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 access to care. In addition to being cost-prohibitive, innovations may reduce availability of older services, an understudied source of inequity. I propose a model of surgical specialization with productivity spillovers to study these effects. When innovations compete for inputs to other procedures, total access to care drops, causing some patients to forego care altogether. This crowd-out may be inequitably borne across patient groups or markets. I apply the model to aortic valve replacement and support interventions, showing that innovation reduced intervention volumes, particularly for patients of marginalized groups.

Keywords: Innovation Diffusion, Health Inequities

JEL codes: I12, I14, O30, D63

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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, which are typically high-cost, can be inaccessible to lower-income individuals immediately following adoption, generating well-documented financial barriers to care (Hoagland and Kipping, 2024; Arcaya and Figueroa, 2017). In addition, innovations create indirect effects which affect access to other, older technologies; these effects vary based on the characteristics of the innovating technology. On the one hand, technological advancements 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 and subsequently, barriers to access (Gowrisankaran and Rysman, 2012). On the other hand, innovations that instead inhibit availability of older technologies may reduce overall access insofar as they compete for scarce inputs; for example, capacity-constrained physicians with limited availability post-adoption (Gandhi, 2023; Kalouptsidi, 2014).

Importantly, scarcity-driven inequities may result in reduced overall access to both old and new technologies, resulting from a confluence of two mechanisms. First, hyper-specialized physicians facing innovation become more selective in performing older procedures. Second, if physicians benefit from specialization, reduced availability may be compounded by a loss of skill, leading to volume reductions for older techniques that outpace innovation take-up.[1] This may result in some patients losing access to specialized treatment entirely, with unique impacts on equitable access to healthcare. To ensure procedural innovations maximize social welfare gains, it is important to understand under what conditions these inequities arise and how severe their effects might be.

I present a model of physician decision-making characterizing these effects. 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).

[1] "Hyper-specializing" may allow hospitals and medical professionals to achieve higher-quality outcomes (Clarify Health Institute, 2023).

Innovations increasing 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 receiving any intervention at all.

The model's central insight is that extensive margin changes may inequitably affect some patient groups. Inequitable crowd-out may arise directly—because different groups have different surgical appropriateness—or indirectly—because risk is imperfectly observed across groups. Studying this crowd-out highlights that in settings where a substantial fraction of patients cannot immediately access interventions, incorrect or biased perceptions of risk may make some groups less likely to receive care, independent of underlying need. An innovation's effects on total availability may further exacerbate these differences.

I empirically test these predictions using the dissemination of transcatheter aortic valve replacement (TAVR) procedures in the US. TAVR is a minimally invasive and cost-effective alternative to open-heart surgery treating aortic stenosis; importantly, TAVR expanded both supply and demand for valve replacements, as it is performed by interventional cardiologists (instead of only cardiothoracic surgeons) and is appropriate for patients deemed too high-risk for traditional open-heart surgery. Hence, I use TAVR's adoption in a local market as a shock to the high-intensity intervention in the model. TAVR's adoption has been used previously to study physician learning and centralized access to innovations (Yang, 2023) and hospital- and market-level adoption decisions (Huckman and Stern, 2022; League, 2023).

I estimate how adoption affected the availability of lower-intensity procedures, focusing on the provision of valve support interventions (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. This validates the model predictions: patients foregoing care are higher risk—on the margin between selecting into treatment interventions at all—and inequitable differences are observed both within and across markets. Across markets, patients who lose access are more likely to reside in markets with greater health deprivation or a greater share of nonwhite patients. Within a commuting zone, patients living in more disadvantaged zip codes, are dual eligible, or are nonwhite appear to be more affected by reductions in intervention availability post-TAVR. Importantly, inequitable crowdout is associated with poorer outcomes for patients; following adoption, more PCIs are precipiated by acute cardiac events, and more PCI patients experience cardiac events post-procedure.

The model and empirical findings fit into a discussion of the potentially unequal impact of technological change (Skinner and Staiger, 2015). 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 and funding for clinical trials (Acemoglu and Linn, 2004; Moradpour and Hollis, 2020). The flow of health innovations is also sensitive to market features such as drug coverage (Agha et al., 2022), procurement environments (Clemens and Rogers, 2020), and tax incentives (Gamba et al., 2021; Yin, 2008). My work highlights the previously overlooked spillover effects of such directed technological change on equitable access to adjacent technologies and specialty care more broadly, similar to the study of spillovers from medical innovations within a disease category (Callison et al., 2023). The inequities I identify arise when economies of scale cause an innovation shock in one sector to affect technological returns in another, reducing patient welfare in possibly unequal ways.

I present the first theoretical framework for considering equity impacts of health innovations, contributing to literature on both health innovation and equity. Recent work has explored policies to equitably improve access to high-value services through physician payments (Kaarboe and Siciliani, 2023) or limiting geographic variation in service provision (Chandra et al., 2022). I argue technological advancement contributes to these disparities, modeling responses to susceptible innovations and identifying policy prescriptions.

Health disparities have increased in recent years, with some groups even experiencing disproportionate decreases in life expectancy (Case and Deaton, 2015; Olshansky et al., 2012). This paper highlights that procedural innovations are not guaranteed to improve access, with inequities potentially spilling over into adjacent services; this is related to previous work studying the spillover effects of health events (Fadlon and Nielsen, 2019; Hoagland, 2024), as well as work studying how hospital procedural decisions may differ on the basis of race (Singh and Venkataramani, 2024). Policymakers aiming to improve equitable access to innovative care may widen their focus beyond accessing innovations alone, considering also 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 crowding out older procedures may limit these effects, particularly in the short run. For example, promoting thicker markets for interventional cardiologists or investments in catheterization labs may have helped to offset the spillover effects of TAVR's adoption.

Using TAVR as a case study underscores that inequities arise primarily when innovations compete with older technologies for scarce inputs. These results are therefore generalizable

to a broader class of innovations, including procedural healthcare innovations, which are understudied relative to pharmaceutical developments (Dranove et al., 2022; Trajtenberg, 1989). However, results may also apply to a more expansive set of innovations, such as developments in education (Biasi et al., 2021; Biasi and Ma, 2022).[2] Finally, my work is related to discussion of identification of treatment effects across multiple margins of impact (Mountjoy, 2022).

2 Setting and Data

2.1 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 (after hypertension and coronary artery disease) in the world.

TAVR is a minimally-invasive alternative to surgical aortic valve replacement (SAVR), involving the 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 (Dvir et al., 2012); 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 them (Li et al., 2022).

The adoption of TAVR is ideal for studying the potentially unequal impacts of innovation for two reasons. First, TAVR was market-expanding: the median number of valve replacements in the US increased by one-third following adoption, with the number of operating surgeons nearly doubling (Appendix Table A.1). 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 disrupted the supply of valve replacement surgeries and procedures:

[2]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; Bacher-Hicks et al., 2021). If innovations in classrooms directly compete for other resources—e.g., teacher attention—expanded internet-based learning may inequitably disrupt student learning.

whereas SAVR could be performed only by cardiothoracic surgeons, TAVR is performed by a team of surgeons and interventional cardiologists (Adams et al., 2014). Importantly, these two specialists receive differentiated training: after residency, interventional cardiologists complete three years of cardiology fellowship and an additional year specific to interventional cardiology, while cardiac surgeons complete six to seven years of cardiothoracic surgery fellowships (Huckman and Stern, 2022). These unique training paths allow surgeons to hyper-specialize in different approaches at the expense of other skills. By 2017, 20% of TAVRs were performed by interventional cardiologists (Appendix Figure A.1), highlighting the comparative advantages of the two interventions (Breg, 2022).

2.2 Data

I assess the impact of TAVR adoption for traditional Medicare patients seeking cardiology care using fee-for-service (FFS) claims data from 2010 to 2017.[3] I observe 100% of inpatient procedures performed, with patient risk and demographic information including race, sex, dual eligibility, area-level disadvantage scores, and risk score (Ellis et al., 2022).[4] I identify surgeon specialization using the Medicare Data on Provider Practice and Specialty (MD-PPAS) file. I perform analysis at both the local market level (measuring total surgical volume) and individual patient-level analyses, described below.

Labor 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 available in the Beneficiary Summary file, to avoid problems of market definitions should patients travel to another market to receive a preferred procedure (Dingel et al., 2023). There are roughly 700 CZs commuting zones in the latest (2020) definition (Fowler et al., 2016); 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 CMS inpatient claims data.

Patient Definitions. In addition to market-level analyses, I report results at the patient level measuring the probability of receiving cardiothoracic interventions. I obtain patient-level demographics and claims information using the 20% Beneficiary Summary and Carrier

[3]Note data excludes individuals enrolled in Medicare Advantage plans.

[4]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).

files. I include all observed patients in these files in the denominators of the main patient-level analyses, rather than limit attention to only patients who are candidates for the interventions I am considering, in order to avoid misclassifiation. Identifying medically-managed patients with aortic stenosis who are candidates for surgical interventions is difficult given that aortic stenosis is a common condition among elderly patients, but typically is of minor severity. Hence, patients may not have aortic stenosis diagnostic information included on their outpatient claims in the Carrier file even though they have the condition, as it may be undiagnosed or superseded by other conditions (Chiang et al., 2016; Hoagland et al., 2024). Furthermore, many of the patients with aortic stenosis on their chart may not realistically be candidates for interventions, given that their condition is likely not severe enough to warrant the risks of a procedure. Despite these concerns, my results are robust to limiting patient-level denominators to patients with an observed aortic stenosis diagnosis in the Carrier file prior to interventions.[5] My main sample includes 10,874,161 Medicare patients, of whom 1,343,580 have an aortic stenosis diagnosis and 6,780 receive a valve replacement or valve support intervention during the window of observation.[6]

Procedure Definitions. I define both valve replacement procedures and valve support procedures, in keeping with the model setup. Valve replacement procedures include SAVR, the original open-heart surgical method to treat severe aortic stenosis; and TAVR, the innovative, minimally-invasive alternative. Valve support procedures include all valve-related cardiac procedures to treat aortic stenosis and other conditions for patients who are not candidates for valve replacement surgeries. The most common of these procedures are angioplasty (also referred to as percutaneous transluminal coronary angioplasty, or PTCA), coronary artery bypass grafting (CABG), and cardiac catheterization (also referred to as angiogram). Importantly, prior to TAVR's adoption, these revascularization interventions were used either in combination with SAVR or as a lower-intensity alternative for patients too high-risk for open surgical replacements (Goel et al., 2012). Appendix Table A.2 defines the relevant codes used to identify both valve replacements and valve supports. For market-level analysis, I restrict the relevant procedures to those 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 what surgical specialty performed them.

[5]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.

[6]Note that this is a prevalence rate of about 12.4%, roughly in line with estimated AS prevalence (Osnabrugge et al., 2013).

2.2.1 Summary Statistics.

Table 1 presents relevant summary information across the different procedures considered in the empirical exercise, including valve replacements and supports. Valve replacements are roughly four times costlier than valve support procedures, including for both SAVR and TAVR. Note that TAVR is performed on riskier patients than SAVR (a difference of 15.8%), but that the average PCI recipient is similarly riskier than the average valve replacement recipient (a difference of 14.5%). While TAVR is performed on riskier patients, it achieves comparable outcomes to SAVR—in terms of mortality and readmission—even in the first year of adoption. Aside from TAVR's use on older patients (an average age of 82.8 years for TAVR compared to 78.6 years for SAVR), there are few other observable differences in patient demographics across valve replacements, during the year of innovation. In contrast, valve supports tend to be performed more on dual eligible and Black patients than SAVR or TAVR.

3 Model

Suppose there is a continuum of patients suffering from a single disease. 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 ($s = 2$).[7] Empirically, $s = 2$ corresponds to valve replacements (SAVR/TAVR) while $s = 1$ corresponds to valve supports (PCIs).[8]

A procedure's patient-specific appropriateness depends on a risk index θ_{is} for patient i. When observed perfectly, θ_{is} captures both diagnostic severity and surgical risk; hence, individuals with lower θ_{is} receive more intensive treatment. In practice, θ_{is} is not observable, but proxied by observable characteristics Z_{is} (see Section 4.3). The expected utility of a procedure U_{is} is given by

$$U_{is} = \beta_{is} Z_{is} + \alpha_s P_s + \varepsilon_{is}, s \in \{0, 1, 2\}, \tag{1}$$

where P_s represents the fraction of the population receiving treatment s. Equation 1 in-

[7] Note that the model abstracts away from issues related to physicians as imperfect agents, assuming instead that the physician and patient act as a joint decision maker in determining care (Chandra et al., 2011).

[8] Chandra and Staiger (2007) use only two sectors—intervention and maintenance—and resulting spillovers. My model introduces vertically-differentiated interventions, with maintenance care as the outside option; although there are spillovers across all sectors, those between the surgical interventions are particularly salient. These spillovers arise because both interventions require surgeons to specialize differently, reducing capacity to perform all procedures.

	Valve Replacements			Valve Supports		
	All	SAVR	TAVR	All	PTCA	Cath.
Panel A: Procedure Costs and Risks						
Billed Cost	\$62,542	\$65,999	\$60,018	\$14,973	\$16,870	\$ 9,549
	(\$ 562)	(\$ 965)	(\$ 657)	(\$ 31)	(\$ 41)	(\$ 33)
Patient Risk	5.02	4.61	5.33	5.75	5.50	5.90
	(0.076)	(0.108)	(0.104)	(0.013)	(0.019)	(0.025)
Readmission	20.48	20.11	20.77	13.79	15.28	16.41
	(0.790)	(1.193)	(1.052)	(0.078)	(0.131)	(0.150)
Mortality	5.02	5.05	5.17	4.79	2.91	3.39
	(0.427)	(0.652)	(0.574)	(0.048)	(0.061)	(0.073)
Panel B: Patient Demographics						
Age	81.0	78.6	82.8	73.0	72.5	71.5
	(0.17)	(0.27)	(0.20)	(0.02)	(0.04)	(0.04)
Female	0.43	0.41	0.45	0.44	0.39	0.49
	(0.010)	(0.015)	(0.013)	(0.001)	(0.002)	(0.002)
Black	0.03	0.03	0.02	0.10	0.07	0.12
	(0.003)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)
Hispanic	0.00	0.00	0.00	0.01	0.01	0.01
	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Dual Eligible	0.12	0.10	0.13	0.23	0.20	0.26
	(0.006)	(0.009)	(0.009)	(0.001)	(0.001)	(0.002)
Total Volume	2,612	1,129	1,488	196,514	75,530	60,858

Notes: Summary statistics from relevant valve procedures, 2010–2017. Means and standard errors shown for the year of TAVR adoption at the CZ level. Cath. refers to cardiac catheterization. Patient risk, readmission, and mortality rates are calculated at the 30-day level.

Table 1. Summary Statistics: Procedures

corporates productivity spillovers in the second term, in the style of Chandra and Staiger (2007); if $\alpha_s > 0$, increased local use of s improves average outcomes regardless of Z_{is}.

Given linear utility, patients' treatment decisions can be characterized as two-way comparisons for any θ_{is}. To simplify these comparisons, I make the natural assumption that optimal treatment intensity is perfectly distributed across θ_{is}; this is equivalent to assuming the marginal utility of treatment with respect to risk is greater (in absolute value) for more intensive interventions.[9] Patients then choose treatment only along two margins: a choice between valve replacement and valve supports, or a choice between supports and no

[9] $|\partial U_{i2}/\partial\theta_2| > |\partial U_{i1}/\partial\theta_1| > |\partial U_{i0}/\partial\theta_0|$. When θ_{is} perfectly captures patient appropriateness, this is not a special case.

intervention at all. This allows me to represent risk as a single measure across treatments, θ_i.

A patient thus chooses the intensive treatment, $s = 2$, only if $U_{i2} > U_{i1}$. Over the distribution of Z_i, this probability is given by:

$$\begin{aligned}\Pr\{s=2\} &= \Pr\{U_{i2} - U_{i1} > 0\} \\ &= \Pr\{(\beta_{i2} - \beta_{i1})Z_i + \alpha_2 P_2 - \alpha_1 P_1 > \varepsilon_{i1} - \varepsilon_{i2}\} \\ &= \Pr\{\beta_{21} Z_i + \alpha_2 P_2 - \alpha_1 P_1 > \varepsilon_{12}\}, \end{aligned} \tag{2}$$

and the probability that a patient chooses the intermediate treatment ($s = 1$) is:

$$\begin{aligned}\Pr\{s=1\} &= \Pr\{U_{i1} - U_{i0} > 0\} \\ &= \Pr\{(\beta_{i1} - \beta_{i0})Z_i + \alpha_1 P_1 - \alpha_0 P_0 > \varepsilon_{i0} - \varepsilon_{i1}\} \\ &= \Pr\{\beta_{10} Z_i + \alpha_{10} P_1 + \alpha_0 P_2 - \alpha_0 > \varepsilon_{10}\}. \end{aligned} \tag{3}$$

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

$$P_1 = \int_Z \Pr\{\beta_{10} Z + \alpha_{10} P_1 + \alpha_0 P_2 - \alpha_0 > \varepsilon_{10}\} f(Z) dZ \tag{4}$$

$$P_2 = \int_Z \Pr\{\beta_{21} Z + \alpha_2 P_2 - \alpha_1 P_1 > \varepsilon_{12}\} f(Z) dZ. \tag{5}$$

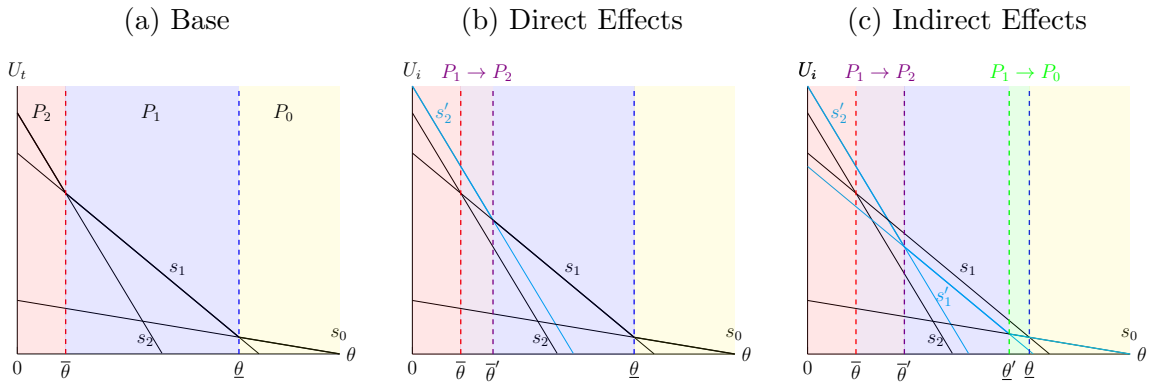
An equilibrium can be conceptualized in a single-crossing framework: any initial allocation generates utility benefits that induce marginal patients to switch between the three treatment options. These flows, in turn, affect the returns to each procedure, further shifting patients and returns until a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

Figure 1 (a) plots $U_s(\theta_i)$ for each s, illustrating the allocation of patients to treatments. Overall, utility is declining in risk; however, by assumption, declines are steeper for more intensive treatments. 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 $\overline{\theta}$ and $\underline{\theta}$; combined with the distribution of θ, these define each treatment's market share.

3.1 The Effect of Innovations

Consider an innovation in valve replacements (TAVR) affecting high-intensity treatments, s_2. This innovation can be characterized as a uniform cost reduction across θ without affecting survival utility, as TAVR is cost-effective and risk-reducing (Section 2); hence suppose U_1

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).

shifts by a fixed τ.[10]

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 directly attracts patients who switch from low-intensity intervention (shown in purple). This flow changes the returns to intermediate treatments, lowering expected returns even for inframarginal patients who continue to receive s_1 (in blue).[11]

Importantly, these spillover externalities result in further utility increases for s_2 and corresponding decreases in U_1. Panel (c) shows these indirect effects as two separate flows out of s_1: some into s_2 and others into s_0 (shown in green). The new equilibrium has updated risk thresholds $(\overline{\theta}', \underline{\theta}')$.

Notably, the shift in $\underline{\theta}$ defines a share of patients who now forego treatment. To quantify

[10] τ need not be constant for results to hold, but is assumed to be fixed here for ease of exposition.

[11] Note: one possibility that readers may consider at this point is whether the innovation could provide a benefit for the productivity of incumbent technologies; in the empirical context, this amounts to the extent to which performing TAVR enhances surgical skill for other PCIs such as angioplasty and catheterization. These types of spillovers are possible, particularly as both TAVR and other PCIs such as angioplasty commonly involve guiding catheters or replacement valves through the femoral artery to the heart. However, spillovers across surgical categories are unlikely to be equal in size to spillovers within an intervention type; hence in the model, these can be differenced out or set to zero without loss of generality. Although similar, the procedures considered are still fundamentally different: for example, TAVR involves the inflation and placement of a new aortic valve in a patient's heart, while catheterization requires using the guide wires and catheter to remove blockages.

this crowd-out, note that the risk thresholds $\overline{\theta}$ and $\underline{\theta}$ are defined, in expectation over ε, by

$$\beta_2\overline{\theta} + \alpha_2 F(\overline{\theta}) + \tau = \beta_1\overline{\theta} + \alpha_1\left(F(\underline{\theta}) - F(\overline{\theta})\right) \tag{6}$$

$$\beta_1\underline{\theta} + \alpha_1\left(F(\underline{\theta}) - F(\overline{\theta})\right) = \beta_0\underline{\theta} + \alpha_0\left(1 - F(\underline{\theta})\right). \tag{7}$$

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

$$\frac{\partial\overline{\theta}}{\partial\tau} = \frac{\beta_{10} + (\alpha_0 + \alpha_1)f(\underline{\theta})}{\alpha_1^2 f(\overline{\theta})f(\underline{\theta}) - [\beta_{21} + f(\overline{\theta})(\alpha_1 + \alpha_2)][\beta_{10} + f(\underline{\theta})(\alpha_0 + \alpha_1)]} \tag{8}$$

$$\frac{\partial\underline{\theta}}{\partial\tau} = \frac{\alpha_1 f(\overline{\theta})}{\alpha_1^2 f(\overline{\theta})f(\underline{\theta}) - [\beta_{21} + f(\overline{\theta})(\alpha_1 + \alpha_2)][\beta_{10} + f(\underline{\theta})(\alpha_0 + \alpha_1)]}, \tag{9}$$

where $\beta_{ij} = \beta_i - \beta_j$ for $i, j \in \{0, 1, 2\}$.

When the innovation is market-expanding for s_2, the shift in the extensive margin (Equation 9) is nonpositive—so patients are crowded-out from treatment—if and only if

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

$$\Leftrightarrow \underbrace{-\alpha_0 f(\underline{\theta})}_{\partial P_0/\partial\theta} \underbrace{- \alpha_1[f(\underline{\theta}) - f(\overline{\theta})]}_{\partial P_1/\partial\theta} \geq \beta_1 - \beta_0. \tag{11}$$

The terms on the left side of the inequality represent post-innovation reductions in productivity spillovers for both s_0 and s_1. The right side captures differences in the marginal utility of each treatment. Hence, crowd-out occurs when the marginal utility gains from receiving any surgical intervention (the switch from s_0 to s_1) outweigh the losses from diminished productivity spillovers for s_1. As utility gains from treatment tend to be large relative to provider specialization, this condition is likely to be met in many cases.[12]

3.2 Exacerbating Inequities

Any loss in efficient access to specialty care may be considered a market distortion. However, these losses may differ substantially across patient groups, particularly if groups have heterogeneous risk; losses may be further exacerbated if some groups have systematically misperceived risks.[13]

[12] For example, however, innovations requiring extensive physician re-training with uncertain clinical benefits may not generate these effects.

[13] Here, I focus on patients affected at the extensive margin; however, patients remaining on s_1 also have reduced expected utility post-innovation. As these patients are adjacently at-risk, they may also be

Assume that the condition for crowd-out is satisfied (Equation 11), so that there is a region C of patients who received s_1 prior to an innovation and s_0 post-adoption ($C = [\underline{\theta}, \underline{\theta}']$). However, suppose that clinicians do not observe θ directly but a proxy $\hat{\theta}$.[14] Assume $\hat{\theta}$ is a linear combination of observable characteristics Z_{is} correctly predicting θ except for an idiosyncratic, mean-zero error ν_{is}:

$$\theta_{is} = \underbrace{Z_{is}\gamma}_{\hat{\theta}} + \nu_{is}. \tag{12}$$

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.[15] If membership is informative ($\gamma_d \neq 0$), 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:

$$s_{C,g} = Pr(i \in g | i \in C) = Pr(i \in C | i \in g) \frac{Pr(i \in g)}{Pr(i \in C)} \tag{13}$$

$$= \frac{s_g}{s_C} \left[Pr(Z_{it,-g}\gamma_{-g} + \gamma_g \in [\underline{\theta}, \underline{\theta}']] \right. \tag{14}$$

$$= \frac{s_g}{s_C} \left[\int_{\underline{\theta}-\gamma_d}^{\underline{\theta}'-\gamma_d} f(Z_{it,-g}\gamma_{i,-g}) d(Z_{it,-g}\gamma_{i,-g}) \right] \tag{15}$$

$$= s_g \frac{\int_{\underline{\theta}-\gamma_d}^{\underline{\theta}'-\gamma_d} f(Z_{it,-g}\gamma_{i,-g}) d(Z_{it,-g}\gamma_{i,-g})}{\int_{\underline{\theta}}^{\underline{\theta}'} f(\theta) d\theta}. \tag{16}$$

Here, s_g indicates the share of group g in the population, and $s_C = F(\underline{\theta}) - F(\underline{\theta}')$ is the relative size of C. As these are not equal in general, C may over- or under-represent g. Figure 2 presents the intuition of this result, illustrating the crowd-out region (Figure 1) for heterogeneous risk distributions across two hypothetical groups. Even when risk is correctly measured, these groups have different likelihoods of losing access to specialty treatment.

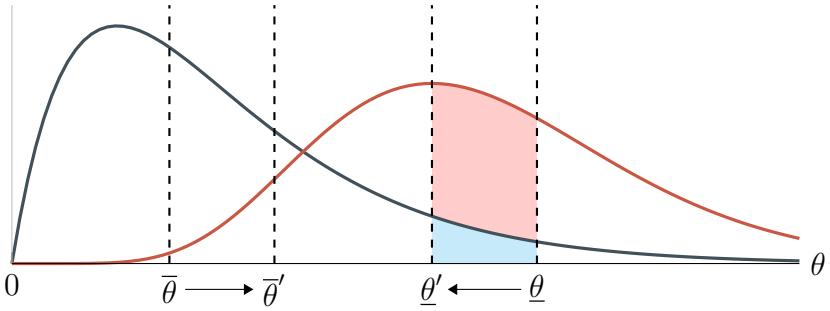
Further inequities arise, however, when γ_d is incorrectly measured. Imperfect proxying may arise from provider error or other factors, including patient beliefs or biased health measurements like risk scores (Obermeyer et al., 2019). This measurement error distorts the

disproportionately represented by certain groups.

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

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

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 $\{\overline{\theta}, \underline{\theta}\}$. Innovations shift these cutoff values, creating a crowd-out region (shaded).

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" $\hat{\gamma}_g$:

$$\hat{\gamma}_g = \gamma_g + \nu, \tag{17}$$

where ν is an idiosyncratic error in group risk measurement.[16] I measure $\nu's$ effects on crowd-out representation as the ratio of group membership $s'_{C,g}(\nu)$ to the original representation, $s_{C,g}$:

$$I(\nu) = \frac{s'_{C,g}(\nu)}{s_{C,g}} \tag{18}$$

$$= \frac{1}{s_{C,g}} \int_{\underline{\theta}-\gamma_d-\nu}^{\underline{\theta}'-\gamma_d-\nu} f(X_{i,-g}\gamma_{i,-g}) d(X_{i,-g}\gamma_{i,-g}). \tag{19}$$

Importantly, notice that

$$\frac{\partial I}{\partial \nu} = \frac{\left[f_{X_{-g}\gamma_{-g}}(\underline{\theta} - \gamma_d - \nu) - f_{X_{-g}\gamma_{-g}}(\underline{\theta}' - \gamma_d - \nu)\right]}{s_{C,g}}. \tag{20}$$

That is, risk perception error ν affects group-specific crowd-out proportionately to the initial composition of g in C. Appendix Figure A.2 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.

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

3.3 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.

Three empirical implications arise from this model. First, I test for the direct and indirect effects of innovation by assessing how adopting physicians substitute patients along treatment margins; this is done by examining intervention volume both overall as well as by intervention type (and within intervention type, by procedure). I then identify *which* patients are affected based on their risk, paying particular interest to the existence and magnitude of crowd-out regions. Finally, I examine whether crowded-out patients are inequitably made up of different demographic groups, including patient race, income, and ADI. I identify aggregate differences across groups that result from both true and misperceived risk differences, with a back-of-the-envelope calculation separating these effects.

In addition to implications for access to interventions within a single market, the above model can easily be extended to consider multiple markets, as in previous work (Chandra and Staiger, 2007). In particular, equilibrium allocations of patients across treatments (which in turn determine productivity spillovers and, in part, equilibrium shifts in allocations post-innovation) may differ across markets, leading to different estimated effects of an innovation's adoption in different regions. Similar logic as in Section 3.2 implies that these differential effects may also generate inequitable loss in access to treatments *across* markets as well as within them; this is particularly important given that racial and socioeconomic segregation in the United States often imply that demographic differences *across* commuting zones are likely larger than differences *within* them (Fu et al., 2023; Carpenter et al., 2022). I therefore consider both differences within and across markets when estimating inequitable impacts of technology adoption for valve interventions.

4 Methods

I assess the effects of TAVR's adoption on access to valve replacements (SAVR/TAVR) and valve supports (PCIs, including angioplasty and CABG) within a local market. Due to the high comorbidity of aortic stenosis and coronary artery disease, PCIs are frequently performed when a patient's risk is too high for SAVR. Hence, as TAVR becomes available in a local market, patients and physicians working together to evaluate risk and select treatment options may be change their behavior in response to treatment availability and the

(potentially market-varying) estimated returns to each procedure. TAVR's adoption may therefore induce a flow of some patients from PCI to TAVR, especially when their risk previously made them poor candidates for SAVR; this, in turn, will alter the availability of and expected returns to PCI procedures in that market.

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 60-day mortality on patient demographics and health conditions (Appendix Table A.3). This 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.[17]

The empirical distribution of predicted risk in my sample closely matches population STS-PROM predictions (Appendix Figure A.3). 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.

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), which uses a "stacked" regression of treated units combined with their clean controls to estimate treatment effects without bias from naive staggered adoption designs with heterogeneous treatment effects (Roth et al., 2023). The regression uses local projections methods to restrict the estimation sample so that previously-treated observations (which may be experiencing time-varying or heterogeneous treatment effects post-adoption) are not included in the control group, eliminating bias. The LP-DID regression performs similarly to other approaches in this context, including weighted stacked DID regressions (Wing et al., 2024; Cengiz et al., 2019) and imputation estimators (Sun and Abraham, 2020; Callaway and Sant'Anna, 2021). Formally, for h periods pre- and post-treatment, I estimate the equation

$$y_{m,t+h} - y_{m,t-1} = \beta_h^{\text{LP-DID}} \Delta D_{mt} + \alpha_m + \tau_t + \varepsilon_{mt}^h, \tag{21}$$

[17] Some work questions the STS-PROM in physician decision-making (Catalano et al., 2020); however, as it is still commonly used by practitioners to approximate θ, I incorporate it here.

where the sample is restricted to newly treated ($\Delta D_{it} = 1$) or clean controls ($\Delta D_{i,t+h} = 0$).[18] Outcomes include intervention volumes at the market m 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 the overall average post-treatment effect with each dynamic regression. The LP-DID results I report are robust to including both comparisons between early and late adopters of TAVR and comparisons to never-treated units, as well as only to never-treated units.[19]

Throughout, the identifying assumption is that the timing of TAVR's adoption is exogenous at the local market level, in the sense that there are parallel trends and no anticipatory changes in valve *support* procedures (not TAVR/SAVR volumes). 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 PCI interventions; while hospitals certainly made strategic decisions about when to adopt TAVR adoption based on anticipated valve replacement volume, my estimation is well-identified provided there were no spillovers in these anticipated events. This can be examined directly by assessing differential pre-trends between adopting and non-adopting markets for indications that volumes were changing before adoption.

4.3 Heterogeneity & Inequities in Post-Innovation Access

I also examine heterogeneity across two key dimensions: patient risk and market indicators for access to healthcare. I assess inequities across three dimensions: the racial makeup of a market, a market's Area Deprivation Index (ADI) score, and a region's socioeconomic status (proxied by the fraction of patients who are dually-eligible for Medicaid). For each, I assess heterogeneous treatment effects by binning markets and estimating traditional difference-in-differences regressions.[20] Where applicable, I adjust these results for multiple inferences using sharpened false discovery rate control methods (Anderson, 2008) and smooth using weighted local nonlinear regressions, allowing for a direct comparison of adoption effects across patients of differing surgical risk and markets of differing disadvantage.

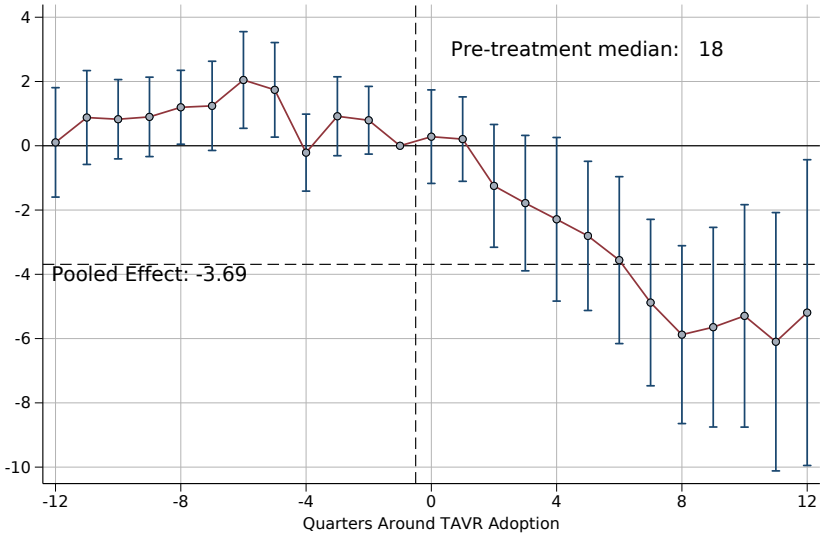
5 Results

Figure 3 presents the dynamic effects of TAVR adoption on interventional cardiology procedures at the commuting zone level, following Equation 21. Prior to adoption, I observe no

[18] Note that the regression equation for patient-level outcomes is similar to Equation 21.
[19] Effects were estimated using the LPDID package in Stata (Busch and Girardi, 2023).
[20] Results are robust to using average "pooled" LP-DID effects instead of DID coefficients.

meaningful variation in procedure volumes.[21] However, post-adoption I observe a marked decline in total surgical volume, with average volume dropping by 3.7 interventions quarterly, or 14.8 interventions annually. This is roughly 20% (7.8%) of the total volume of the median (average) commuting zone, which performs 18 (47.3) procedures per quarter. These effects are first observed one year after TAVR's adoption, becoming more pronounced within the first three years post-innovation.

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



Notes: Estimated impact of TAVR adoption on total volume of surgical interventions performed by interventional cardiologists. Here, the outcome variable is the count of all valve interventions performed at a CZ level, including valve replacements (SAVR/TAVR) and valve supports (PCIs). Markets performing ≤ 5 inpatient procedures quarterly are dropped from estimation. Standard errors are clustered by commuting zone.

These effects are dominated by reductions in overall availability of valve supports, swamping the expansion of valve replacement options. Given that supplying these interventions involves different costs (Table 1), I disaggregate the overall adoption effects across specific interventions in Appendix Figure A.4.[22]

In keeping with the model, the availability of valve replacements increased post-adoption at an average rate of 1.48 valve replacements per quarter. In general, TAVR's adoption

[21] The pre-treatment pooled LP-DID estimate is 0.558, with a 95% confidence interval of $[-0.576, 1.692]$.

[22] The figure shows results for valve replacements (SAVR/TAVR), angioplasty (PTCA), cardiac catheterization, and all other PCI interventions; each of these last three groups constitutes roughly one-third of all valve supports in our sample. Note that only 213 patients in my sample (.02%) received more than one valve replacement; hence, the observed results are unlikely driven by repeat patients. Importantly, only 5.6% of SAVR patients in the sample required a follow-up PCI prior to TAVR's adoption; this indicates that the declines here are unlikely to be driven by TAVR's adoption reducing the need for follow-up PCI interventions following a valve replacement.

expanded valve replacement procedures to patients that are on average 4.1 years older and 1.5 percentage points higher-risk. On the other hand, TAVR's adoption led to overall declines in other intervention volumes that outpaced their relative cost-savings, with average reductions of 3.7 PTCAs and 2.6 other PCI interventions; I find no significant effects on cardiac catherization.[23] This implies that roughly 4 valve supports were eliminated for each TAVR procedure adopted by the average CZ, roughly consistent with the cost differential across PCIs and TAVR.

Analysis of the dynamic treatment effects—rather than simple DID estimation—provides important insight into the changing landscape of TAVR utilization and substitution post-adoption. The quality of TAVR my be improving over time for two reasons: first, providers gaining experience in the procedure may induce improved outcomes (as suggested by the model); second, subsequent clinical trials expanded TAVR utilization to lower-risk patients (see Section 2). Hence, the results in Figures 3 and A.4—which show increasing adoption and substitution over time—are likely influenced by this move down the "appropriateness curve". One important concern in interpreting these dynamic effects, then, is that they may be endogenous to market characteristics, especially if hospitals or CZs that expected increased dynamic returns (from specialization or expanded patient markets) were more likely to adopt TAVR earlier than others. However, these strategic decisions would serve only to reinforce inequitable access to surgeries, as these decisions impact overall volume of valve interventions.

These results—tested at the market level—also hold for individual patients. In Appendix Figure A.5, I use the 20% sample of all Medicare beneficiaries to estimate changes in the likelihood that individual patients receive procedures (measured in rates per 1,000 patients). As at the market level, reductions in the overall probability of receiving an intervention are driven by large reductions in valve support utilization, swamping expansions in valve replacements.

Importantly, this patient-level analysis allows for a more in-depth exploration of patient-physician interactions and heterogeneity across patient severity. I highlight two facts in the Appendix: First, Figure A.6 shows that following TAVR's adoption, interventional cardiologists are roughly 35% more likely to screen patients for appropriateness for SAVR/TAVR. This suggests that physicians may adapt their diagnostic screening strategies in response to available technology (Mullainathan and Obermeyer, 2021) or learning about surgical outcomes and availability (Hoagland et al., 2024). Second, I also show that while the overall

[23]Note that there are significant pre-trends for PTCA effects; this may be related to either investment costs as TAVR is preparing to be deployed in a region, or strategic delays in valve replacements for some patients until after TAVR becomes available. These differences, however, appear to be anticipation effects that would serve only to understate true declines in overall surgical volume that are highlighted here.

availability of valve supports declines post-adoption, urgent PCI procedures—including angiography for patients following a heart attack—are not delayed (Figure A.7).

Finally, I consider relationships in the average differences in quarterly TAVR utilization and total intervention volume between 2010 and 2017, shown in Figure A.8. The figure shows a strong overall negative relationship, indicating that local markets that invested more heavily on TAVR experienced larger declines in total intervention volume by the end of the data period. As expected, there are several local markets where TAVR's uptake is particularly concentrated, with roughly 15 commuting zones performing more than 100 TAVR's quarterly post-adoption. However, my results do not appear to be driven by these large markets; on average, the observed declines in total intervention volume are on the order of ten interventions per each individual TAVR adopted quarterly—greater than the one to four intervention tradeoff estimated, on average, in Appendix Figure A.4. Additionally, effects are observed even for markets that perform fewer overall interventions or specialize less in TAVR. Taken together with Figure 3, this evidence suggests a strong relationship between adoption of a novel technology and future restrictions in overall availability of medical interventions.

5.1 Which patients lose access to treatments?

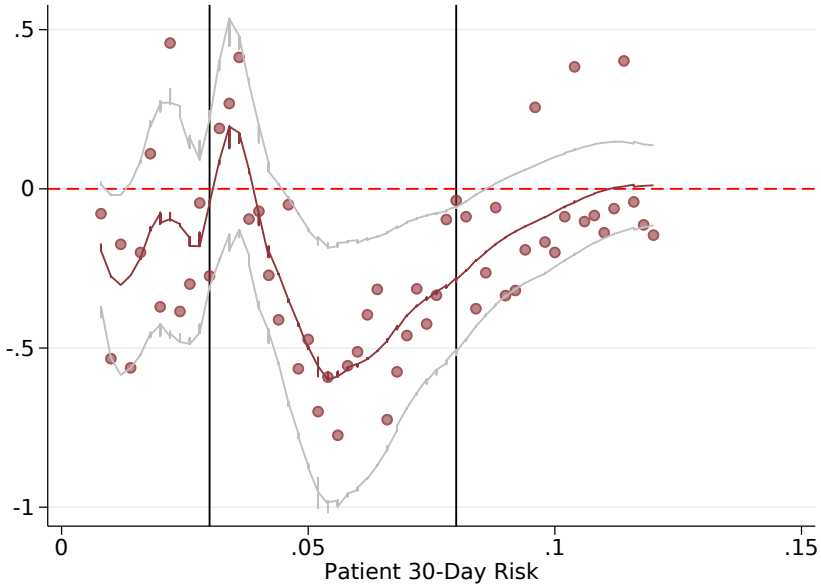
These findings corroborate the model's predictions that patients will be crowded out from access to surgical care. Next, I isolate which patients are losing access to treatments based on patient risk. Although TAVR expands access to valve replacements to riskier patients, I do not observe a corresponding increase in the relative average risk of patients receiving valve supports (Appendix Figure A.9). This suggests that the composition of valve support patients changed along *both* margins, with a corresponding exit of higher-risk patients as predicted by the model. I investigate this further, estimating treatment effects separately across bins of patient risk to identify the crowd-out region.

Figure 4 shows the results across the distribution of 30-day risk. Each point in the figure represents an estimated coefficient; these effects 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.[24] The figure therefore identifies which patients experienced the largest declines in access to cardiac interventions following TAVR's adoption in their market.

The results corroborate the model predictions that patients whose risk placed them on the margin between low-intensity procedures (valve supports) and maintenance care were

[24] Results are similar across 60- and 90-day risk. Appendix Figure A.10 presents a version without smoothing.

Figure 4. Effects of TAVR Adoption on Total Intervention Volumes by Patient Risk



Notes: Estimated heterogeneous treatment effects of adoption on total volume for valve replacements and valve supports, stratifying patients by risk bin (width=0.2pp). Each point is a bin-specific difference-in-differences coefficient, with effects smoothed nonparametrically using local linear regression weighted by patient volume. Standard errors are adjusted for multiple hypothesis testing (Anderson, 2008; Benjamini et al., 2006). See Appendix Figure A.10 for non-smoothed version. Vertical lines indicate STS-PROM delineation between low- and high-risk patients. Results are robust to using "pooled" post-treatment LP-DID average effects.

more likely to forego care post-adoption. Figure 4 shows a clear region of patients crowded out from treatment, specifically those whose risk is between 4.5% and 9%.

5.2 Inequities in Access to Surgical Care

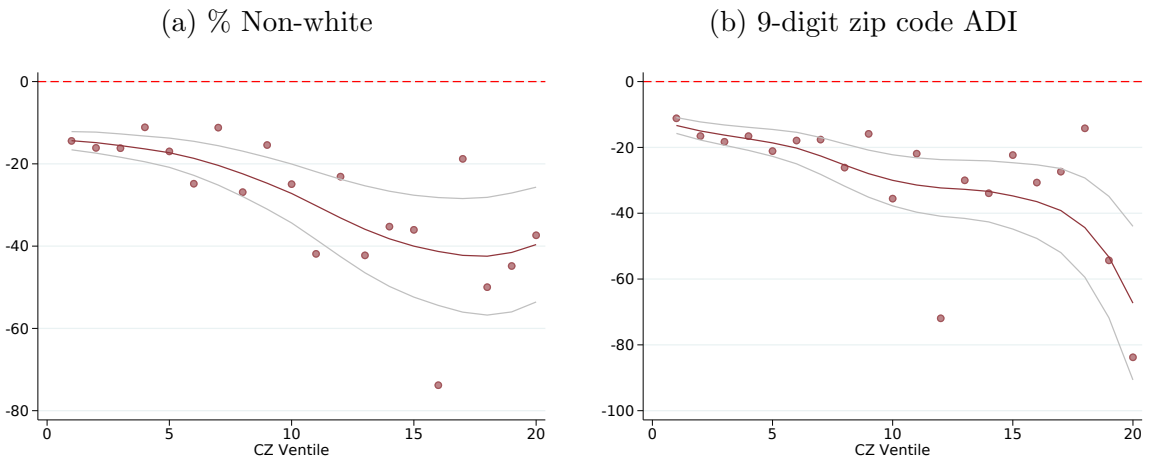
The results suggest TAVR induced some relatively low-risk patients to switch into valve replacements, but also drove higher-risk patients out of receiving valve support procedures. As my model predicts, this lost access may differentially affect the most vulnerable populations, especially if groups have heterogeneous risk. I estimate how TAVR adoption affected crowd-out across these groups, both across and within markets.

5.2.1 Market-Level Inequities

First, I consider how inequitable restrictions to access may propagate across markets, by considering market-level differences in patient populations. This allows me to use the full analytical sample, rather than the 20% carrier file available for patient-level analysis. I sort commuting zones into ventiles based on the stratifications above, including the share

of nonwhite patients, the share of dually-eligible patients, and the average ADI across zip codes in a CZ. For each ventile, I follow the same procedure applied in Section 5.1, estimating DID coefficients for total change in intervention volume and then smoothing using weighted nonlinear regression.

Figure 5. Inequities in TAVR's Effects on Local Access to Interventions: CZ Level



Notes: Heterogeneous effects of TAVR adoption on surgical volume across binned (ventiles) of CZs according to disadvantage, measured in (a) as the fraction of nonwhite patients, and in (b) as the average ADI in the market. Each point represents a difference-in-differences coefficient, where the outcome is total surgical volume at the market level as in Figure 3; effects are smoothed nonparametrically using local linear regression weighted by patient volume. Standard errors are adjusted for multiple hypothesis testing (Anderson, 2008; Benjamini et al., 2006). See Figure A.11 for results for dually-eligible patients. Results are robust to using "pooled" post-treatment LP-DID average effects.

Figure 5 presents the results. In both panels, a clear gradient emerges; in panel (a), local markets with the most racial diversity experience a decline in total surgical access twice as large the least diverse areas. These differences are estimated to be even larger when examining local markets with limited employment, education, and housing, as measured by average ADI in panel (b).[25] These results suggest the local adoption of some innovations may generate distinct experiences across patient groups, with vulnerable groups foregoing access more readily than others.

Such an analysis leverages the large variation across markets in patient demographics, including racial makeup and local measures of disadvantage. However, given that the model predictions imply potential inequities within markets, I next consider differences in TAVR's effects within a commuting zone by examining patient-level data.

[25] I also stratify markets by dual eligibility, finding little evidence of inequities along this dimension (Appendix Figure A.11).

5.2.2 Patient-Level Inequities

I consider how differences in patient characteristics may affect the dynamic treatment effects presented in Figure 3. This limits my analysis to the 20% carrier file, where I observe patient geography (zip-code level ADI), dual eligibility status, race/ethnicity, and sex (Section 2). Within each stratification, I present subgroup analysis estimating Equation 21 separately for each group; I report the pooled post-treatment indicators for each.

Group	Estimate	% Change	90% Confidence Interval	p-value
Overall	-3.65	-7.25	[-13.33, -1.17]	0.050
Panel A: Patient Geography				
ADI: Lowest Quintile	-0.46	-5.75	[-14.66, 3.16]	0.284
ADI: Highest Quintile	-2.44	-15.20	[-28.65, -1.75]	0.064
Panel B: Patient Eligibility				
Not Dual Eligible	-2.51	-6.43	[-13.19, 0.33]	0.118
Dual Eligible	-1.13	-10.08	[-17.72, -2.44]	0.030
Panel C: Patient Race				
White	-3.13	-7.10	[-13.59, -0.62]	0.072
Black	-0.45	-10.51	[-21.29, 0.26]	0.106
Hispanic	0.02	3.64	[-14.01, 21.28]	0.673
Other Non-White	-0.09	-6.57	[-17.57, 4.43]	0.314
Any Non-White	-0.52	-8.40	[-16.52, -0.28]	0.088
Panel D: Patient Sex				
Male	-2.25	-7.83	[-15.17, -0.50]	0.080
Female	-1.40	-6.51	[-11.50, -1.51]	0.033

Notes: Table presents pooled LP-DID regression coefficients estimating the effect of TAVR adoption on total surgical interventions performed by interventional cardiologists (Equation 21), stratified by patient groups. Patients and demographic information are identified based on the 20% Carrier file. The outcome variable is the count of interventions performed within the patient group at the CZ level; markets with ≤ 5 procedures quarterly are dropped. Regressions include CZ and quarter fixed effects, with standard errors clustered at the CZ level. Percentage changes are relative to the mean CZ-quarter intervention volume for the indicated group.

Table 2. Within-Market Inequities: Pooled LP-DID Estimates

Table 2 presents the results. Overall, the 20% Carrier file suggests a post-TAVR decline in surgical volume of 7.25% on average (in line with Figure A.5). Across the four panels, I observe that patients in at-risk populations experience larger declines, relative to majority populations. In panel (a), patients living in areas of higher disadvantage (even *within the same CZ*) experience larger declines in intervention volume post-TAVR. When comparing those in the highest quintile of ADI values (most disadvantaged) to those in the lowest

(least disadvantaged), the differences in declines are roughly 2.6 times as large for the more disadvantaged areas. Similarly, I observe a significant 10% reduction in volume for dual-eligible patients, compared to an insignificant change in volume for non-dual eligible patients. In panel C, I observe relatively large declines in intervention volume among White patients (7.10%), but larger declines for all non-White patients (8.40%) and Black patients specifically (10.51%). Finally, I observe few differences between male and female patients, perhaps as expected given that there is little prior reason to suspect inequitable differences in access to valve procedures based on patient sex, particularly when compared to more meaningful indicators such as race, ethnicity, income, and geography.

An important note, however, when comparing these effects, is that the estimated differences in intervention volume are not statistically different across groups. That is, although I observe significant declines for some sub-groups and not others (for example, for dual eligible patients but not for ineligible patients), the estimated coefficients for each group are contained in the 90% confidence interval of the other.[26] In part, this is likely driven by limited sample size, given the rarity of observed valve procedures in the 20% Carrier file. Additionally—and perhaps more importantly—this noise across groups is likely driven by the fact that variation *within* commuting zones across patient race, income, and ADI, is very small, particularly when compared to the differences that exist *across* commuting zones (Fu et al., 2023; Carpenter et al., 2022). Despite this lack of variation, however, my results provide consistent weak evidence that patients within a CZ may be differentially affected by TAVR's adoption, in keeping with the model.

Taken together, the estimated differences both within and across markets suggest that patients from at-risk populations experience differential declines in access to valve procedures. Although interpretation is limited by imprecise identification of within-market effects across patient groups, the combined estimates suggest that the effects of an innovation's adoption on total intervention availability—including for adjacent procedures—may serve to widen gaps in access to care for patients who already face barriers to accessing care.

5.3 Patient Outcomes & Potential Mechanisms

These differences in access may harm downstream patient outcomes. Although potentially detrimental effects may lag adoption by several years, identifying them is important to quantify the potential severity of foregone care. For example, if valve supports such as PCIs were over-used in some markets, the results in Figure 5 may not be welfare-decreasing (Chandra

[26] Note that here, I use 90% confidence intervals to account for the fact that patient-level analysis is only performed on those included in the 20% carrier file, which significantly reduces the count of already relatively rare valve procedures.

and Staiger, 2020). I therefore explore two additional patient outcomes in Appendix Figure A.12: the rate at which PCIs were accessed only following acute cardiac events, and post-operative outcomes. In the short run, TAVR-adopting markets experience an increase in the fraction of PCIs precipitated by a cardiac event, estimated at 0.86 percentage points (a 1.5% increase). This suggests that post-adoption, the health threshold for surgical intervention was *higher*; importantly, these effects are driven by both diverse and disadvantaged markets.[27]

I also investigate post-operative outcomes, measured as the rate at which PCI recipients experience cardiac events within a year post-procedure. Appendix Figure A.12 suggests markets with more nonwhite individuals experienced increases in these events of 1.97 percentage points (9.1%) post-adoption. Although suggestive, results indicate potential differences in health outcomes that may persist and even worsen with time. Finally, I examined the effect of TAVR's adoption on risk-adjusted outcomes for valve support interventions, including readmission and mortality (Appendix Figure A.13). I find statistically insignificant effects, precisely estimated enough to rule out increases of 17 percentage points in the likelihood of readmission and 1 percentage point in the likelihood of post-operative mortality.

6 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 technologies.

I present a theoretical framework considering these implications. The model highlights a tension between innovation takeup and overall service availability, stemming from physician specialization, limited availability, and productivity spillovers. This tension implies that post-innovation, overall availability to interventions may be reduced, leaving some patients crowded-out of access to care. Importantly, crowd-out may differ systematically across a population, differentially affecting vulnerable groups. I test these predictions empirically using aortic valve replacement surgeries as a case study.

Studying TAVR's adoption provides important insights for policymakers seeking to promote equitable access to healthcare. My results suggest that a policy focus on infrastructure to scale up innovative treatments—without compromising availability of adjacent

[27] I observe markets with *more* dual-eligible patients fare better than others. This is potentially attributable to expanded coverage and reduced cost-sharing among this population (Ryan & Super, 2003), but warrants future research.

procedures—can limit inequitable spillover effects (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. Additionally, my results suggest that policies aiming to reduce inequities in risk assignment may have spillover *benefits*: improvements in risk estimation which rely less on demographic information or provider bias—such as improvements in precision medicine (Matthew, 2019; Hoagland, 2024)—may generate large reductions in population-level differences in access. These potentially snowballing effects may make policies targeting equality across patient groups particularly appealing. For example, while recent concerns have highlighted how naive artificial intelligence (AI) models assisting clinical decision-making may inadvertently exacerbate health inequities even in cardiology care (Gichoya et al., 2022), adjusting these models to include a specific equity focus may both reduce disparities in access to key services such as cardiovascular imaging and, ultimately, reduce downstream healthcare costs (Dankwa-Mullan et al., 2021). Finally, investments in primary care screenings and diagnoses may have large dividends, given that these diagnostic inequities typically persist and widen as patients move "upstream" in the treatment cycle (Marcus et al., 2023; Hoagland et al., 2024).

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 long-run impacts of innovation on equity, including for outcomes not directly observable in my data such as wait times, complications, and endogenous patient risk.[28] 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 (Cram et al., 2008; 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).

[28] 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, structural changes in the market for aortic stenosis treatments may have occurred.

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A Appendix

A.1 Tables

	All Procedures (N)			Cardiothoracic Surgeons			Interventional Cardiologists		
	All	SAVR	TAVR	All	SAVR	TAVR	All	SAVR	TAVR
2010	36,458	36,453	0	95.97%	95.97%	0.00%	2.62%	2.62%	0.00%
2011	38,084	37,376	705	94.37%	93.29%	1.08%	4.034%	3.32%	0.72%
2012	40,564	35,124	5,463	92.02%	83.52%	8.54%	6.69%	1.81%	4.90%
2013	44,736	35,369	9,409	91.10%	75.99%	15.21%	8.34%	1.76%	6.59%
2014	47,530	33,638	13,944	88.54%	68.02%	20.62%	10.67%	1.46%	9.23%
2015	53,301	33,225	20,134	85.55%	59.88%	25.77%	13.23%	1.13%	12.12%
2016	58,539	30,104	28,469	80.91%	49.37%	31.60%	17.88%	0.99%	16.90%
2017	60,896	25,933	35,010	77.15%	40.92%	36.31%	20.57%	0.76%	19.83%

Table A.1. Role of Cardiologists in Aortic Stenosis Procedures, 2010–2017

Table Notes: Each cell represents the fraction of the intervention type performed by the type of medical professional in a given year. Sample is limited to all aortic valve replacements (TAVR/SAVR) procedures. Totals do not add up to 100% because some procedures are performed by a team comprised of both cardiothoracic surgeons and interventional cardiologists, and others are performed by physicians with other listed specialties (e.g., internal medicine). Cardiothoracic surgeons are those whose primary specialty is listed as "cardiac surgery", "thoracic surgery", or "general surgery"; interventional cardiologists are those whose primary specialty is listed as "interventional cardiology", "cardiology", or "cardiovascular disease."

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
	3721–3723	Cardiac catheterization
ICD-10-PCS	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 A.2. 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.

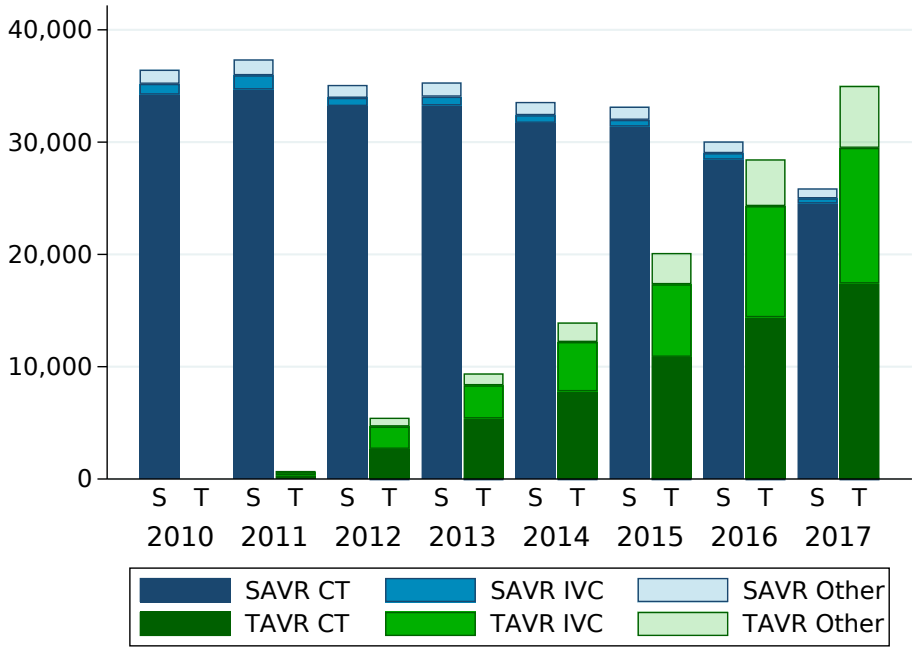
	30-Day Mortality		60-Day Mortality		90-Day Mortality	
	ME	95% CI	ME	95% CI	ME	95% CI
Panel A: Patient Demographics						
Patient age	-0.000	[-0.001,-0.000]	-0.000	[-0.000,-0.000]	0.000	[-0.000,0.000]
Female	0.007	[0.006,0.008]	0.006	[0.004,0.007]	0.004	[0.002,0.006]
Black	0.011	[0.008,0.014]	0.009	[0.006,0.013]	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 A.3. 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 the $N = 377,532$ patients who received TAVR or SAVR procedures during the analytic period.

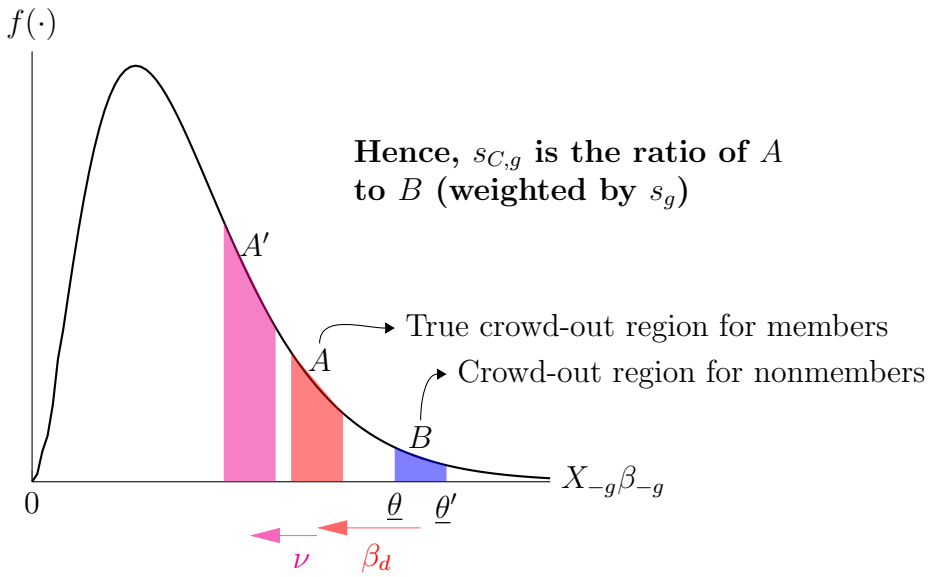
A.2 Figures

Figure A.1. 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.

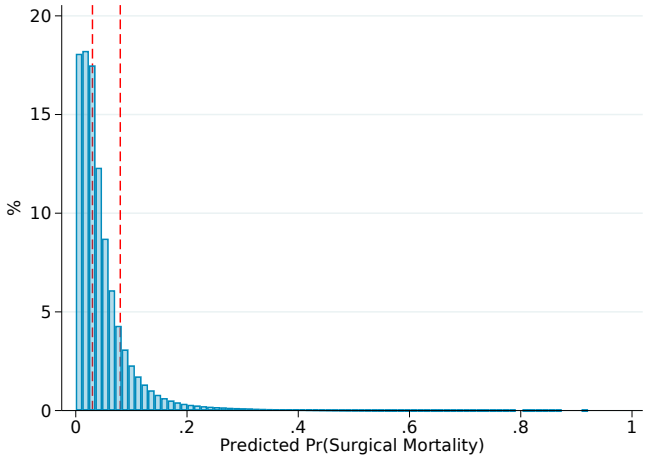
Figure A.2. Inequities in Crowdout Associated with Imperfect Risk Assessment



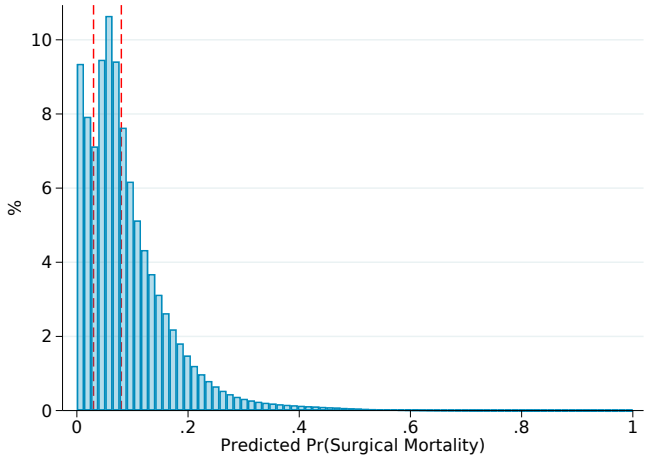
Notes: Figure illustrates the relative "crowd-out regions" for members and nonmembers of a group g when used in a proxy for patient risk, as well as the effect of measurement error in β_d on the relative crowd-out rates of members and nonmembers. The figure plots an inverse gamma distribution with parameters $(3, 1)$ 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 affecting $\hat{\beta}_d$ shift the region A', ultimately affecting the relative representation of members of group g in the crowd-out region.

Figure A.3. Predicted Patient Risk of Surgical Mortality (STS-PROM)

(a) Pr(30-Day Mortality)



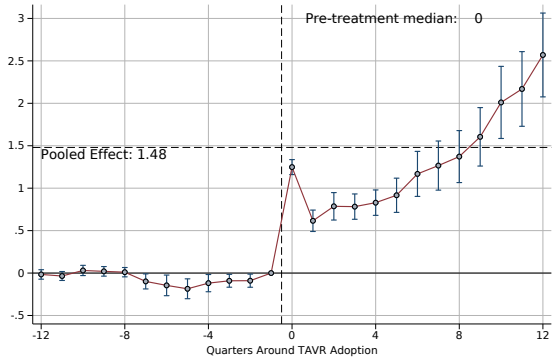
(b) Pr(90-Day Mortality)



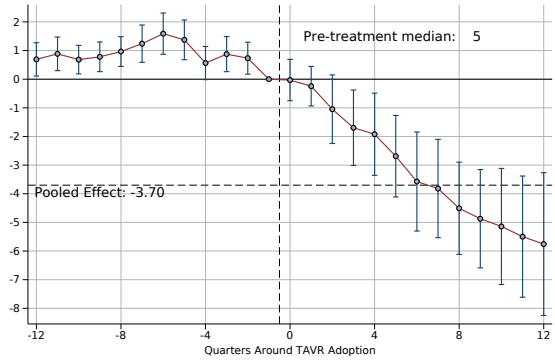
Notes: Figure shows predicted surgical risk from TAVR and SAVR, estimated using the STS-PROM model presented in Table A.3. The current STS-PROM model classifies a similar population as 33% low-risk, 42% intermediate-risk, and 25% high-risk (Kumar et al., 2018).

Figure A.4. Procedural Volume Responses to TAVR Adoption, by Intervention Type

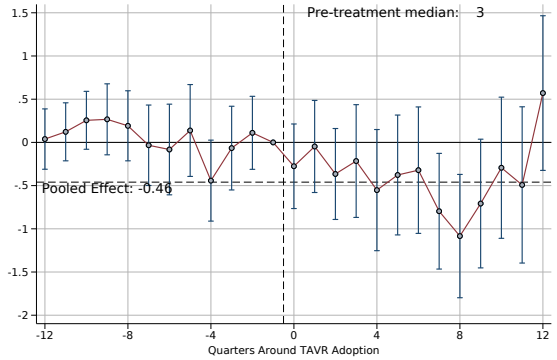
(a) SAVR/TAVR Surgeries



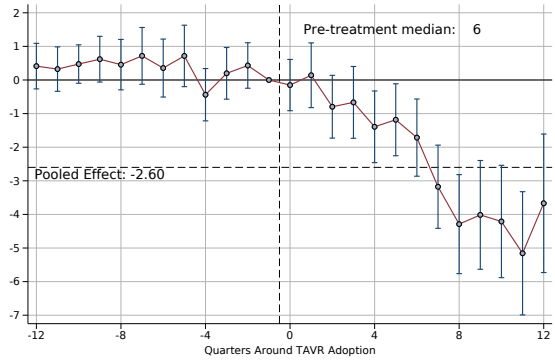
(b) PTCA



(c) Catheterization



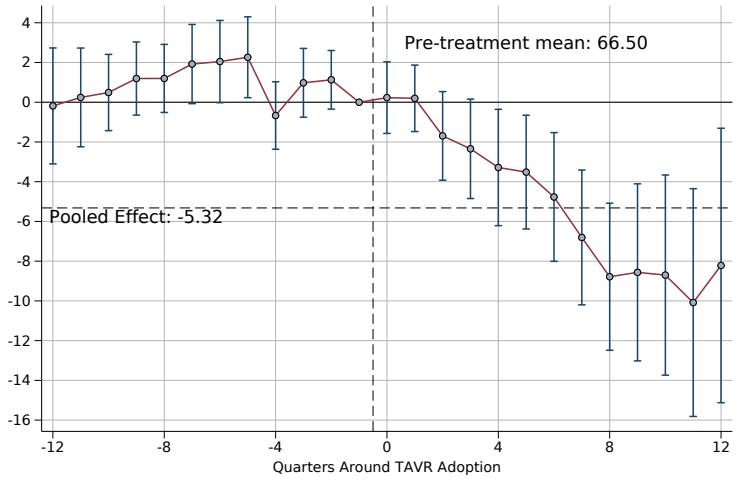
(d) All Other PCIs



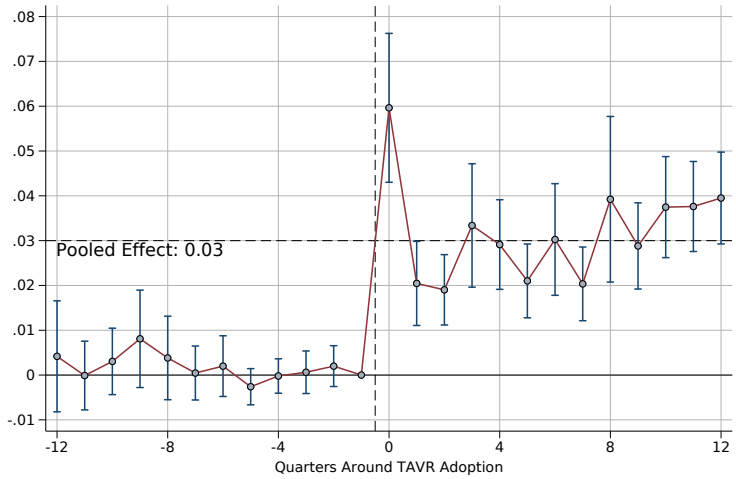
Notes: Figure shows estimated impact of TAVR adoption on the total volume of valve interventions performed in a local market, divided into major service types. In each panel, the outcome variable is the total market volume of a given intervention at a CZ level. Panel (a) shows the effect on all SAVR/TAVR 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. Markets with fewer than 5 inpatient procedures quarterly are dropped from estimation, and standard errors are clustered at the CZ level.

Figure A.5. Individual-Level Responses to TAVR Adoption

(a) All Interventions (Rate/1,000 patients)

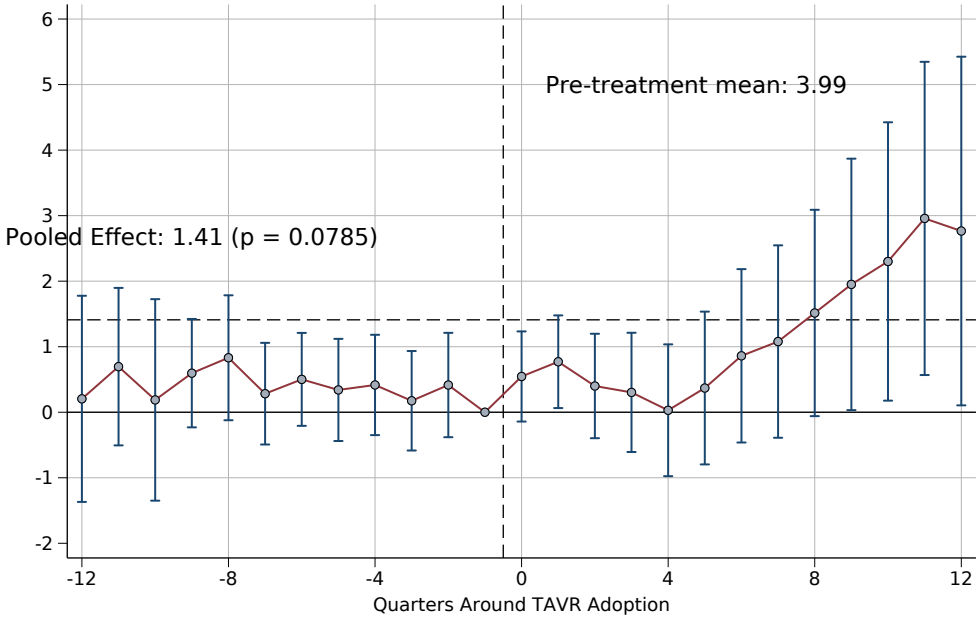


(b) Valve Replacement (Rate/1,000 patients)



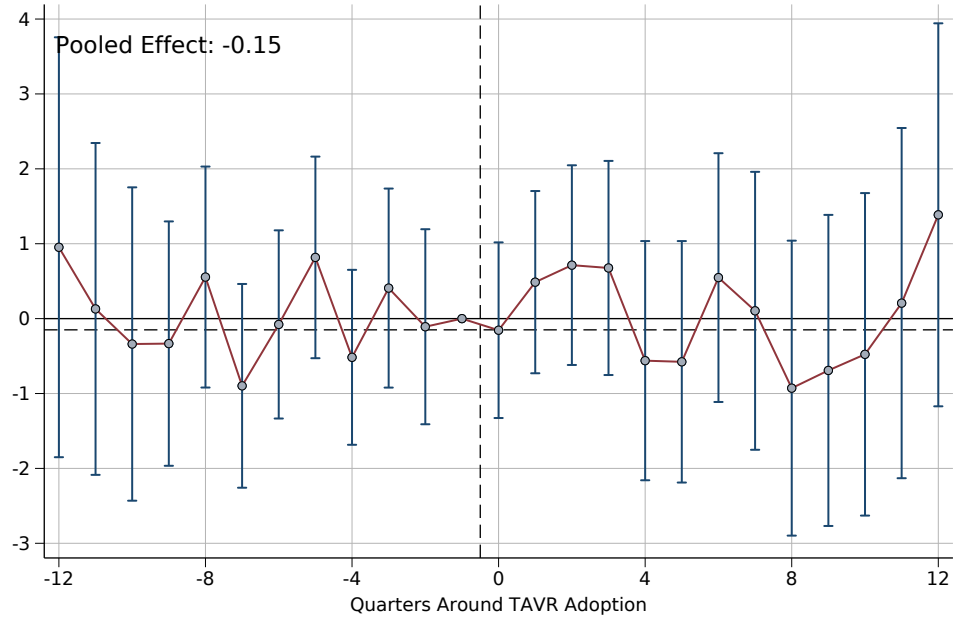
Notes: Figure shows estimated likelihood of an individual patient receiving (panel A) any valve intervention or (panel B) valve replacement following TAVR's adoption in their commuting zone. Here, the denominator is the full CZ population from the 20% carrier file; results are robust to limiting the denominator to only patients with an aortic stenosis diagnosis prior to the intervention, as discussed in Section 2. Markets with fewer than 5 inpatient procedures quarterly are dropped from estimation, and standard errors are clustered at the CZ level.

Figure A.6. Effect of TAVR Adoption on Screening for Surgical Viability



Note: Figure shows effect of TAVR adoption at the CZ level on the fraction of interventional cardiologists performing Computed Tomography Angiography (CTA) screening to diagnose aortic stenosis and discuss valve replacement or support options (CPT code 71275). Regressions are estimated as in Equation 21. Markets with fewer than 5 inpatient procedures quarterly are dropped from estimation, and standard errors are clustered at the CZ level.

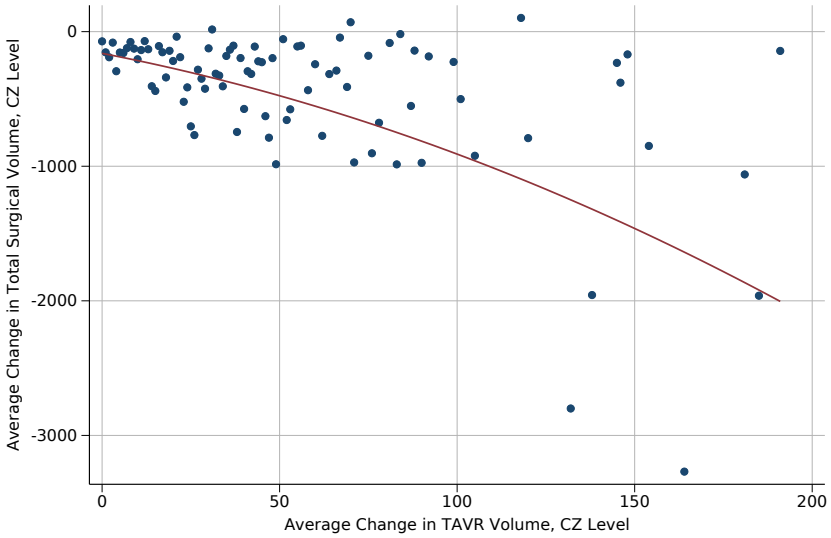
Figure A.7. TAVR Adoption Effects on Acute Angiography for NSTEMI Patients



Note: Figure shows estimated treatment effects of TAVR's adoption on the percentage of Non-ST-Elevation Myocardial Infarction (NSTEMI) patients receiving an angiogram within 72 hours (the maximum acceptable wait time recommended by the European Society of Cardiology guidelines) (Hansen et al., 2018). Markets experiencing fewer than 5 NSTEMI patients quarterly are dropped from estimation.

Figure A.7 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.

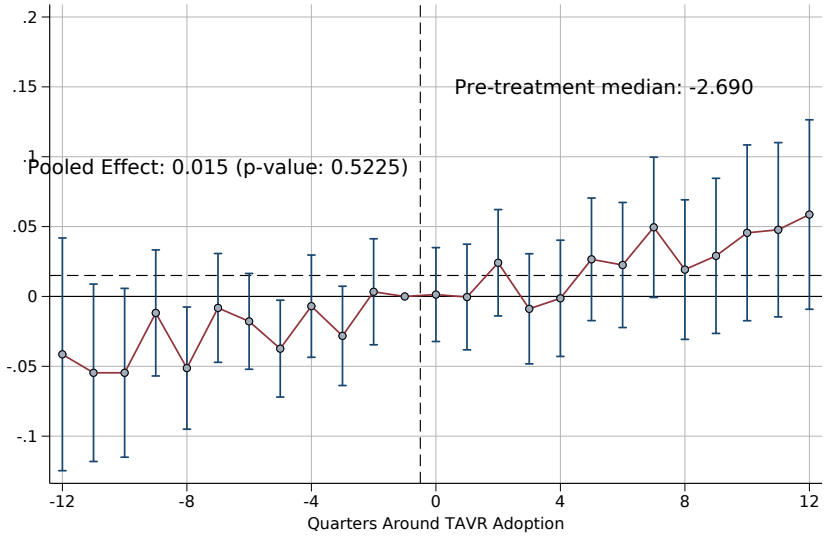
Figure A.8. Market Relationships Between TAVR Takeup and Overall Intervention Volume



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.

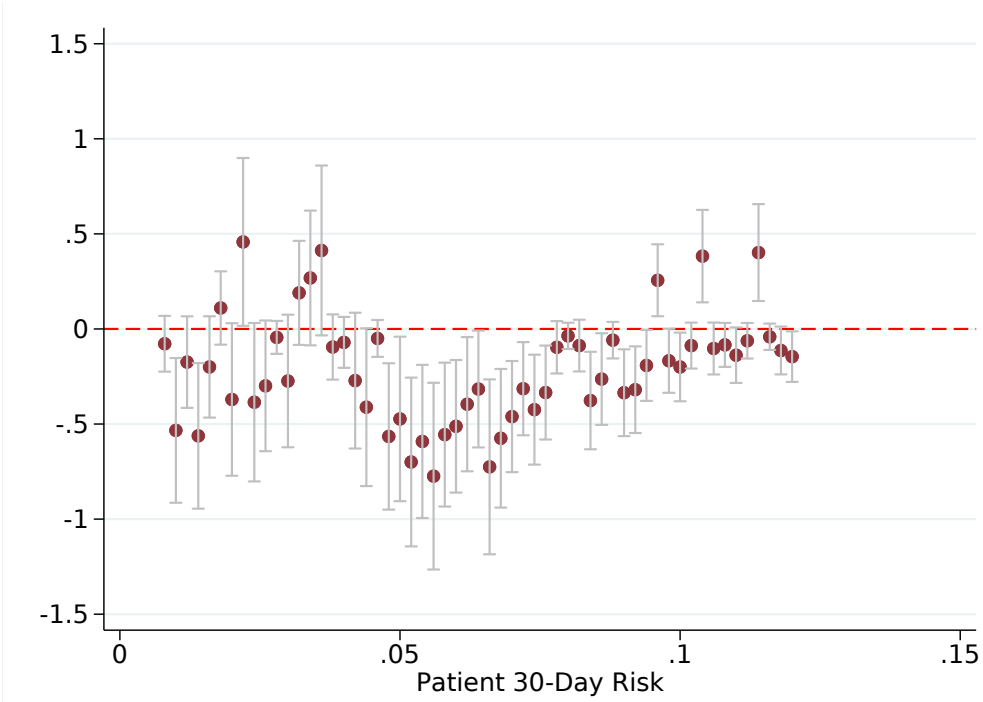
Figure A.9. Effect of TAVR Adoption on Average Risk of Valve Support Patients

(a) Log(90-day STS-PROM Risk)



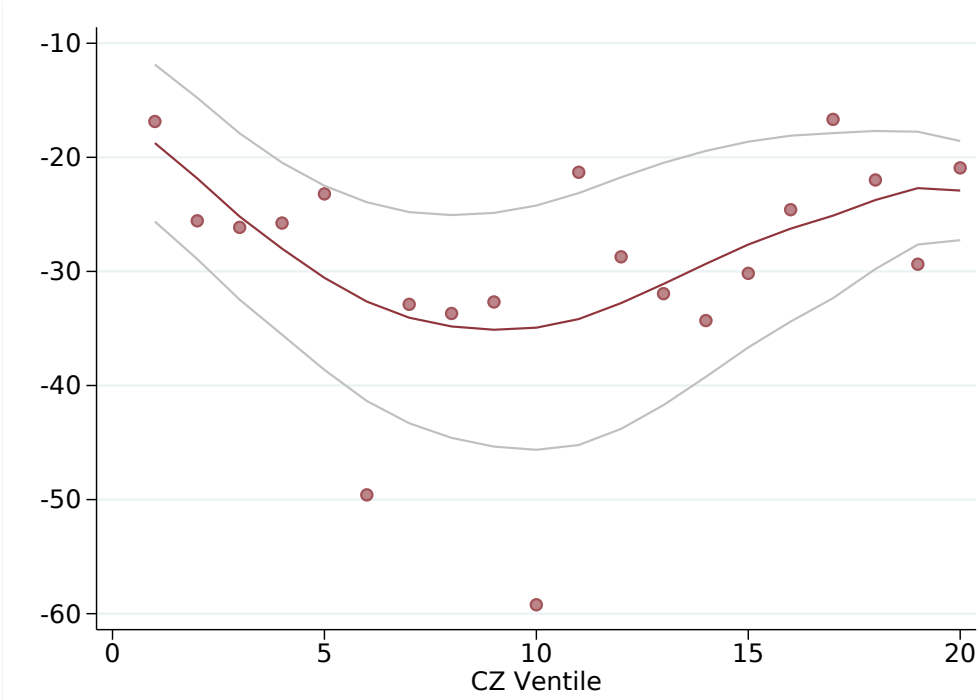
Note: Figure shows effect of TAVR adoption at the CZ level on estimated mortality risk (STS-PROM) for patients receiving low-intensity treatments (valve supports). Figure shows results for 90-day predicted risk, with a log-transformed outcome variable. Results are similar for 30- and 60-day risk. Regressions are estimated as in Equation 21, with standard errors clustered at the CZ level.

Figure A.10. Heterogeneous Effects of TAVR Adoption on Procedural Volumes by Patient Risk



Note: 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) and Benjamini et al. (2006). 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 4.

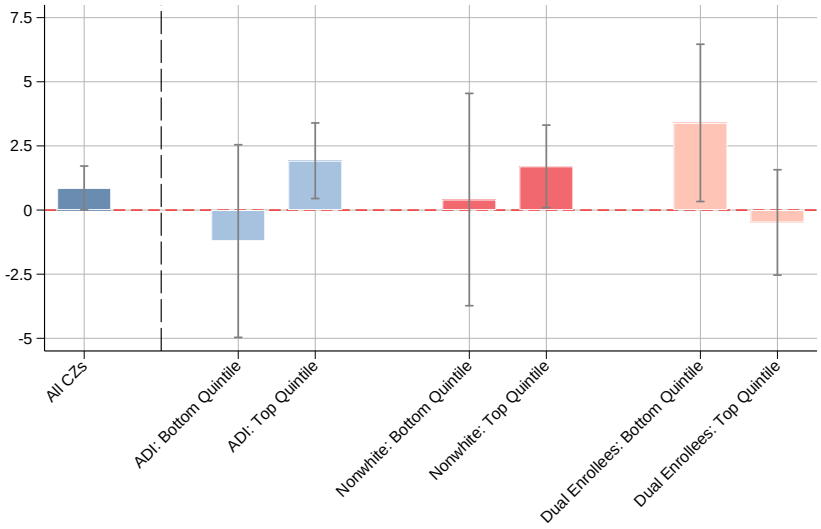
Figure A.11. Effects of TAVR Adoption on Procedural Volumes by Dual-Medicaid Eligibility



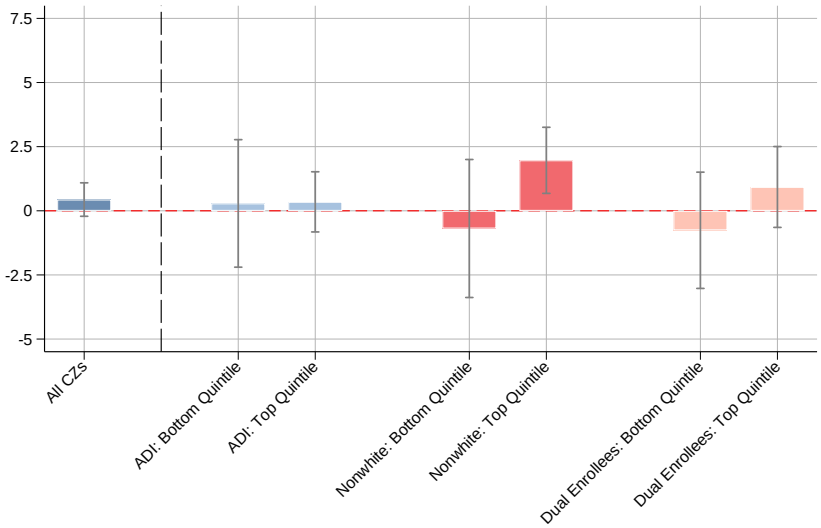
Note: Figure show heterogeneous effects of TAVR adoption on total volumes of valve replacements in a commuting zone. CZs are binned by ventiles according to the fraction of patients in a market who are dually-eligible for Medicaid. Each point represents a difference-in-differences coefficient; effects are smoothed nonparametrically using local linear regression weighted by patient volume. Results are robust to using "pooled" post-treatment LP-DID average effects. Standard errors are adjusted for multiple hypothesis testing according to Anderson (2008) and Benjamini et al. (2006). Markets performing fewer than 5 interventions annually are dropped. Compare with Figure 5.

Figure A.12. Incidence of Cardiac Events Prior to or Following PCI

(a) Hospitalization Preceding PCI



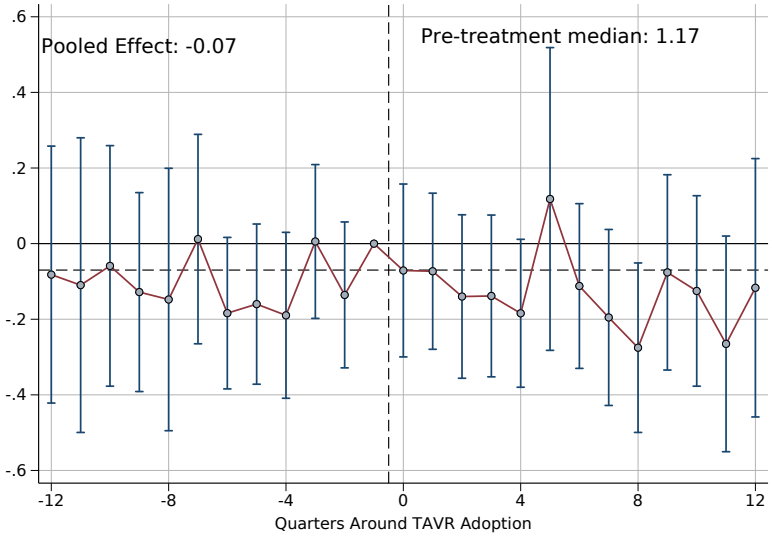
(b) Hospitalization Following PCI



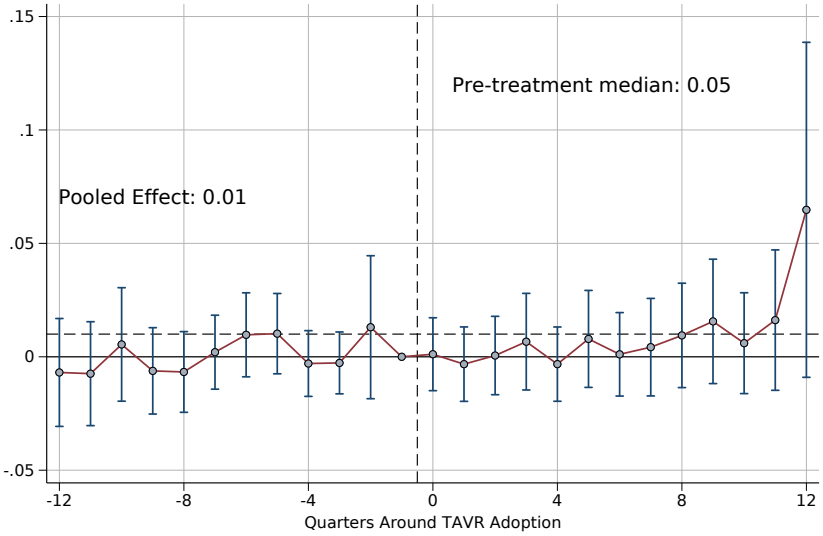
Notes: Figure shows difference-in-differences coefficients estimating the effect of local TAVR adoption on the percentage of PCI patients who either (a) had their procedure precipitated by a hospitalization (less than a year prior to PCI) or (b) experienced a cardiac event within a year following PCI. Cardiac events are limited to inpatient stays for heart attacks or heart failure. Across each group, markets in the top and bottom quintile are compared. Regressions adjust for CZ and quarter-of-year fixed-effects, and 95% confidence intervals are shown. Results are robust to using pooled LP-DID coefficients.

Figure A.13. Effect of TAVR Adoption on Valve Support Intervention Outcomes

(a) Readmission



(b) Mortality



Note: Figures show effect of TAVR adoption at the CZ level on readmissions (panel A) and mortality (panel B) within 60 days following valve support (PCI) procedures. Regressions are estimated as in Equation 21, with standard errors clustered at the CZ level. Results are robust to limiting to 30- or 90-day windows for health events.