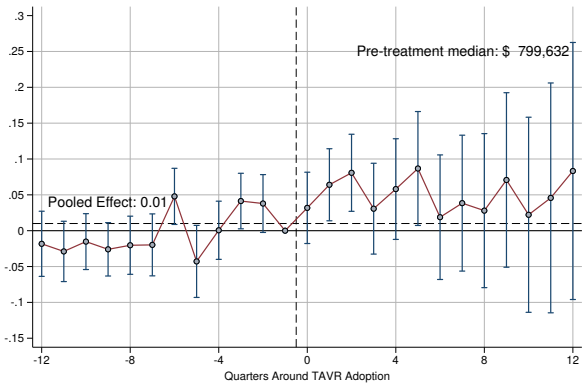
I next investigate differences in capacity constraints by estimating TAVR's effects on utilization of catheterization labs. These labs are examination and operating rooms where PCIs and TAVRs are typically performed; TAVR's adoption may consume valuable time in these labs and limit time for PCIs. I measure changes in access to cath labs by comparing changes in the total number of patients served relative to changes in overall lab utilization. As a single TAVR takes roughly twice as long as a less intensive PCI, one may expect that each individual patient may consume more of the lab's resources, ultimately restricting the number of patients receiving interventions.

Figure 4. Utilization of Catheterization Labs around Local TAVR Adoption

(a) Total # of Unique Patients Using Cath Lab



(b) Lab Utilization (Medicare Charges)



Notes: Figures estimate the effects of TAVR adoption in a CZ on utilization of catherization laboratories over time (Equation 13). Panel (a) measures the total number of patients receiving care in a cath lab in a given CZ-quarter; panel (b) measures utilization as the total volume of Medicare charges for patients receiving care in the cath lab. Results are robust to using Medicare payments or total Medicare inpatient days as alternative outcomes. Markets with fewer than 5 inpatient interventions per quarter are dropped, and standard errors are clustered by CZ.

Figure 4 shows this to be the case. I observe that TAVR's adoption meaningfully reduced the total number of unique patients receiving care in a catheterization lab (panel a),

while not affecting the total utilization of the lab (panel b). The average number of patients receiving care in these labs declines by 14%. However, the overall average capacity of catheterization labs remains constant across this time period, as proxied by various measures of total utilization.[34] This suggests capacity constraints for operating space are binding in these markets, so that innovation adoption limits availability of other interventions.

Taken together, the results suggest that in addition to worsened PCI outcomes, binding capacity constraints limited PCI availability after TAVR's adoption. While these mechanisms likely generalize to other innovations beyond TAVR, other mechanisms may be more context specific. For example, Medicare's specific volume thresholds for TAVR certification or mandatory imaging steps required for TAVR may impose a greater aggregate burden for adoption resulting in larger post-adoption volume declines (Yang, 2023). While these factors are TAVR-specific, other classes of innovation have their own unique regulations that similarly impact spillover effects, including fields such as robotic and orthopedic surgery (Horn et al., 2022; Randsborg and Chen, 2021).

6.3 Which patients lose access to treatments?

These findings corroborate the model's predictions that patients will be crowded out from accessing interventions. I identify which patients experience this crowdout based on their risk. Given that TAVR's adoption did not meaningfully change the average risk of PCI patients (Appendix Figure B16), the composition of PCI patients must have changed along *both* margins, including an exit of higher-risk patients as predicted by the model. I investigate this by estimating how TAVR affected intervention volume across bins of patient risk.

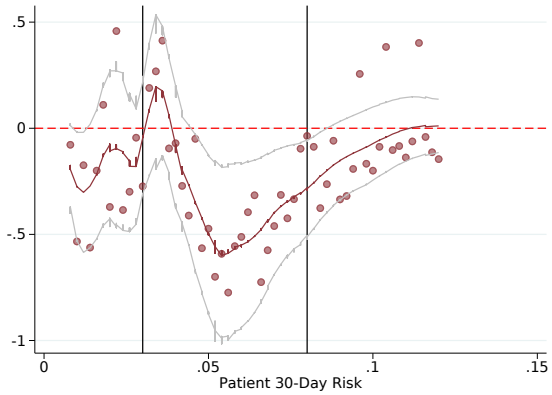
Figure 5 shows the results across the distribution of 30-day risk. Each point in the figure represents an estimated treatment effect, which are then smoothed using a local linear regression weighted by the number of patients in each bin, with standard errors corrected for multiple hypothesis testing.[35] The figure therefore identifies which patients experienced the largest declines in access to care following TAVR's adoption in their market.

The results corroborate the model predictions that patients on the margin between low-intensity procedures (valve supports) and maintenance care were more likely to forego care post-adoption. Figure 5 shows a clear region of patients crowded out from treatment, specifically those whose risk is between 4.5% and 9%. This group exactly overlaps the STS-PROM

[34] Figure 4b measures utilization as total Medicare charges; results are robust to alternative measurements including (a) Medicare payments, (b) inpatient days for the 100% sample of inpatient claims or (c) number of total catheterization lab procedures in the 20% sample of inpatient and outpatient claims instead. The 14% decline is roughly consistent with a value of $\delta = 2.2$ in the model framework given the baseline intervention volumes, consistent with the idea that a TAVR consumes 2–3 times the resources as a PCI.

[35] Results are similar across 60- and 90-day risk. Appendix Figure B18 presents a non-smoothed version.

Figure 5. Effects of TAVR Adoption on Total Intervention Volumes by Patient Risk



Notes: Estimated volume effects of TAVR adoption stratified by patient risk (bin width=0.2pp). Each point is a bin-specific DD coefficient, with effects smoothed using local linear regression weighted by patient volume. Standard errors are adjusted for multiple hypothesis testing (Anderson, 2008). See Appendix Figure B18 for non-smoothed version and Figure B19 for a version scaled by overall decline in intervention volume. Vertical lines indicate STS-PROM delineation between low- and high-risk patients. Results are robust to using "pooled" post-treatment LP-DID average effects.

delineation between medium- and high-risk patients; patients in this group lost access to cardiac interventions at an average rate of 0.5 procedures per quarter per bin. I next consider how this lost access differentially affected vulnerable populations.

Market-Level Inequities. First, I consider how inequitable outcomes may propagate across markets by considering market-level differences in patient populations. I sort CZs into quintiles based on the the share of nonwhite patients and the (population-weighted) average CZ ADI, and then estimate TAVR's effects on intervention volume within each quintile.

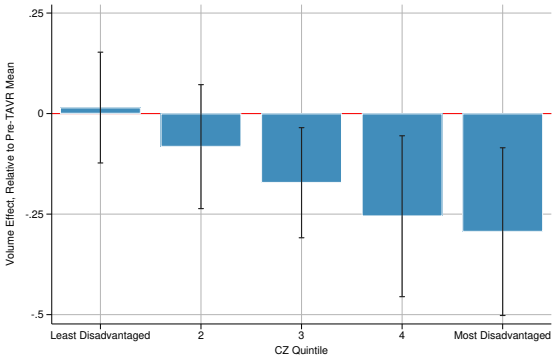
Figure 6 presents the results. In both panels, a clear gradient emerges. Local markets with greater racial diversity (panel a) or greater are disadvantage (panel b) experienced declines in volume over three times larger than the average decline, with a 25% reduction in total intervention volume for the most marginalized areas.[36] If anything, the least disadvantaged markets experienced *increases* in total volume, underscoring the importance of considering variation across markets as well as within them.

These results may be surprising if one assumes disadvantaged areas would experience reduced exposure to innovations like TAVR. We would then expect little, if any, crowding out to occur in these markets. In Appendix Figure B21, I illustrate that TAVR's adoption impacted patients in all markets approximately equally, relative to baseline PCI access. The figure shows two facts: first, patients in low-disadvantage areas had more than triple the number of PCI operators as high-disadvantage areas, a difference that was unaffected by

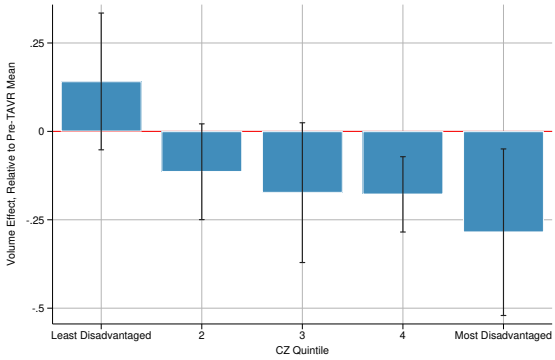
[36]Recall that average ADI corresponds to employment, education, and housing outcomes. I also stratify markets by dual eligibility, finding little evidence of inequities along this dimension (Appendix Figure B20).

Figure 6. Inequities in TAVR's Effects on Local Access to Interventions: CZ Level

(a) % Non-white



(b) 9-digit zip code ADI



Notes: Figures show heterogeneous volume effects by quintiles CZs according to disadvantage, measured in (a) as the fraction of nonwhite patients, and in (b) as the average market ADI in the market using 9-digit ZIP codes. Each bar indicates "pooled" post-treatment LP-DID effects (Figure 3), rescaled relative to pre-adoption means to facilitate comparisons. In each regression, both treated and control groups are limited to the quantile of interest, so comparisons are between CZs within a specified category of (dis-)advantage. See Appendix Figure B20 for results for dually-eligible patients.

TAVR's adoption. However, a market's relative exposure to TAVR was directly proportional to this access. Across markets, there was on average 1 TAVR operator per 12–13 PCI operators in the year of adoption, and 1 TAVR operator per 5 PCI operators by 2016. This suggests the results of Figure 6 are not driven by differential exposure to innovation.

Patient-Level Inequities. Second, I consider how differences in patient characteristics may affect crowd out probabilities. The model predicts that even within a market, patients of different groups may have systematically different locations on the risk curve and therefore be more or less likely to lose access to interventions. In order to look within markets, I limit attention to patient-level analysis using the 20% sample of enrollees.

Table 3 presents pooled post-treatment estimates across groups. Overall, I observe a decline in total volume of 26.86%, consistent with Figure 3. In general, patients in at-risk populations experience larger declines relative to majority populations. Even within a market, patients living in a high-disadvantaged region had a 4.4 percentage point larger decline than those in low-disadvantage regions. Racial and ethnic minorities were 1.4 to 1.9 times less likely to receive interventions post-TAVR than non-Hispanic White patients; these differences are only statistically significant for Hispanic patients ($p = .037$). I did not observe differences across patients based on sex, age, or dual eligibility for Medicaid.

Overall, these estimates suggest that both across and within markets, an innovation's adoption may affect equitable access to care within markets. These effects may particularly

Group	Estimate	% Change	95% Confidence Interval	p-value, difference
Overall	-1.12	-26.86	[-32.59, -21.12]	—
Panel A: Patient Geography				
ADI: Lowest Decile	-0.12	-27.27	[-34.00, -20.55]	—
ADI: Highest Decile	-0.19	-31.67	[-38.89, -24.45]	0.050
Panel B: Patient Eligibility				
Not Dual Eligible	-0.84	-27.10	[-32.67, -21.53]	—
Dual Eligible	-0.29	-27.10	[-33.86, -20.34]	0.500
Panel C: Patient Race				
White	-0.54	-14.92	[-19.04, -10.80]	—
Black	-0.08	-23.53	[-31.66, -15.40]	0.133
Hispanic	-0.02	-28.57	[-51.25, -5.89]	0.037
Other Non-White	-0.03	-21.43	[-35.85, -7.01]	0.198
Panel D: Patient Sex				
Male	-0.67	-26.69	[-32.37, -21.02]	—
Female	-0.46	-27.71	[-33.63, -21.80]	0.454

Notes: Table presents pooled stratified post-treatment effects (Equation 13). The outcome variable is the rate of interventions performed within the patient group at the CZ level (for the first year post-adoption); markets with ≤ 5 procedures quarterly are dropped. Analysis uses the 20% Medicare sample. Standard errors are clustered by CZs. Percentage changes are relative to average intervention volumes and are used in hypothesis testing; results are robust to considering the median instead.

Table 3. Within-Market Inequities: Pooled LP-DID Estimates

affect patients living in geographically deprived regions or in regions with a high concentration of marginalized racial and ethnic groups.

6.4 Allocative Inefficiencies

The welfare impacts of crowd-out for patients depends on whether care was efficiently allocated prior to TAVR's adoption. If PCIs were over-used prior to adoption, Figures 3 and 6 do not necessarily imply welfare losses (Chandra and Staiger, 2020). To address this, I examine differences in TAVR's effects across markets with different underlying propensities to perform PCIs for patients conditional on clinical severity. Although suggestive, this exercise highlights that if patients are losing access in markets which already have lower than average propensities to treat patients, innovation crowdout may be particularly inefficient.

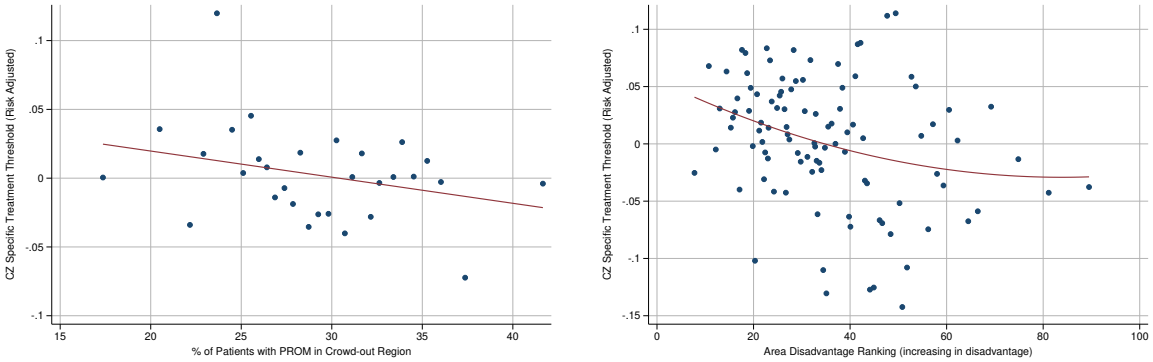
I therefore use the rich set of patient, physician, and geographic controls used in predicting patient risk (Appendix Table B2) to calculate risk-adjusted treatment rates at the CZ level

($\hat{\varphi}_{CZ}$), following Equation 12.[37] I estimate these treatment propensities on the pre-adoption data, to evaluate how markets treated the same patient in potentially different ways prior to the spillover effects induced by TAVR. I then compare these market-level estimates of treatment propensities to measures of crowd-out severity.

Figure 7. Market Level Relationships between Treatment Propensity and Crowd-Out Risk

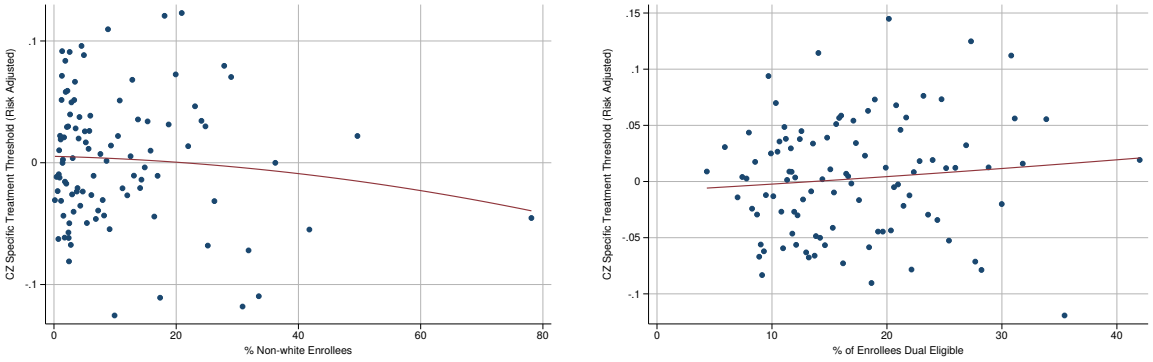
(a) % of Patients in Crowd-out Region

(b) ADI (9-digit ZIP code)



(c) % of Nonwhite Patients

(d) % of Dual-Eligible Patients



Notes: Figures show binscatter relationships between the estimated values of $\hat{\varphi}_{CZ}$ (using Equation 12) and CZ-levels of disadvantage, including: the % of patients with risk between 4.5% and 9% (panel a); the population-weighted average ADI of a CZ (panel b); the % of nonwhite Medicare enrollees in a CZ (panel c); and the % of dual-eligible Medicare enrollees in a CZ (panel d). Increases in the y-axis ($\hat{\varphi}_{CZ}$) indicate increased likelihood of treatment for a patient with a given risk.

Figure 7 presents results highlighting the correlations between treatment propensities and disadvantage measures, including the share of patients likely to be crowded out from care based on their risk (following Figure 5). I first observe that markets with a greater percentage of patients in the crowd-out region are also markets with lower treatment propensities; to put this correlation into context, I estimate that a market increasing the share of these patients by 10% (roughly 3 percentage points) would move about 5 spots down in the ranking

[37] Appendix Figure B22 shows the distribution of these predicted values. In general, the distribution is centered around zero, as expected since treatment propensity is determined on average by included covariates.

of $\hat{\varphi}_{CZ}$ (about a 1.5% decline). Similarly, I observe a strong negative correlation between the population-weighted average ADI of a CZ and its treatment propensities—this relationship is particularly strong, with a one unit increase in the average ADI ranking of a CZ corresponding to a 2.5% decline in a market's treatment generosity. Negative correlations are weaker for markets with a high share of nonwhite residents; in contrast, I observe a weak positive correlation between dual eligibility and treatment propensities.

In Appendix Table B6, I estimate how TAVR's adoption effects on volume differed across these treatment propensities. I find that markets that were the least restrictive in treating patients pre-adoption also had the lowest levels of treatment crowd-out. Without additional, stronger parametric assumptions, I cannot directly identify changes in efficiency across TAVR's adoption. However, these results suggest that rather than correcting over-use of PCIs prior to adoption, TAVR's arrival reduced the availability of treatments where access was already limited. Hence, the inequitable effects documented in the preceding section may serve only to exacerbate disparate access to treatment across groups.

7 Conclusion

Inequities in access to high-return health services have persisted for decades, leaving patients of lower incomes or marginalized groups with inferior treatments and, subsequently, health outcomes. Innovations in health treatments—despite their significant health benefits—may further entrench these differences if they inhibit access to older, adjacent technologies.

I present a theoretical framework considering these implications. The model highlights a tension between innovation takeup and overall intervention availability due to operator skill development and capacity constraints. This tension implies that innovations may reduce overall access to interventions, potentially differentially affecting vulnerable patients.

I test these predictions empirically using aortic valve replacement surgeries as a case study. My results—which suggest that TAVR both affected capacity and operator skill in PCI provision—suggest the need for infrastructure to scale up innovative treatments without compromising availability of adjacent procedures (Hoagland and Kipping, 2024). Identifying these adjacent treatments and incentivizing their continued provision—for example, by adjusting physician reimbursement rates or centralizing access to innovations (Yang, 2023)—could maximize the social impact of technological change.

This framework and its empirical results may be useful in evaluating the potential spillover effects of a broader class of innovations. In general, innovative practices in healthcare may either augment or compete with existing adjacent technologies, potentially affecting the availability of a broad set of interventions or procedures and, therefore, overall (equitable) access to specialized care. To ensure procedural innovations maximize social welfare

gains, it is important to carefully consider the potential for these spillover effects and how large changes in equitable access might be. These effects are likely context dependent; for example, the use of catheterization labs and the presence of minimum volume requirements for both TAVR and PCIs may influence the reported empirical results in this study. The constellation of physician skill, hospital policies, and other contextual factors such as prices or government interventions likely will influence evaluation of other innovations.

It is important to underscore that innovation itself does not inherently cause crowd-out or inequity. Rather, specific market conditions—such as capacity constraints or the complexity of required skills——determine the extent to which a novel procedure disrupts the supply of adjacent procedures. Policymakers aiming to promote equitable healthcare access might therefore consider targeted interventions, including infrastructure investment to alleviate capacity bottlenecks, adjustments in reimbursement structures to incentivize broader skill retention, or more flexible Medicare guidelines around volume thresholds. Such strategies could help ensure that the benefits of medical innovation reach all patient populations.

Future work examining the potentially unequal impact of technological change can build on this paper in several ways. As innovations like TAVR mature, future work can consider the longer-run impacts of innovation on equity, including for harder to observe outcomes such as wait times, complications, and endogenous patient risk.[38] New research may also incorporate long-run physician entry, exit, and specialization decisions. Additionally, future work may consider how selection affects market outcomes, whether selective innovation takeup by providers (Huckman and Stern, 2022) or "cherry-picking" patients post-innovations (Desai et al., 2009). Finally, this framework can be extended to many other inequities and structural forces that worsen health outcomes for marginalized groups, including discrimination at the point of care and systematic gaps in seeking out healthcare due to eroded trust in the healthcare system (Webb Hooper et al., 2019).

[38]Wait times for SAVR/TAVR have increased in other countries, leading to higher rates of heart failure for those with severe aortic stenosis (Albassam et al., 2020). This might be due to high centralization of access. Additionally, this paper only examined years that TAVR was available for high-risk patients; as TAVR became more widely available, more structural market changes may have occurred.

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A Appendix: Additional Model Derivations

A.1 Proof of Equilibrium Existence and Uniqueness

The model presented in Section 2 defines its equilibrium as a fixed point that solves the system of equations 5 and 6. In this section I argue that such an equilibrium exists and, under generally mild conditions, is unique.

For convenience, define the following two functions:

$$Z_1 = \beta_{10}\theta + (\alpha_1 + \alpha_0)P_1 + \alpha_0 P_2 - \alpha_0 - c_{10}((P_1 + (1+\delta)P_2) - k) \tag{14}$$

$$Z_2 = \beta_{21}\theta + \alpha_2 P_2 - \alpha_1 P_1 - c_{21}((P_1 + (1+\delta)P_2) - k). \tag{15}$$

Then, it follows that the equilibrium system of equations can be written as a transformation mapping:

$$T_2(P_1, P_2) = \int_\theta \Pr\{Z_2 > \varepsilon_{12}\} f(\theta) d\theta. \tag{16}$$

$$T_1(P_1, P_2) = \int_\theta \Pr\{Z_1 > \varepsilon_{10}\} f(\theta) d\theta - T_2(P_1, P_2). \tag{17}$$

This transformation takes (P_1, P_2) to $(T_1(P_1, P_2), T_2(P_1, P_2))$, and the equilibrium condition is that $(P_1^*, P_2^*) = (T_1(P_1^*, P_2^*), T_2(P_1^*, P_2^*))$. Since $P_s \in [0, 1]$ for each $s \in \{0, 1, 2\}$, the domain of this transformation is $[0, 1]^2$. Given standard assumptions on the distribution of θ and ε—for example, that both have continuous CDFs—T_2 is obviously continuously differentiable and maps to $[0, 1]$.

Similarly, T_1 also satisfies these properties. To see this, note that $\int_\theta \Pr\{Z_1 > \varepsilon_{10}\} f(\theta) d\theta \leq 1$ and $T_2 \geq 0$, so that $T_1(P_1, P_2) \leq 1$. T_1 is also weakly positive as a result of the assumption that optimal treatment intensity is perfectly distributed across θ_{is}. That is, since $|\partial U_{i2}/\partial\theta_2| > |\partial U_{i1}/\partial\theta_1| > |\partial U_{i0}/\partial\theta_0|$, it follows that whenever $Z_2 \geq \varepsilon_{12}$, then $Z_1 \geq \varepsilon_{10}$. This directly implies that $T_2 = \int_\theta \Pr\{Z_2 > \varepsilon_{21}\} f(\theta) d\theta \leq \int_\theta \Pr\{Z_1 > \varepsilon_{10}\} f(\theta) d\theta$, so that $T_1 \geq 0$.

Since each coordinate of the mapping T_i is continuous and maps to a closed and compact interval, $[0, 1]$, Brouwer's fixed point theorem asserts that at least one fixed point of T exists.

I next consider conditions under which this fixed point is unique. Specifically, under mild assumptions on the relative weights placed on provider specialization and waiting costs, one can show that $T(\cdot)$ is a globally univalent transformation via the Gale–Nikaido theorem, meaning that any fixed point is unique.

To see this, first consider the Jacobian matrix J of T. Using the chain rule:

$$\frac{d}{dP_s} \int Pr(Z_s > \varepsilon_s) f(\theta) d\theta = \int f_{\varepsilon_s}(Z_s(P_1, P_2, \theta)) \frac{\partial Z_s}{\partial P_s} f(\theta) d\theta. \tag{18}$$

Hence, J can be expressed as

$$J(P_1, P_2) = \begin{pmatrix} \frac{\partial T_1}{\partial P_1} & \frac{\partial T_1}{\partial P_2} \\ \frac{\partial T_2}{\partial P_1} & \frac{\partial T_2}{\partial P_2} \end{pmatrix} = \begin{pmatrix} \left(\alpha_1 + \alpha_0 - c_{10}\right) m_1(P_1, P_2) & \left(\alpha_0 - c_{10}(1+\delta)\right) m_1(P_1, P_2) \; - \; 1 \\ -\left(\alpha_1 + c_{21}\right) m_2(P_1, P_2) & \left(\alpha_2 - c_{21}(1+\delta)\right) m_2(P_1, P_2) \end{pmatrix},$$

where I have defined the integrals as nonnegative "weights" placed on each entry in J, m_i:

$$m_i(P_1, P_2) \;=\; \int f_{\varepsilon_i}\big(Z_i(P_1, P_2, \theta)\big)\, f(\theta)\, d\theta, \quad i \in \{1, 2\}.$$

I argue that under relatively weak conditions, J is a P-matrix everywhere, meaning that each of its principal minors are strictly positive regardless of the starting point (P_1, P_2). Note that if these conditions are not met, the existence of an equilibrium is guaranteed but there may be multiple equilibria. These conditions, however, are generally easy to satisfy, particularly in the context of dynamic effects discussed below in Appendix Section A.4.

Although there are many different sets of assumptions that can ensure this condition, a relatively intuitive one is to impose simple assumptions on the relative magnitudes of productivity effects and waiting costs, particularly in the long run. It is sufficient to show that J is a P-matrix everywhere for us to show that each row of J is strictly diagonal dominant, meaning:

$$|J_{11}| > |J_{12}| \Rightarrow |(\alpha_1 + \alpha_0 - c_{10})m_1| > |(\alpha_0 - c_{10}(1+\delta))m_1 - 1| \tag{19}$$
$$|J_{22}| > |J_{21}| \Rightarrow |(\alpha_2 - c_{21}(1+\delta))m_2| > |-(\alpha_1 + c_{21})m_2|. \tag{20}$$

The first condition is immediately met as long as $(\alpha_1 + \delta c_{10})m_1 \geq -1$. This is obviously met provided that productivity spillovers and differential waiting costs are nonnegative regardless of the value of m_1. The second condition can be rewritten as $\alpha_2 - \alpha_1 > c_{21}(2+\delta)$, as long as we impose the assumption that $\alpha_1 + c_{21} \geq 0$ (and remembering that c_{21} is negative). Hence, this condition is satisfied if $\alpha_2 \geq \alpha_1$.

To summarize, then, under the relatively mild assumptions that

$$c_{10} \geq 0 \tag{21}$$
$$\alpha_1 \geq -c_{21} \tag{22}$$
$$\alpha_2 \geq \alpha 1, \tag{23}$$

then one can conclude that J is a P-matrix everywhere. Since $[0,1]^2$ is a convex set (and $(0,1)^2$ is a convex open set) and T is a continuously differentiable mapping as proven above, this implies that T is globally univalent, meaning that if $(P_1, P_2) \neq (P_1', P_2')$, then $T(P_1, P_2) \neq T(P_1', P_2')$. Therefore, there can be at most one fixed point for T in the space $[0,1]^2$.

A.2 Derivation of Equations 7 and 8

Given the assumptions of linear utility with marginal utilities increasing in absolute value with more intensive interventions, equilibrium allocations of patients to treatments are well-ordered in θ. That is, the highest risk individuals receive $s = 0$, while those with intermediate risk receive $s = 1$ and the lowest risk receive $s = 2$. Therefore, in equilibrium, the cutoffs

for treatment thresholds must satisfy

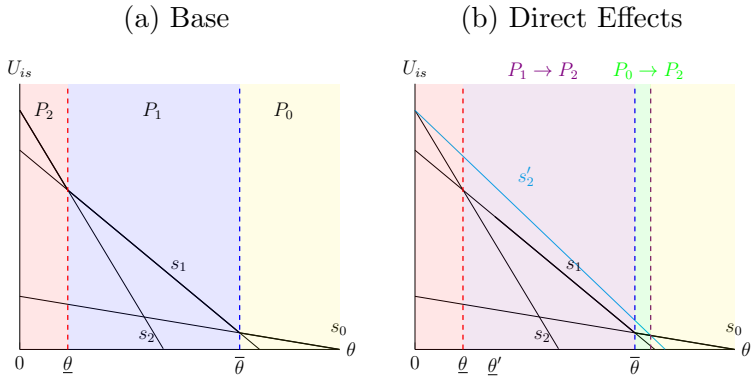
$$P_2 = F(\underline{\theta})$$
$$P_1 = F(\overline{\theta}) - F(\underline{\theta})$$
$$P_0 = 1 - F(\overline{\theta}).$$

These thresholds are defined such that

$$\mathbb{E}[U_{i2}(\underline{\theta})] = \mathbb{E}[U_{i1}(\underline{\theta})]$$
$$\mathbb{E}[U_{i1}(\overline{\theta})] = \mathbb{E}[U_{i0}(\overline{\theta})],$$

which, taken together with the above definitions and Equation 1, produce the desired result.

Figure A1. Alternate Treatment Decisions Based on Patient Risk



Notes: Compare with Figure 1 in the main text. Illustrates model equilibrium pre- and post-innovation under an alternate framework for innovation. Panel (a) presents treatment utilities given θ prior to innovation, which define treatment regions for s_2 (red, P_2); s_1 (blue, P_1); and s_0 (yellow, P_0). Panel (b) presents direct effects of innovation, which changes the threshold between interventions.

A.3 Inequalities in crowd-out

This section formalizes the discussion in Section 2.4, concerned with identifying potential inequalities and inequities arising from an innovation's impact on the total volume of interventions provided in a market. The analysis identifies the relative share of patients from two groups likely to be in the "crowd-out region" of patients losing access to interventions as a result of the innovation.

Inequalities in Crowd-out. Assume that the condition for crowd-out is satisfied (Equation 10), so that there is a region C of patients who received s_1 prior to an innovation and s_0 post-adoption ($C = [\overline{\theta}', \overline{\theta}]$), where $\overline{\theta}' < \overline{\theta}$ to indicate that there is an extensive margin decline in volume. However, suppose that clinicians do not observe θ directly but a proxy $\hat{\theta}$.[39] Assume $\hat{\theta}$ is a linear combination of observable characteristics Z_{is} correctly predicting

[39] $\hat{\theta}$ is a combination of physician assessment, patient beliefs, and clinical histories.

θ except for an idiosyncratic, mean-zero error ν_{is}:

$$\theta_{is} = \underbrace{Z_{is}\gamma}_{\hat{\theta}} + \nu_{is}.$$

Group membership can be represented as a binary variable $d_{ig} \in Z_{is}$ indicating if patient i is a member of a group g. Groups may include demographic (e.g., low-income) or clinical indicators (e.g., patients with diabetes, smokers); such indicators routinely inform patient risk calculations (van Ryn and Burke, 2000). The coefficient γ_d captures discrete shifts in predicted risk across groups.[40] If membership is informative (so that $\gamma_d \neq 0$), patients in different groups constitute different shares of the crowdout region, $s_{C,g}$, determined by the underlying distributions of θ and $Z_{is}\gamma$ and Bayes' rule:

$$\begin{aligned}
s_{C,g} = Pr(i \in g | i \in C) &= Pr(i \in C | i \in g) \frac{Pr(i \in g)}{Pr(i \in C)} \\
&= \frac{s_g}{s_C} \left[Pr(Z_{it,-g}\gamma_{-g} + \gamma_g \in [\overline{\theta}', \overline{\theta}]) \right] \\
&= \frac{s_g}{s_C} \left[\int_{\overline{\theta}'-\gamma_d}^{\overline{\theta}-\gamma_d} f(Z_{it,-g}\gamma_{i,-g}) d(Z_{it,-g}\gamma_{i,-g}) \right] \\
&= s_g \frac{\int_{\overline{\theta}'-\gamma_d}^{\overline{\theta}-\gamma_d} f(Z_{it,-g}\gamma_{i,-g}) d(Z_{it,-g}\gamma_{i,-g})}{\int_{\overline{\theta}'}^{\overline{\theta}} f(\theta) d\theta}.
\end{aligned}$$

Here, s_g indicates the share of group g in the population, and $s_C = F(\overline{\theta}) - F(\overline{\theta}')$ is the relative size of C. As these are not equal in general, C may over- or under-represent g.

Inequities in Crowd-out. These inequalities in access may correspond to *inequities* in access when risk distributions are imperfectly or incorrectly observed. Imperfect proxying may arise from provider error or other factors, including patient beliefs or biased health measurements like risk scores (Obermeyer et al., 2019). This measurement error distorts the likelihood that members of g are represented in C. To quantify this relationship, suppose that instead of using γ_g in risk calculations, $\hat{\theta}$ relies on the use of a "noisy signal" $\hat{\gamma}_g$:

$$\hat{\gamma}_g = \gamma_g + \nu,$$

where ν is an idiosyncratic error in group risk measurement.[41] Consider how this term changes the representation of group g in the crowd-out region C (that is, $s'_{C,g}(\nu)$) relative to

[40] For ease of exposition, assume d_{ig} is independent to all covariates $Z_{is,-g} = Z_{is} \setminus d_{ig}$.

[41] ν is not classical measurement error or necessarily centered around 0. In addition, ν can be allowed to vary across providers or patients.

the original representation, $s_{C,g}$. Define this ratio to be $I(\nu)$ and notice:

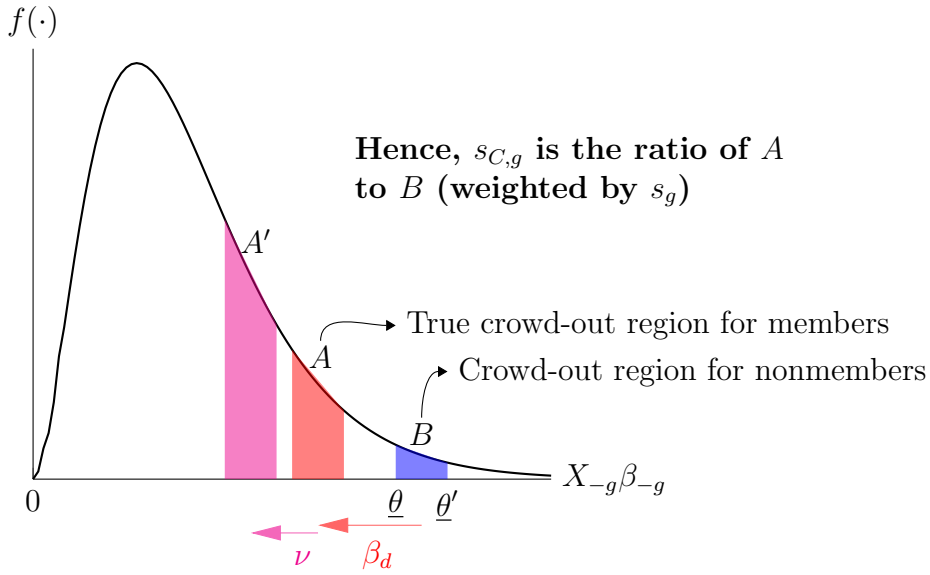
$$I(\nu) = \frac{s'_{C,g}(\nu)}{s_{C,g}}$$
$$= \frac{1}{s_{C,g}} \int_{\overline{\theta}-\gamma_d-\nu}^{\overline{\theta}'-\gamma_d-\nu} f(X_{i,-g}\gamma_{i,-g}) d(X_{i,-g}\gamma_{i,-g}).$$

Importantly, this ratio changes in keeping with the size of the measurement error, ν:

$$\frac{\partial I}{\partial \nu} = \frac{\left[f_{X_{-g}\gamma_{-g}}(\overline{\theta}-\gamma_d-\nu) - f_{X_{-g}\gamma_{-g}}(\overline{\theta}'-\gamma_d-\nu)\right]}{s_{C,g}}.$$

That is, risk perception error ν affects group-specific crowd-out proportionately to the initial composition of g in C. Figure A2 presents the intuition behind this result; intuitively, ν incorrectly shifts patients of one group up or down along the risk distribution, θ, leading the "over-estimated group" more likely to lose access to care.

Figure A2. Inequities in Crowdout Associated with Imperfect Risk Assessment



Notes: Figure illustrates the relative "crowd-out regions" for members and nonmembers of a group g when used in a proxy for patient risk, as well as the effect of measurement error in β_d on the relative crowd-out rates of members and nonmembers. The figure plots an inverse gamma distribution with parameters $(3, 1)$ for observable non-group covariates used in predicting patient risk, $f(X_{-g}\beta_{-g})$. The figure assumes that the membership variable d_{ig} is independent of all other covariates X_{-g}. The region A (in red) represents the crowd-out region for members of a group g given β_d, and region B (in blue) the corresponding region for nonmembers. Hence, the relative sizes of A and B (weighted by the overall size of the group g in the population) indicate the representation of members of g in the crowd-out region. Changes in ν shift the region A', ultimately affecting the relative representation of members of group g in the crowd-out region.

The figure shows, for a given distribution of observable *non-group* characteristics $X_{-g}\gamma_{-g}$ and risk cutoffs $\overline{\theta}$ and $\overline{\theta}'$, the regions for which different types of patients will be crowded out

of low-intensity interventions by the medical innovation. When the patient is a member of group g, the discrete risk shift γ_d results in them being crowded out of treatment when their proxied non-group risk lies in the red region A. Similarly, for patients that are not members of g, the crowd-out region is defined simply by having a proxied risk level $\hat{\theta}_{-g} \in [\overline{\theta}', \overline{\theta}]$ (the blue region B). Hence, the fraction of crowded-out patients in g is given by the ratio of A to B (weighted by s_g).

A.4 A Dynamic Extension of the Model

While the model presented in Section 2 treats the market for cardiology care as static, in reality innovations like TAVR diffuse over time, so both productivity spillovers and capacity constraints evolve. To see how the timing of adoption affects the gains from any intervention $P_s, s \in \{0, 1, 2\}$, consider a path of adoption $\{P_{s,t}\}_{t \geq 0}$ instead. For example, the path for the intensive intervention may be at a steady state prior to an innovation, and then follow a logistic diffusion curve following TAVR's adoption.

Given this setup, one can augment individual utilities to simply be conditional on the point at which they are considered:

$$U_{ist} = \beta_s \theta_{i,t} + \alpha_s P_{s,t} - c_{s,t}(P_{1,t}, P_{2,t}) + \varepsilon_{ist}, \tag{24}$$

where we also allow for patient health θ_{it} to vary over time. As $P_{2,t}$ increases over time, provider specialization will continue to accrue at a rate of α_2; on the other hand, there is potential for new capacity to be introduced, leading to an evolution of the waiting costs $c_{2,t}$ (for example, following Kalouptsidi (2014)).

Patients in this model may not be able to fully optimize the choice of when they receive an intervention due to deteriorations in their own health from waiting for care; however, they may be able to strategically capitalize on the tradeoffs between delaying care slightly and additional provider specialization. If patients are able to do this, I can define a value function

$$V_i = \max_{t \geq 0} \rho^t \max_{s \in \{0,1,2\}} \left[\beta_s \theta_{i,t} + \alpha_s P_{s,t} - c_{s,t}(P_{1,t}, P_{2,t}) + \varepsilon_{ist}\right], \tag{25}$$

where ρ indicates the patient discount factor. Hence, the net benefit of delaying care (to take advantage of larger $P_{2,t}$) can be traded off against reduced health, exogenous changes in waiting costs, and time discounting. Given this value function, one can specify the corresponding Bellman equation with the laws of motion for $\theta_{i,t}$, $P_{s,t}$, and $c_{s,t}$.

In practice, this model would be more difficult to estimate and would likely require a longer time series of data as well as additional modeling assumptions about an innovation's diffusion path. However, notice that under relatively weak assumptions, the dynamic version of this model will yield similar predictions about declines in overall intervention volume as the static model. In particular, provided one assumes that capacity is weakly increasing (so that $c_{1,t}$ and $c_{2,t}$ are weakly decreasing) and that provider specialization is a function of the stock, rather than the flow, of procedures (so that $\alpha_s P_{s,t}$ captures the full productivity spillover), the equations governing the changes in thresholds presented in Section 2 carry through this dynamic version of the model as well.

B Appendix: Additional Empirical Results

B.1 Tables

Version	Codes	General Description
Panel A: SAVR		
ICD-9-PCS	3521, 3522	Open and other replacement of aortic valve
ICD-10-PCS	02RF0*	Open replacement of aortic valves
Panel B: TAVR		
ICD-9-PCS	3505, 3506	Endovascular replacement of aortic valve
ICD-10-PCS	02RF3*, 02RF4*	Percutanenous and/or endoscopic replacement of aortic valves
Panel C: PCIs		
ICD-9-PCS	0061–0066	Percutaneous transluminal coronary angioplasty (PTCA)
	3510–3514	Open heart valvuloplasty without replacement
	3610–3619	CABG
	3721–3723	Cardiac catheterization
ICD-10-PCS	021*	CABG
	0270*—0273*	Dilation of coronary arteries, percutaneous approach
	027F*—027J*	Dilation of heart valves, percutaneous approach
	02NF0ZZ, 02NG0ZZ,	Release heart valves, open approach
	02NH0ZZ, 02NJ0ZZ	Release heart valves, open approach
	02QF0ZZ, 02QG0ZZ,	Repair heart valves, open approach
	02QH0ZZ, 02QJ0ZZ	Repair heart valves, open approach
	037G*–037Q*	Dilation of arteries with intraluminal device, percutaneous
	057L*–057S*	Dilation of veins with intraluminal device, percutaneous

Table B1. Definitions of Interventional Cardiology Procedures

Notes: Table shows inpatient hospital procedure codes (ICD-9-PCS and ICD-10-PCS) used to identify valve replacements (TAVR and SAVR) and valve supports (PCIs). Interventional cardiologists are identified using the Medicare Data on Provider Practice and Specialty (MD-PPAS) files, 2010–2017. * indicates all relevant ICD codes with the listed prefix.

	30-Day Mortality		60-Day Mortality		90-Day Mortality	
	ME	95% CI	ME	95% CI	ME	95% CI
Panel A: Patient Demographics						
Patient age	-0.000	[-0.001,-0.000]	-0.000	[-0.000,-0.000]	0.000	[-0.000,0.000]
Female	0.007	[0.006,0.008]	0.006	[0.004,0.007]	0.004	[0.002,0.006]
Black	0.011	[0.008,0.014]	0.009	[0.006,0.013]	0.009	[0.005,0.012]
Hispanic	0.006	[-0.000,0.013]	0.010	[0.002,0.017]	0.010	[0.002,0.018]
Other Minority Race	0.011	[0.007,0.015]	0.015	[0.010,0.019]	0.014	[0.009,0.019]
ADI (5-digit ZIP)	0.000	[-0.000,0.000]	0.000	[-0.000,0.000]	0.000	[-0.000,0.000]
ADI (9-digit ZIP)	0.000	[0.000,0.000]	0.000	[0.000,0.000]	0.000	[0.000,0.000]
Log(Median Zip Income)	-0.006	[-0.010,-0.003]	-0.010	[-0.014,-0.006]	-0.013	[-0.017,-0.009]
Dual Eligible	0.049	[0.047,0.051]	0.061	[0.059,0.064]	0.069	[0.066,0.072]
Panel B: Chronic Conditions						
# of Chronic Conditions	0.004	[0.004,0.004]	0.006	[0.005,0.006]	0.007	[0.007,0.008]
CC: AMI	0.005	[0.003,0.007]	0.006	[0.003,0.008]	0.005	[0.002,0.007]
CC: COPD	0.008	[0.006,0.009]	0.011	[0.009,0.012]	0.011	[0.009,0.013]
CC: CHF	0.018	[0.016,0.019]	0.024	[0.022,0.025]	0.026	[0.024,0.028]
CC: Diabetes	-0.003	[-0.005,-0.002]	-0.004	[-0.005,-0.002]	-0.004	[-0.005,-0.002]
CC: Hypertension	0.006	[0.004,0.009]	0.006	[0.003,0.009]	0.006	[0.002,0.009]
CC: Stroke	-0.000	[-0.002,0.001]	-0.001	[-0.003,0.001]	-0.002	[-0.004,0.000]
Panel C: Previous Healthcare Utilization						
Any Previous Surgery	0.011	[0.002,0.021]	0.007	[-0.005,0.018]	0.001	[-0.013,0.014]
# of Previous Surgeries	0.006	[0.004,0.008]	0.006	[0.003,0.009]	0.005	[0.002,0.008]
Previous PCI	-0.009	[-0.018,0.001]	-0.004	[-0.016,0.009]	0.003	[-0.011,0.017]
Previous SAVR	0.021	[0.014,0.028]	0.023	[0.014,0.031]	0.022	[0.013,0.031]
Previous TAVR	0.006	[-0.008,0.020]	0.012	[-0.004,0.028]	0.013	[-0.004,0.030]
Any ED Visit	0.016	[0.014,0.018]	0.025	[0.023,0.027]	0.030	[0.028,0.032]
# of ED Visits	-0.001	[-0.002,0.000]	-0.005	[-0.005,-0.004]	-0.006	[-0.007,-0.005]
Any Hospital Stay	0.032	[0.023,0.041]	0.017	[0.008,0.026]	0.004	[-0.006,0.013]
# Hospital Stays	-0.023	[-0.024,-0.022]	-0.034	[-0.035,-0.033]	-0.037	[-0.038,-0.035]
# of Readmissions	0.016	[0.015,0.018]	0.029	[0.028,0.031]	0.034	[0.032,0.035]
# of Days Admitted	-0.000	[-0.000,-0.000]	0.001	[0.001,0.001]	0.002	[0.002,0.002]
Observations	377,532		377,532		377,532	

Table B2. STS-PROM Logistic Regression Coefficients

Notes: Table shows estimated marginal effects (ME) and 95% confidence intervals (CI) according to the STS-PROM model. Regressions include year-quarter fixed effects, and are estimated for $N = 377,532$ cardiology patients, including all those who received valve replacements or supports in the analytical sample.

	(1) Patient Migration	(2) Operator Migration	(3) Traveling for Care
TAVR Treatment Effect, Pooled	-0.026	-0.026	0.012
	(0.0244)	(0.0137)	(0.0164)
p-value	[0.2950]	[0.0632]	[0.4648]
Baseline mean	3.23%	3.71%	0.68%

Notes: Table presents estimates of Equation 13 on three outcomes measuring the effects of TAVR's adoption on patient and physician migration. The underlying sample includes the 20% sample of patients and all physicians who ever provide interventional cardiology or cardiothoracic surgery care. Column (1) indicates the probability that a patient moves CZs in a given year, using the BSF files to measure patient migration. Column (2) indicates the probability that an operating physician moves in a given year, using the MD-PPAS files to measure physician migration. Column (3) indicates the probability that a patient will go out of their home CZ to receive an intervention, using the Inpatient claims files. Note that regressions are estimated at the year level given data availability (column 3 can be estimated at a finer level of time variation without affecting the results, but is presented at the annual level here for consistency with the other models). Reported coefficients are pooled average post-treatment effects over 6 years post-adoption. Markets with ≤ 5 procedures quarterly are dropped, and standard errors are clustered at the CZ level.

Table B3. Effects of TAVR Adoption on Patient and Physician Migration

Market Level Analysis: 100% inpatient claims	
All Interventions	-0.159***
	(0.0137)
Valve Replacements	1.857***
	(0.0745)
PTCA Only	-0.258***
	(0.0174)
Cardiac Catheterization	0.034**
	(0.0133)
All Other PCI	-0.123***
	(0.0117)
Individual Level Analysis: 20% Subsample (Inpatient + Outpatient)	
All Interventions	-0.748***
	(0.0272)

Table B4. Robustness of Main Regression Results to Poisson Estimation

Notes: Table shows estimated regression coefficients from pooled DID analysis using Poisson regression. Compare with Figure 3. Panel A includes 100% of inpatient procedures, and measures total volume at the CZ-quarter level; panel B includes all interventional cardiology procedures for the 20% carrier file (inpatient and outpatient), and measures individual rates of interventions per 1,000 enrollees. Standard errors are clustered at the CZ level.

Complication	Codes
Arterial Embolism	444.*, 445.*, I74.*, I75.*
Bleeding Requiring Transfusion	36430 (CPT-4) or Revenue Center codes 039*
Cardiac Tamponande	423.3*, I31.31, I31.39, I31.4
Cardiogenic Shock	R57.0, 785.51
Heart Failure	428.*, I50.*
Intra-cranial Hemorrhage	430.*, 431.*, 432.*, 433.*1, 434.*1, I60.*, I61.*, I62.*, I63.*
Myocardial Infarction	410.*, I21.*, I22.*
Thrombosis	451.*, I80.*, 452.*, I81.*, 453.*, I82.*
Restenosis	36*.*, 02100ZZ, 021009Z, 021008Z, 02100YZ, 02100WZ, 02110ZZ 021109Z, 021108Z, 02110YZ, 02110WZ, 02120ZZ, 021209Z, 021208Z, 02120YZ, 02120WZ, 02130ZZ, 021309Z, 021308Z, 02130YZ, 02130WZ, 02703ZZ, 027034Z, 027035Z, 02703DZ, 02703EZ, 02713ZZ, 027134Z, 027135Z, 02713DZ, 02713EZ, 02723ZZ, 027234Z, 027235Z, 02723DZ, 02723EZ, 02733ZZ, 027334Z, 027335Z, 02733DZ, 02733EZ, 02300ZZ, 02303ZZ, 02304ZZ, 02310ZZ, 02313ZZ, 02314ZZ, 02320ZZ, 02323ZZ, 02324ZZ, 02330ZZ, 02333ZZ, 02334ZZ, 02V00ZZ, 02V03ZZ, 02V04ZZ, 02V10ZZ, 02V13ZZ, 02V14ZZ, 02V20ZZ, 02V23ZZ,02V24ZZ, 02V30ZZ, 02V33ZZ, 02V34ZZ, 02U00JZ, 02U03JZ, 02U04JZ, 02U10JZ, 02U13JZ, 02U14JZ, 02U20JZ, 02U23JZ, 02U24JZ, 02U30JZ, 02U33JZ, 02U34JZ, 02Q00ZZ, 02Q03ZZ,02Q04ZZ, 02Q10ZZ, 02Q13ZZ, 02Q14ZZ, 02Q20ZZ, 02Q23ZZ, 02Q24ZZ, 02Q30ZZ, 02Q33ZZ, 02Q34ZZ, 02Y00Z0

Table B5. Definitions of Complications from Interventional Cardiology Procedures

Notes: Table shows inpatient hospital diagnostic (ICD-9-CM and ICD-10-CM) and procedure codes (ICD-9-PCS and ICD-10-PCS) as well as CPT-4 codes used to identify complications associated with interventional cardiology procedures, particularly PCIs. * indicates all relevant ICD codes with the listed prefix. Restenosis indicates a follow-up PCI intervention within 30-days.

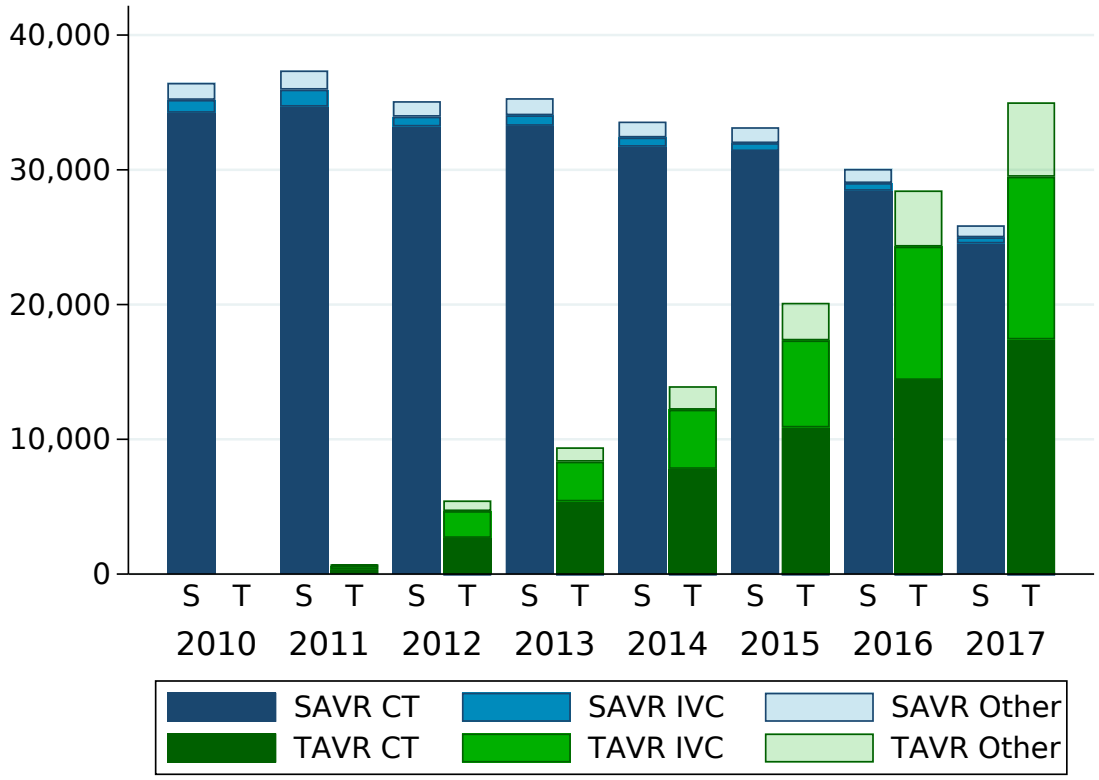
		Quartile, Risk-Adjusted Treatment Propensity (→ Increasing in Treatment Probability)			
	Full Sample	Q1	Q2	Q3	Q4
$\hat{\varphi}_{CZ}$	–	[-0.46, -0.08]	[-0.08, -0.01]	[-0.01, 0.08]	[0.08, 0.51]
Treatment Effect	-3.87	-3.10	-4.38	-3.26	-5.44
	(1.673)	(1.613)	(1.915)	(1.715)	(7.907)
p-value	[0.021]	[0.056]	[0.024]	[0.060]	[0.493]
$N_{CZ-quarters}$	2,922	596	867	753	700

Notes: Table reports pooled effects from LP-DID regressions estimating the effect of TAVR's adoption in a CZ on total intervention volume per quarter (Equation 13; compare with Figure 3). Results are stratified based on each market's risk-adjusted probability to treat a patient with valve replacement or supports, conditional on patient characteristics ($\hat{\varphi}_{CZ}$ in Equation 12; note that higher values of $\hat{\varphi}_{CZ}$ indicate a greater likelihood of treating the same patient). Treatment thresholds are estimated using pre-adoption data only.

Table B6. Adoption Effects on Intervention Volume, by Pre-TAVR Propensity to Treat

B.2 Figures

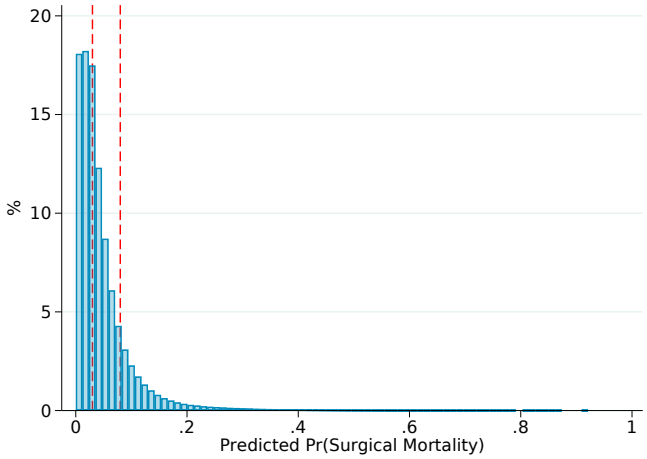
Figure B1. Timeline of TAVR Adoption



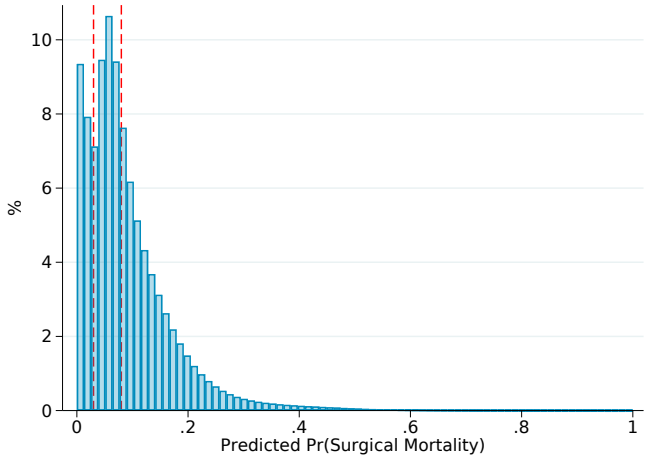
Notes: Figure shows diffusion of TAVR procedures among different cardiac surgeon specialties over time. Total volume of surgical valve replacements (SAVR and TAVR, labelled as "S" and "T" on the x-axis) for the full U.S. Medicare population are shown, with a breakdown of surgeon specialty. Cardiothoracic surgeons ("CT") are those whose primary specialty is listed as "cardiac surgery", "thoracic surgery", or "general surgery"; interventional cardiologists ("IVC") are those whose primary specialty is listed as "interventional cardiology", "cardiology", or "cardiovascular disease". Other surgeons include those with specialties outside of these fields (e.g., internal medicine) who also performed the procedures over time.

Figure B2. Predicted Patient Risk of Surgical Mortality (STS-PROM)

(a) Pr(30-Day Mortality)



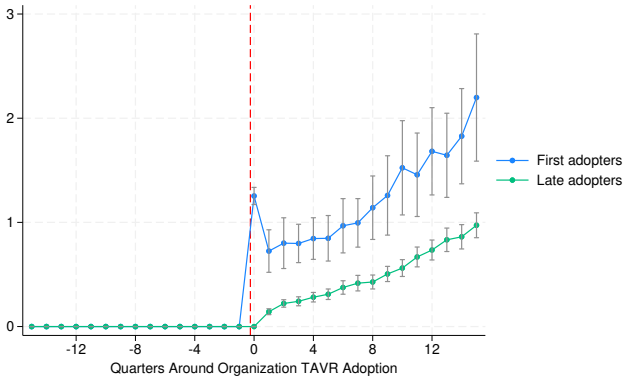
(b) Pr(90-Day Mortality)



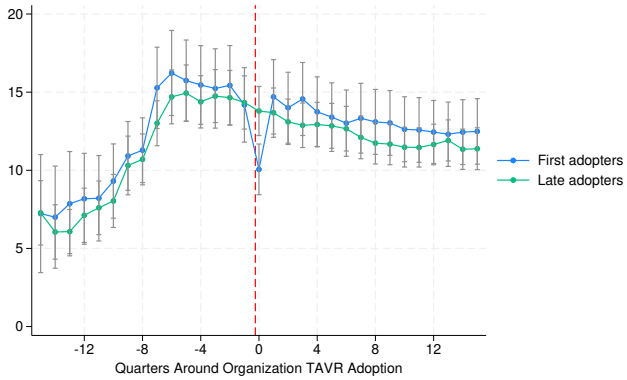
Notes: Figure shows predicted surgical risk from TAVR and SAVR, estimated using the STS-PROM model presented in Table B2. The current STS-PROM model classifies a similar population as 33% low-risk, 42% intermediate-risk, and 25% high-risk (Kumar et al., 2018).

Figure B3. Organization-level trends in utilization around TAVR adoption

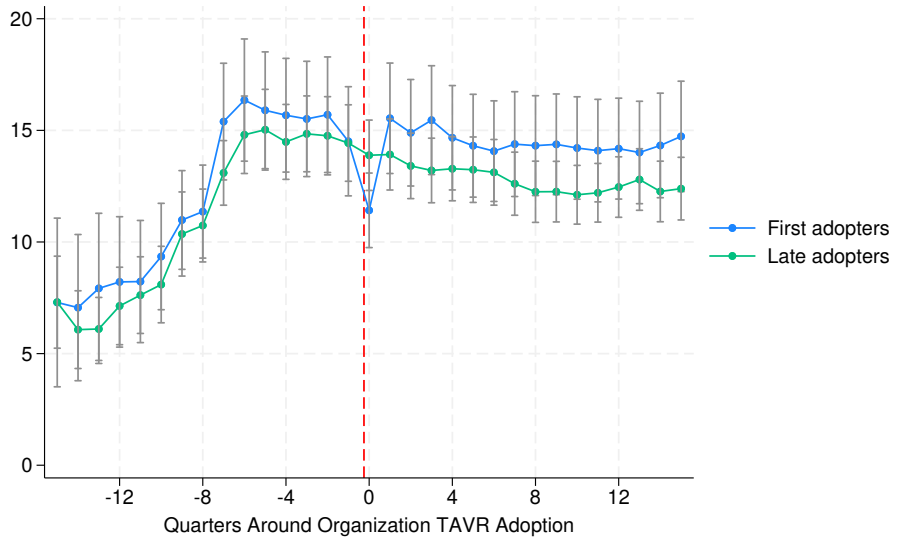
(a) TAVR Surgeries



(b) Other PCI



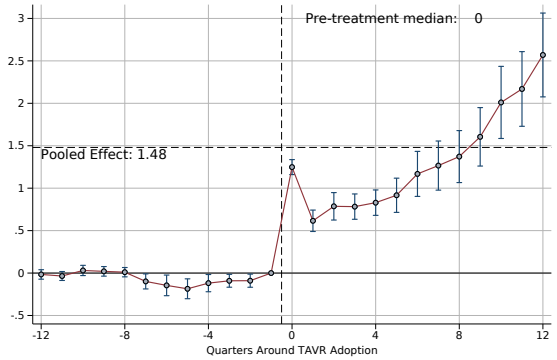
(c) All Interventions



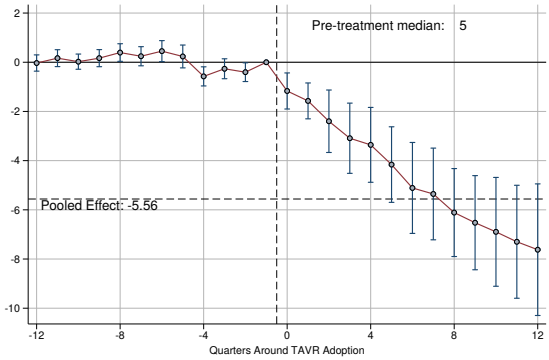
Notes: Figure shows recentered time series indicating average surgical volume at the individual organization level (identified using organization NPI) in the quarters around their own TAVR adoption in a local CZ. Panel (a) shows average TAVR volume; panel (b) average PCI volume; and (c) average total intervention volume. Results are stratified by those who were the first organizations to adopt in their local CZ.

Figure B4. Procedural Volume Responses to TAVR Adoption, by Intervention Type

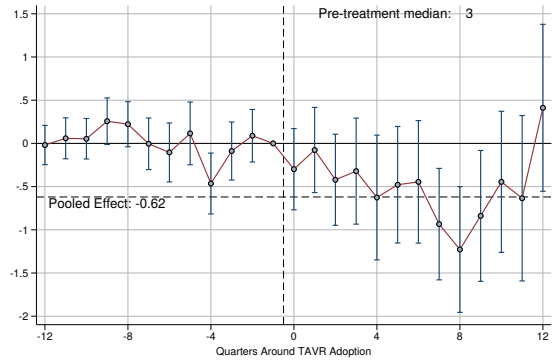
(a) SAVR/TAVR Surgeries



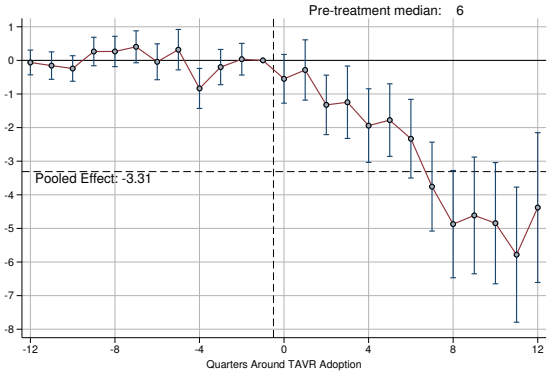
(b) PTCA



(c) Catheterization



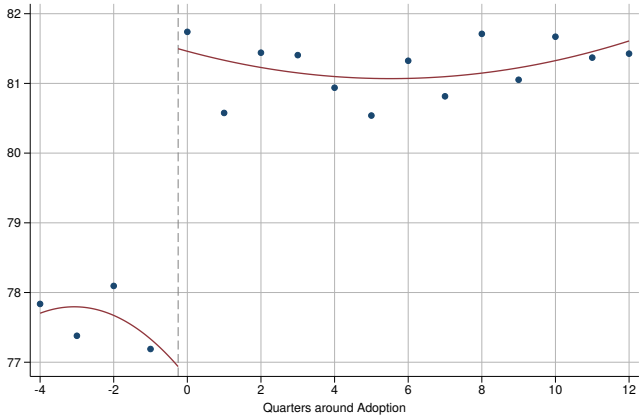
(d) All Other PCIs



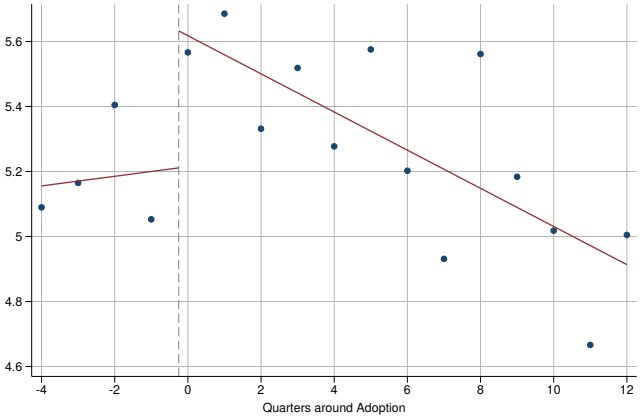
Notes: Figure shows estimated impact of TAVR adoption on the total volume of valve interventions performed in a local market, divided into major service types. In each panel, the outcome variable is the total market volume of a given intervention at a CZ level. Panel (a) shows the effect on all SAVR/TAVR surgeries; panels (b) and (c) show the effects on PTCA and cardiac catheterization, the two major PCI procedures; panel (d) shows effects for all other PCI interventions. Each of panels (b), (c), and (d) constitutes roughly one-third of all valve supports. Markets with fewer than 5 inpatient procedures quarterly are dropped from estimation, and standard errors are clustered at the CZ level.

Figure B5. TAVR Adoption Effects on Demographics of Valve Replacement Patients

(a) Patient Age

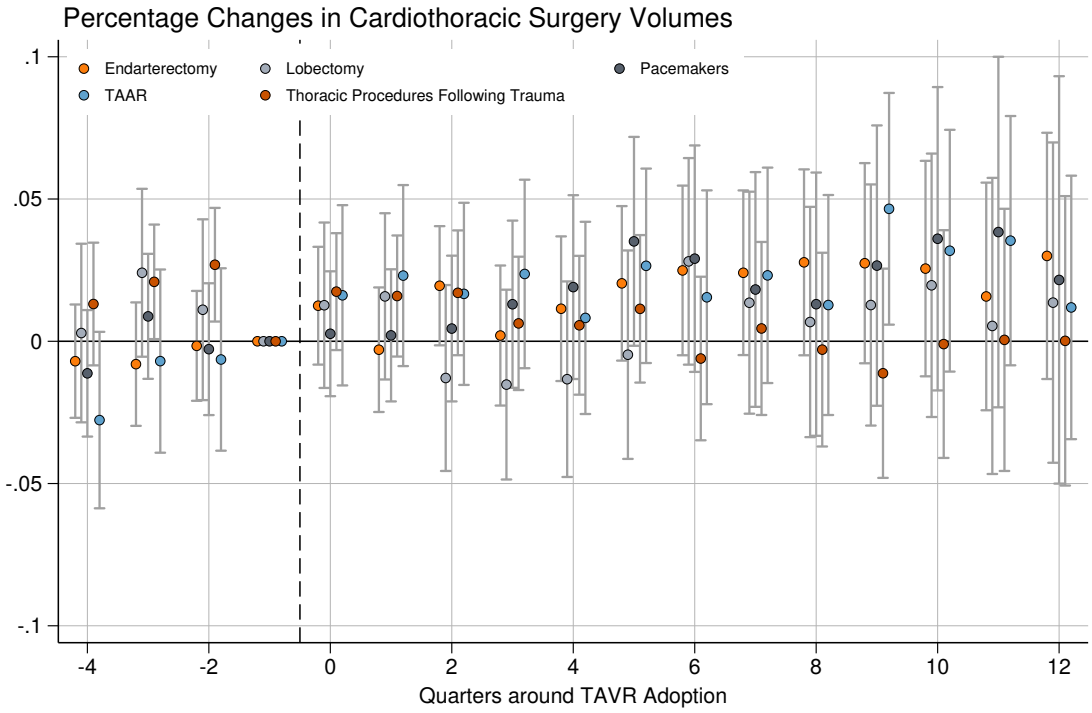


(b) Patient Risk (STS-PROM)



Notes: Each panel reports the estimated impact of TAVR adoption on the demographics of those receiving valve replacements (TAVR and SAVR). Panel (a) reports changes in average patient age, while panel (b) reports changes to STS-PROM 30-day mortality risk scores. Markets performing fewer than 5 inpatient procedures quarterly are dropped from estimation. Standard errors are clustered by commuting zone in both panels.

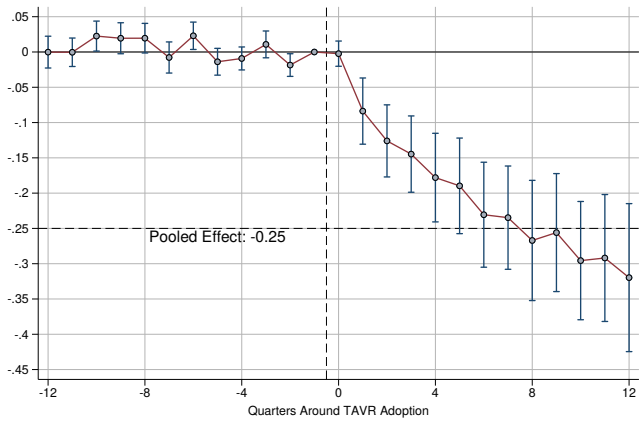
Figure B6. Effects of TAVR Adoption on Cardiothoracic Surgery Volumes



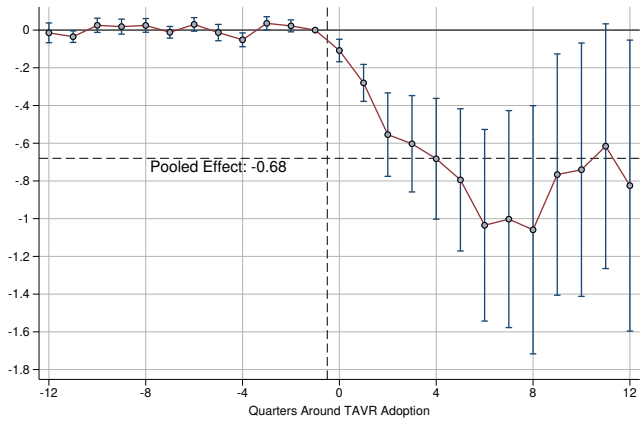
Notes: Figure shows estimated impact of TAVR adoption on total volume of typical procedures performed by cardiothoracic surgeons. Outcomes are reported in logs to approximate percentage changes to facilitate comparison across procedures. Markets performing fewer than 5 inpatient procedures quarterly are dropped from estimation. Compare to Figure 3.

Figure B7. Patient Effects Stratified by Pre-Adoption Operating Volume

(a) Pre-treatment Volumes Below Baseline Mean

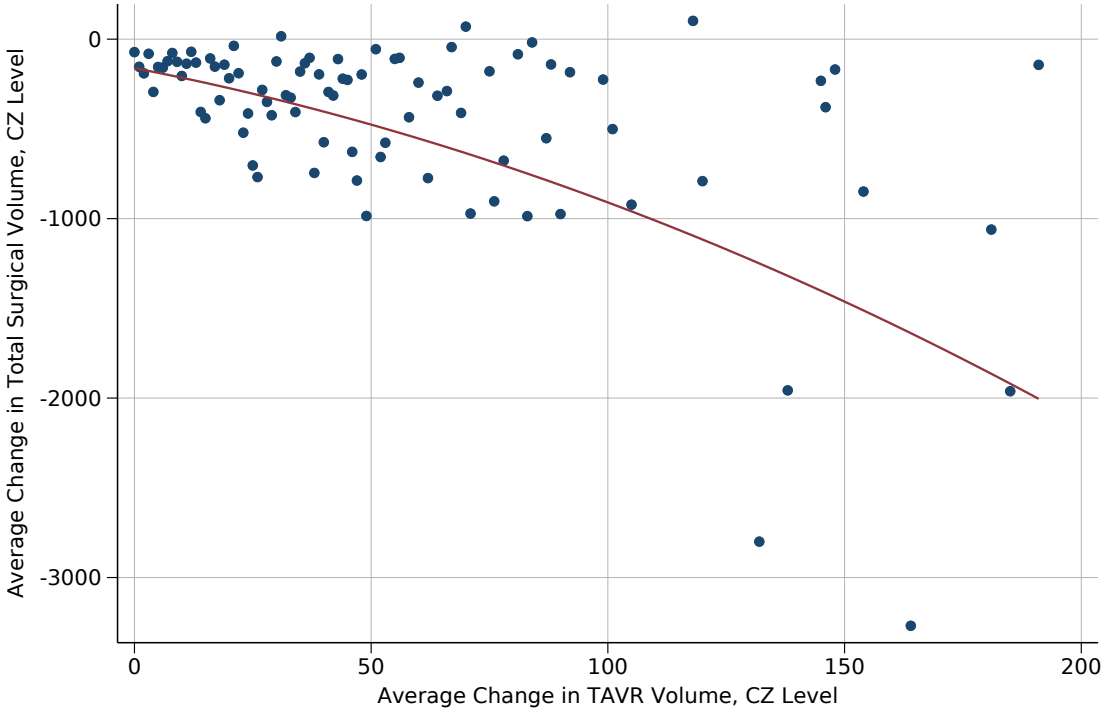


(b) Pre-treatment Volumes Above Baseline Mean



Notes: Each panel reports the estimated impact of TAVR adoption on the rate of any valve intervention at the patient level per 1,000 patients (following Equation 13). Panel (a) restricts the sample to only commuting zones with pre-treatment volumes below the baseline average, while panel (b) restricts to only above-average CZs. In both instances, the outcome measure is scaled by the baseline mean within groups to indicate treatment effects in percentage changes. Compare with Figure 3. Markets performing fewer than 5 inpatient procedures quarterly are dropped from estimation. Standard errors are clustered by commuting zone in both panels.

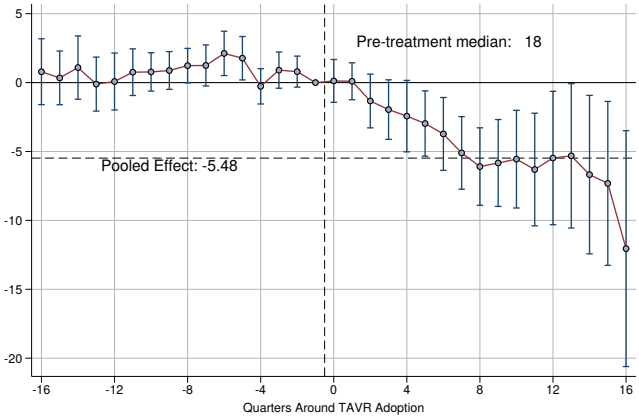
Figure B8. Market Relationships Between TAVR Takeup and Overall Intervention Volume



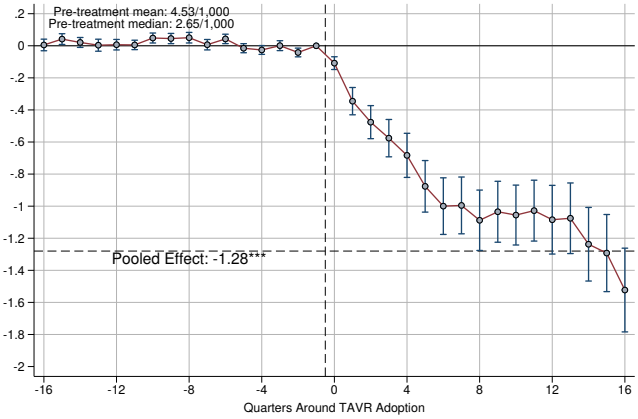
Notes: Figure shows a binscatter plotting the relationship between TAVR takeup in a local market (commuting zone) and changes in total interventional cardiology procedures performed. Each point is a CZ included in the analytical sample; the x-axis shows average quarterly TAVR volume in 2017, and the y-axis shows average differences in total IVC surgical volume (quarterly) between 2010 and 2017. 2 CZs with total 2017 TAVR volume exceeding 200 patients/quarter are dropped from view for visibility; binned regression results are robust to their inclusion/exclusion.

Figure B9. Long-run Effects of TAVR Adoption on Intervention Volume

(a) Commuting Zone Level (100% Inpatient)



(b) Patient Level (100% Inpatient + 20% Outpatient)

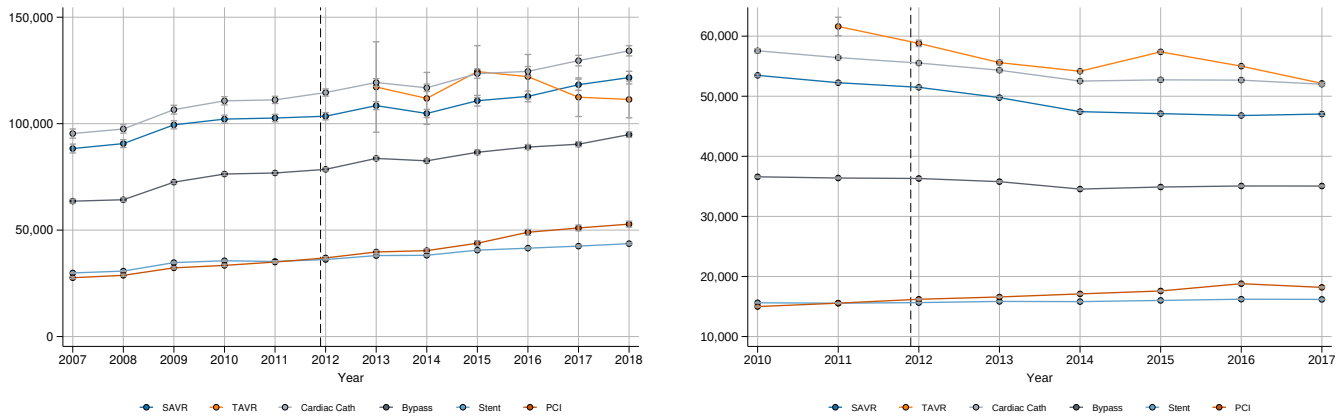


Notes: Figure shows LPDID coefficients and 95% confidence intervals estimating the effect of TAVR adoption in a local market on total intervention volume. Compare with Figure 3.

Figure B10. Average Commercial and Medicare Prices for Interventional Cardiology Procedures and SAVR

(a) Commercial Prices (Merative)

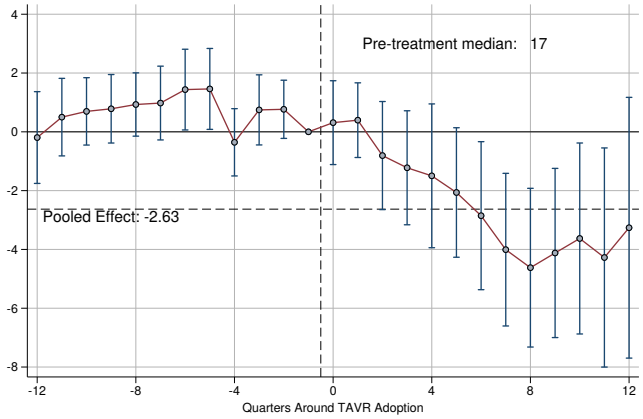
(b) Medicare Prices (DRG Payments)



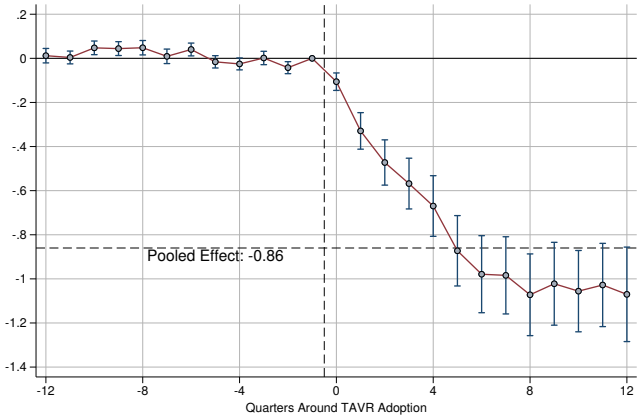
Notes: Figure shows average prices and 95% confidence intervals for key interventional cardiology services (as well as SAVR, which is typically performed by cardiothoracic surgeons instead of interventional cardiologists) around the time of TAVR's adoption. In panel (a), average prices for patients enrolled in commercial, employer-sponsored insurance, are reported using the Merative data (prices are measured as insurer + enrollee payments). In panel (b), the average Medicare payment amount for the relevant DRGs for each procedure are reported. Prices are reported in 2024 USD.

Figure B11. Robustness: Total Intervention Effects, Excluding Patients with Stable Angina or Stable Coronaory Artery Disease

(a) Market Level (# of Inpatient Procedures)

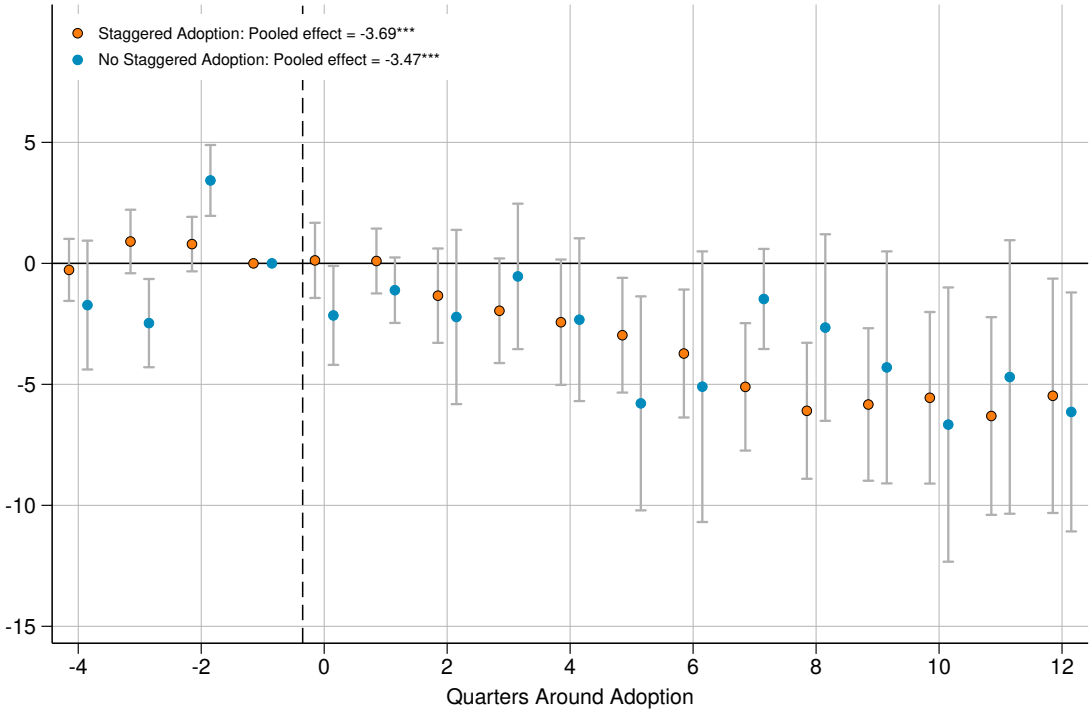


(b) Patient Level (Rate of Interventions/1,000 patients)



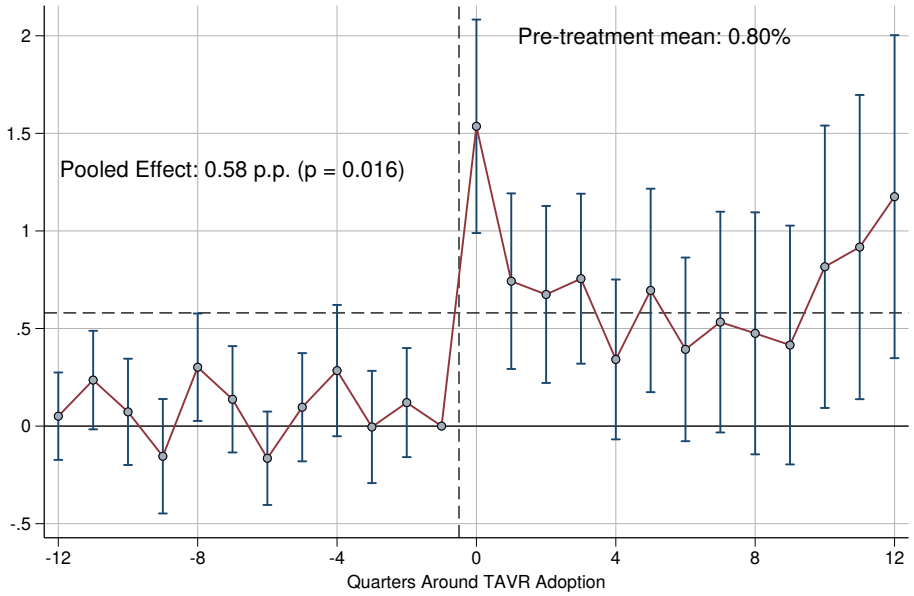
Notes: Compare to Figure 3. Sample excludes patients treated with stable angina or stable coronary artery disease, identified as patients with ICD-9-CM diagnosis code 413.9 or ICD-10-CM diagnosis codes I20.8 or I20.9 anywhere in the first ten diagnoses. Note that this likely a conservative approach, as this may remove patients with a history of stable angina but with new cardiovascular conditions; however, results are unchanged. Markets with fewer than 5 inpatient procedures quarterly are dropped from estimation, and standard errors are clustered at the CZ level.

Figure B12. Robustness: Total Intervention Effects, Dynamic Difference-in-Differences Model Relative to 2011 Quarter 4



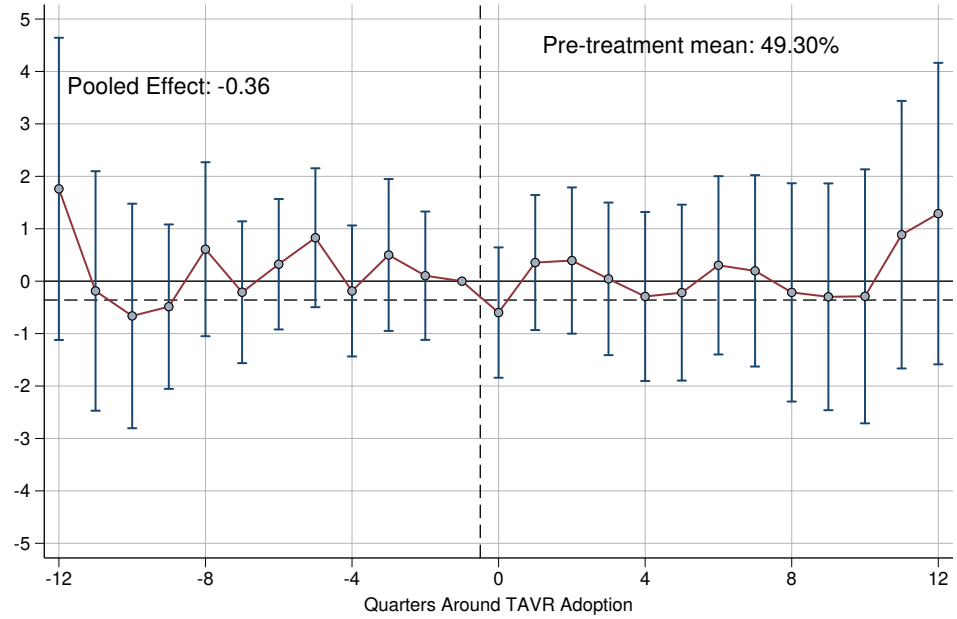
Notes: Figure plots coefficients from Figure 3 next to an alternative specification using a dynamic difference-in-differences model with 2011q4 as the reference period. Hence, regression coefficients compare intervention volumes averaged over all adopting markets compared to all non-adopting markets for each quarter without leveraging staggered adoption. Markets with fewer than 5 inpatient procedures quarterly are dropped from estimation, and standard errors are clustered at the CZ level.

Figure B13. Effect of TAVR Adoption on Screening for Surgical Viability



Notes: Figure shows effect of TAVR adoption at the CZ level on the fraction of interventional cardiologists performing screening for aortic valve replacement appropriateness. Screenings include computed tomography angiography (CTA) screening for the chest (CPT code 71275), cardiac computed tomography (CPT code 75573), and CTA of the heart (CPT code 75574). Screening rates are low at baseline as this includes all patients visiting an interventional cardiologist; however, post-adoption screening increases by 0.58 percentage points, or 72.5% Regressions are estimated as in Equation 13. Markets with fewer than 5 inpatient procedures quarterly are dropped from estimation, and standard errors are clustered at the CZ level.

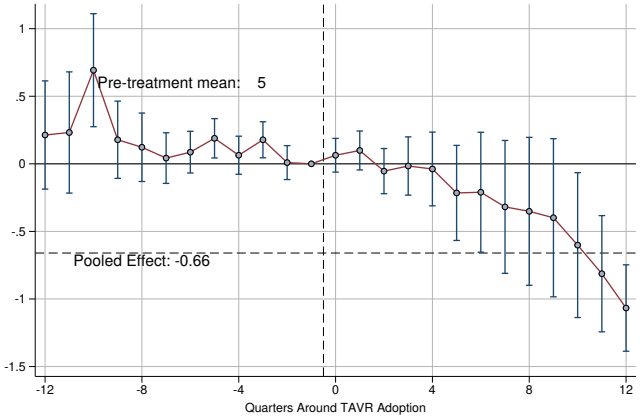
Figure B14. TAVR Adoption Effects on Acute Angiography for NSTEMI Patients



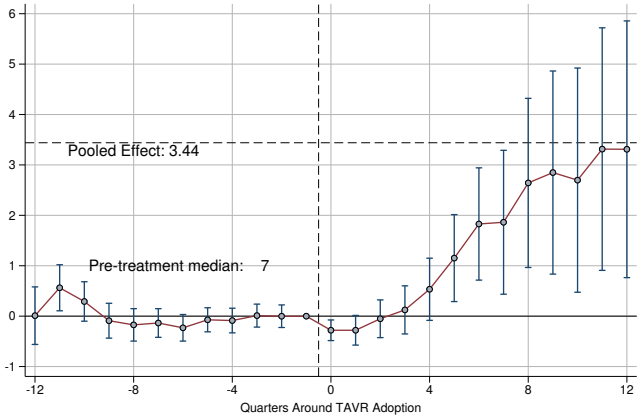
Notes: Figure considers the case of urgently required PCIs, using the case of Non-ST-Elevation Myocardial Infarctions (NSTEMIs). These are less severe heart attacks that typically require angioplasty to reduce patient risk of future, more serious, heart attacks or strokes. The American and European Society of Cardiology guidelines both state that angiography should be performed on NSTEMI patients within 72 hours, in preparation for subsequent angioplasty (Hansen et al., 2018). The figure shows that the percentage of NSTEMI patients meeting this target is not affected by TAVR's adoption, suggesting that the reductions in PCI availability may be for less severe patients. Markets experiencing fewer than 5 NSTEMI patients quarterly are dropped from estimation.

Figure B15. Impact of TAVR Adoption on PCI Volumes, Individual Operator Level

(a) PCI Volume: All Operators



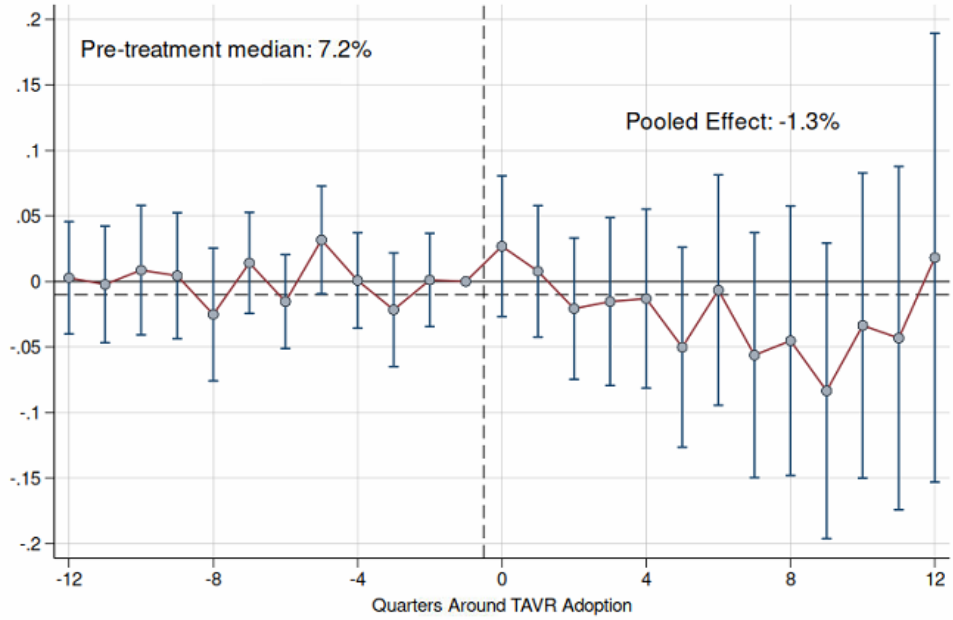
(b) PCI Volume: Only PCI Operators



Notes: Figure shows LP-DID coefficients and 95% confidence intervals estimating the effect of TAVR's adoption at the commuting zone level on the average number of PCIs performed per operator (identified using operator NPIs in the Medicare claims data). Panel (a) reports the unconditional average, while panel (b) reports averages after conditioning on operators performing at least one PCI in that quarter. Standard errors are clustered at the market level.

Figure B16. Effect of TAVR Adoption on Average Risk of Valve Support Patients

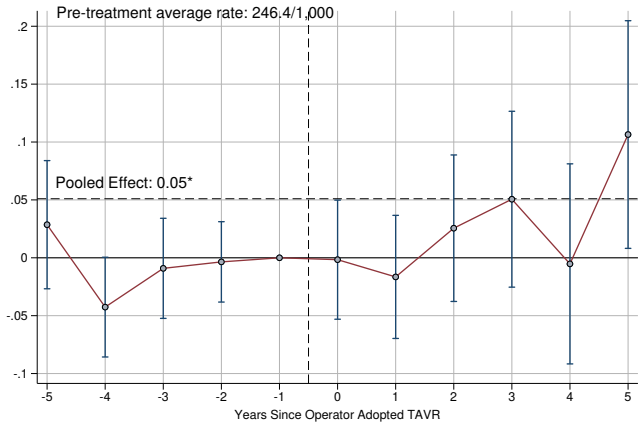
(a) 90-day STS-PROM Risk



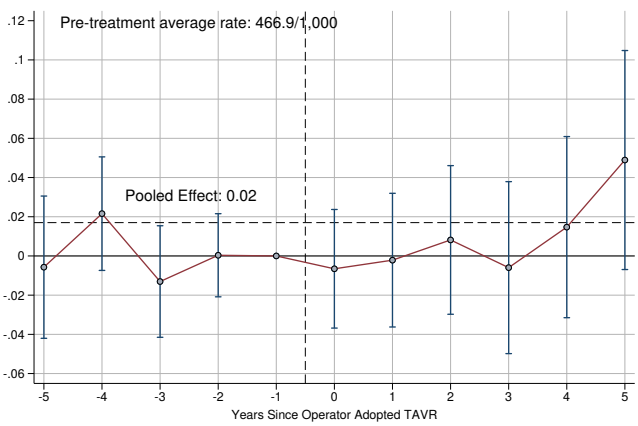
Notes: Figure shows effect of TAVR adoption at the CZ level on estimated mortality risk (STS-PROM) for patients receiving low-intensity treatments (PCIs). Figure shows results for 90-day predicted risk—coefficients have been rescaled relative to the baseline mean, and can therefore be interpreted as approximate percentage changes in average risk. Results are similar for 30- and 60-day risk. Regressions are estimated as in Equation 13, with standard errors clustered at the CZ level.

Figure B17. Dynamic Effects of TAVR's Adoption on PCI Outcomes

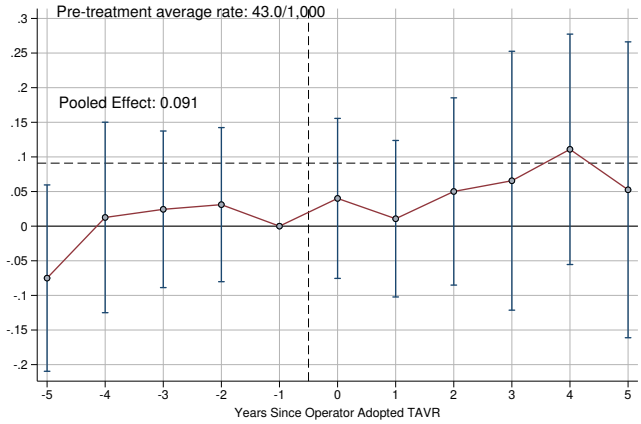
(a) Surgical Complications



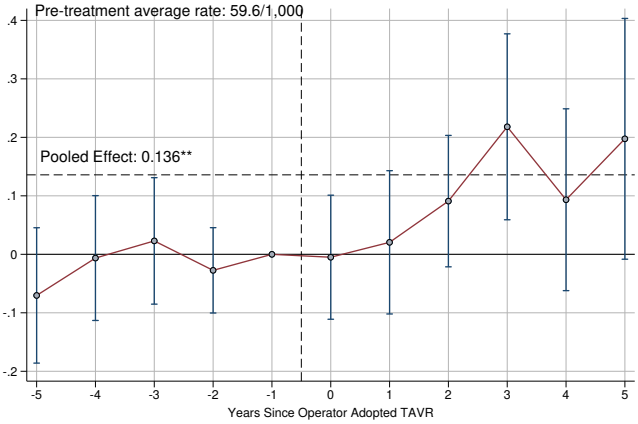
(b) Readmissions



(c) Restenosis

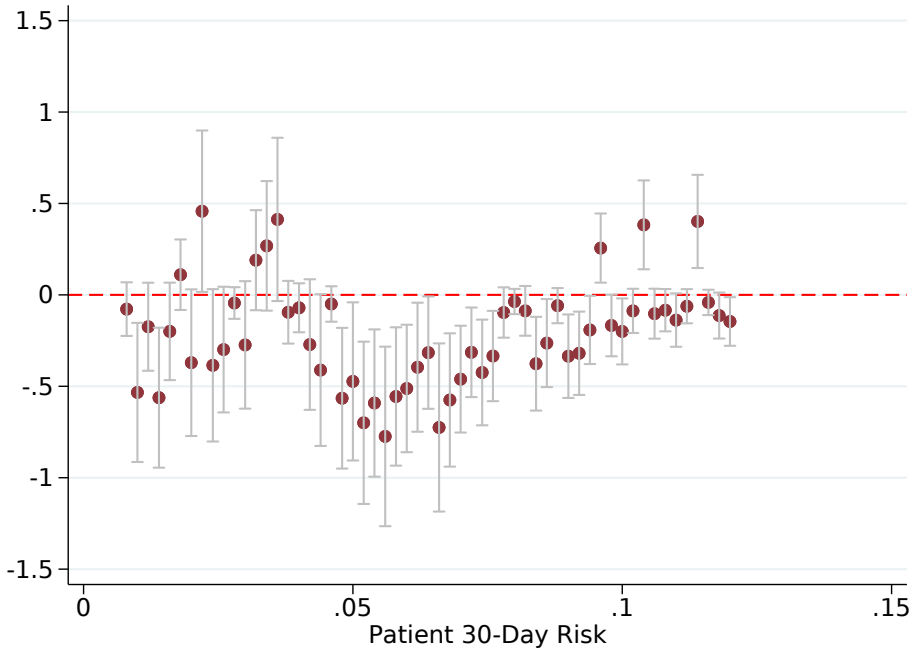


(d) Mortality



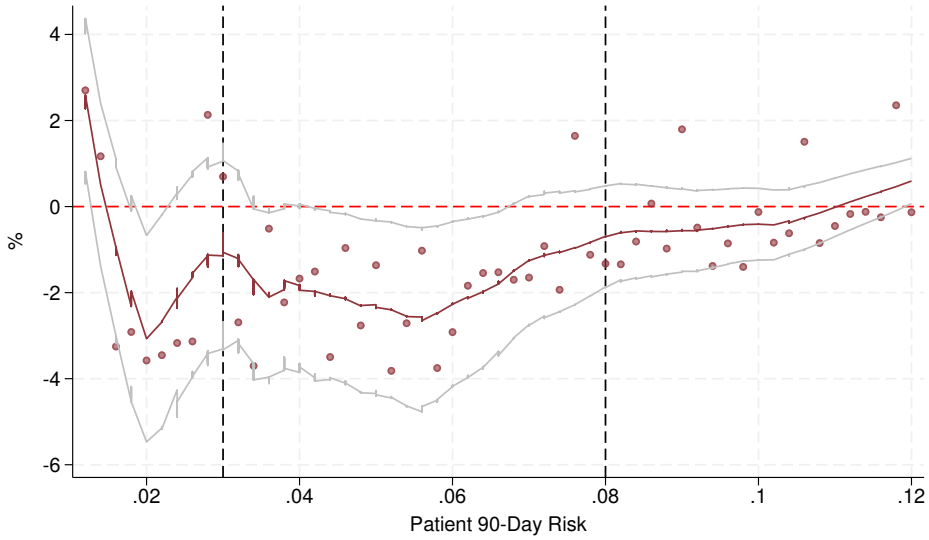
Notes: Figures show LP-DID estimates for how TAVR's adoption affected a PCI operator's outcomes for inpatient procedures. These regressions differ from the pooled regressions reported in Table 2 as they are average complication rates at the operator level. Coefficients are scaled relative to baseline means for comparability. Covariates include operator and quarter fixed effects as well as: indicators for patient risk score, age, chronic conditions, ADI, sex, race, income, dual eligibility status, and whether the patient received a PCI outside of their home CBSA; operator volume; and procedure code fixed effects. Standard errors are clustered at the CZ level.

Figure B18. Heterogeneous TAVR Effects on Procedural Volumes by Patient Risk



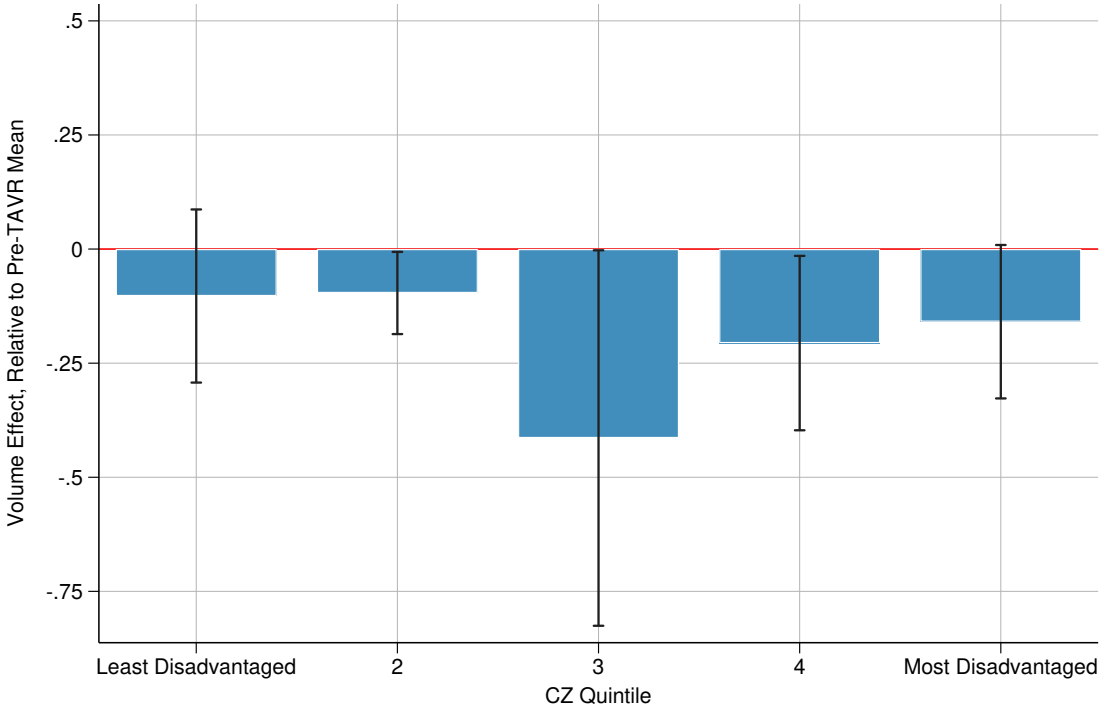
Notes: Figure shows estimated heterogeneous treatment effects of TAVR's adoption on total surgical volume for patients in different risk bins. STS-PROM risk is binned (width=0.2 percentage points); each point represents a difference-in-differences coefficient of TAVR's adoption on surgical volume within the bin. Standard errors are adjusted for multiple hypothesis testing according to Anderson (2008). Markets performing fewer than 10 surgeries per quarter are dropped. Vertical lines indicate STS-PROM delineation between low-risk patients (3%) and high-risk patients (8%). Compare with Figure 5.

Figure B19. Effects of TAVR Adoption on Total Intervention Volumes by Patient Risk: Effects as % of Overall Decline



Notes: See Figure 5 for estimation details. In this figure, coefficients are normalized to be percentages of the total decline in intervention volume, with each coefficient divided by the overall DID estimate. Standard errors are adjusted for multiple hypothesis testing (Anderson, 2008). Vertical lines indicate STS-PROM delineation between low- and high-risk patients. Results are robust to using "pooled" post-treatment LP-DID average effects.

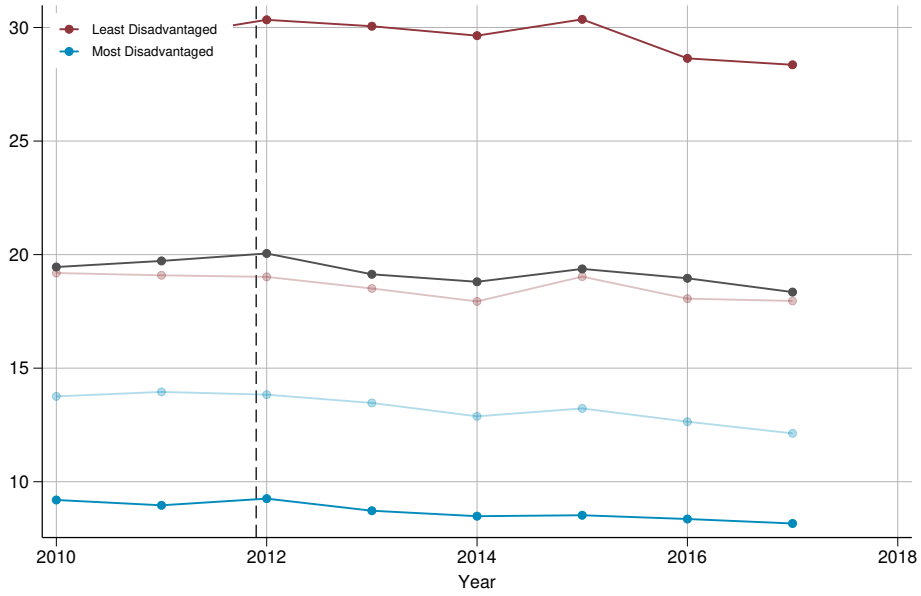
Figure B20. Effects of TAVR Adoption on Procedural Volumes by Dual-Medicaid Eligibility



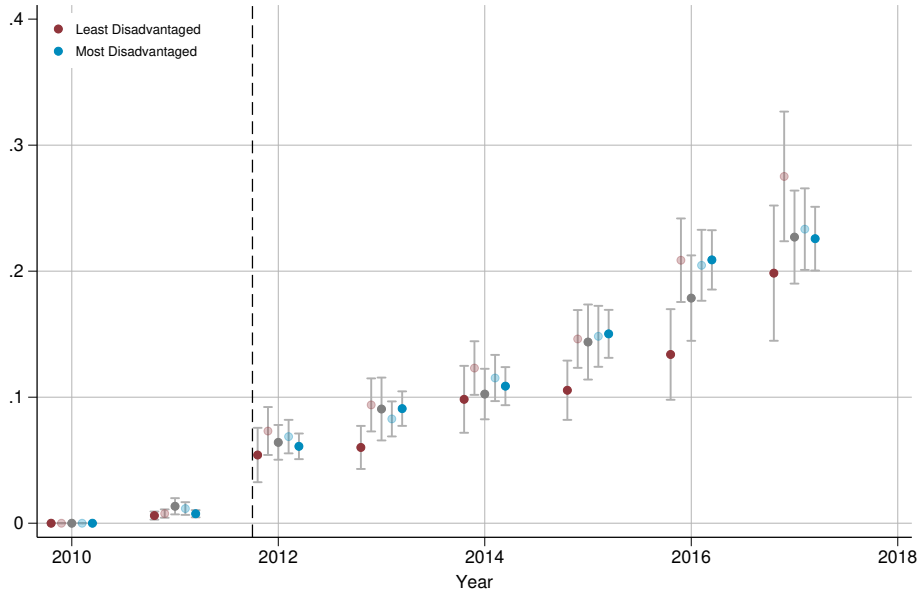
Notes: Compare to Figure 6. Effects of TAVR adoption on surgical volume across binned quintiles of CZs according to disadvantage, measured in the fraction of patients in a market who are dually-eligible for Medicaid (results are robust to defining dual-eligibility at the month or year level). Each point represents a "pooled" post-treatment LP-DID average effects, where the outcome is total surgical volume at the market level as in Figure 3. Appendix Figure B20 for results for dually-eligible patients. Results are robust to using standard difference-in-differences coefficients.

Figure B21. Relative Exposure to TAVR by Overall Access, CZ Level

(a) Unique PCI Operators per CZ

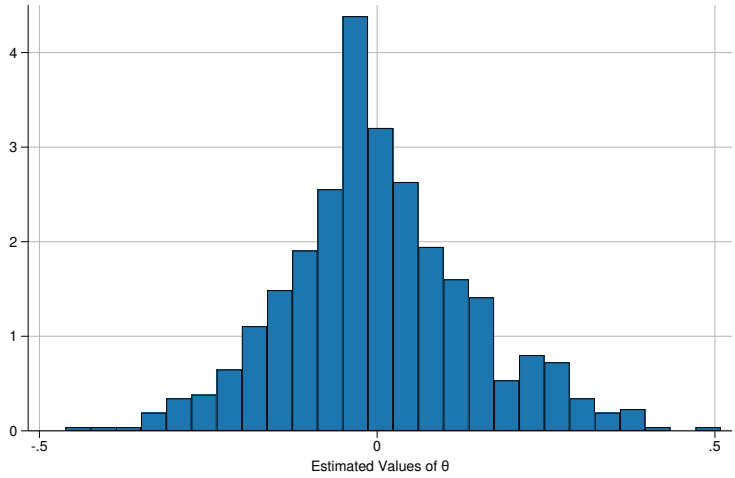


(b) Average # of TAVR Operators per PCI Operator



Notes: Figures illustrate (a) the average number of organizations providing PCI interventions per CZ and (b) the average number of TAVR operators per PCI operator in a CZ over time around TAVR's adoption. Markets are stratified based on average population-weighted ADI ranking over time.

Figure B22. Distribution of Risk-Adjusted Treatment Thresholds, CZ Level ($\hat{\varphi}_{CZ}$)



Notes: Figure shows distribution of estimated values for ($\hat{\varphi}_{CZ}$), following Equation 12. Regression is estimated using a mixed-effects logistic regression, with controls including the full set of patient, clinical, and geographic characteristics used to predict patient risk in Appendix Table B2.