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. I apply the model to aortic valve replacement and support surgeries, showing that innovation reduced surgical 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 (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 surgical 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,

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

2007). Innovations increasing returns to high-intensity procedures change decision-making along two margins. First, some intermediate-risk patients opt 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—high-risk patients respond to reduced returns by opting out of interventions altogether.

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) surgeries in the US. TAVR is a minimally invasive and cost-effective alternative to open-heart surgeries treating aortic stenosis; importantly, TAVR expanded both supply and demand for surgeries, as it is performed by interventional cardiologists (instead of only cardiothoracic surgeons) and is appropriate for patients deemed too high-risk for traditional 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 surgeries (percutaneous coronary interventions, or PCIs). Although adjacent to—not replaced by—TAVR, I observe the provision of PCIs falls dramatically following adoption, causing total surgical volumes to decline. This validates the model predictions: patients foregoing care are higher risk—on the margin between selecting into surgery at all—and reside in markets with greater health deprivation or more nonwhite patients. Importantly, inequitable crowdout is associated with poorer outcomes for patients; following adoption, more PCIs are precipiated by acute cardiac events, and more patients experience cardiac events after surgery.

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. 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, 2022). 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

[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.

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 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 surgery (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 1/3 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 surgeries: 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 cardiolo-

gists (Appendix Figure A.2), highlighting the comparative advantages of the two surgeries (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, 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. My main sample includes 9,858,536 Medicare patients with AS, including patients with and without eventual valve replacements. Appendix Table A.2 presents relevant summary information.

3 Model

Suppose there is a continuum of patients suffering from a single disease. Patients and physicians 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 replacement surgeries (SAVR/TAVR) while $s = 1$ corresponds to valve support surgeries (PCIs).[5]

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

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

where P_s represents the fraction of the population receiving treatment s. Equation 1 incorporates productivity spillovers in the second term, in the style of Chandra and Staiger

[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).

[5] 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.

(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.[6] Patients then choose treatment only along two margins: a choice between valve replacement and valve support surgeries, or a choice between supports and no surgery. 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:

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

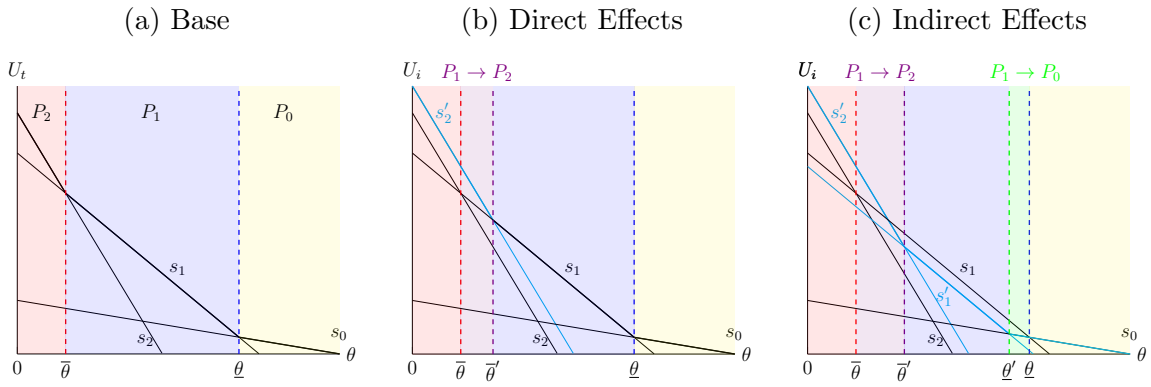
$$P_2 = \int_Z \Pr\{\beta_{21} Z + \alpha_2 P_2 - \alpha_1 P_1 > \varepsilon_{12}\} f(Z) dZ. \tag{5}$$

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).

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

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).

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; hence suppose U_1 shifts by a fixed τ.[7]

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).

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

[7] τ need not be constant for results to hold.

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.[8]

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.[9]

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

[9]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 $\hat{\theta}$.[10] Assume $\hat{\theta}$ is a linear combination of observable characteristics Z_{is} correctly predicting θ except for an idiosyncratic, mean-zero error ε:

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

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.[11] 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.

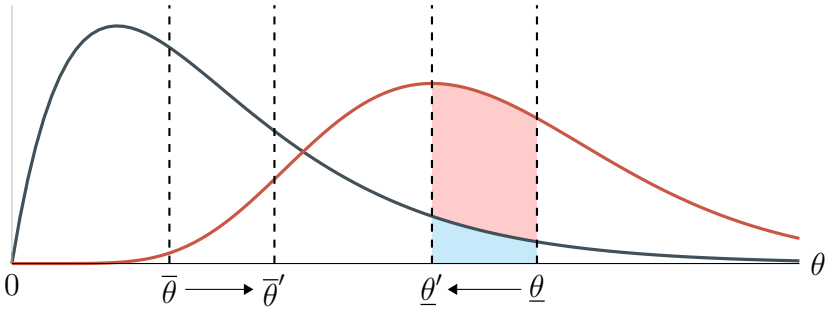
Further inequities arise, however, when γ_d is incorrectly measured. Imperfect proxying may arise from provider error or other factors, including patient beliefs or biased health measurements like risk scores (Obermeyer et al., 2019). This measurement error distorts the likelihood that members of g are represented in C. To quantify this relationship, suppose

disproportionately represented by certain groups.

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

[11] 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).

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.[12] 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.1 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.

[12] 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. I then identify which patients are affected, 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 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.

4 Methods

I assess the effects of TAVR's adoption on access to valve surgeries within a local market.[13] I consider two types of surgical interventions, in keeping with the model: valve replacements (SAVR/TAVR) and valve supports (PCIs). 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, TAVR's adoption meaningfully induces some PCI patients to instead seek TAVR from their interventional cardiologist, especially when their risk previously made them poor candidates for SAVR.

4.1 Estimating Patient Risk

Cardiac surgery risk is typically estimated using risk models constructed by The Society of Thoracic Surgeons (STS), accounting for pre-operative factors that influence surgical outcomes (O'Brien et al., 2009). To predict patient risk θ, I use the STS Predicted Risk of Mortality (STS-PROM), a logistic regression of 60-day mortality on patient demographics and health conditions (Appendix Table A.4). The STS-PROM 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.[14]

[13] I use U.S. commuting zones to define markets; results are robust to other definitions, including HSAs. Appendix Table A.3 lists procedure and diagnosis codes.

[14] 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.

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 "stacked" regression design (Cengiz et al., 2019). This avoids bias from naive staggered adoption designs with heterogeneous treatment effects (Roth et al., 2023). I identify adoption cohorts (at the quarter-year level) $r \in \{1, ..., N^1\}$ and stack them into a single estimation with cohort-specific time and market fixed effects:

$$\Pr(\text{Treatment}_{im,r}) = \alpha_{m,r} + \tau_{t,r} + \sum_{k=-T}^{T} \gamma_k \mathbb{1}\{t - E_{imt,r} = k\} + \varepsilon_{imt,r}. \tag{21}$$

Outcomes include treatment decisions for patients i seen at quarter t, residing in a market m whose TAVR adoption places them in cohort r. I cluster standard errors at the market level. Throughout, the identifying assumption is that the timing of TAVR's adoption is exogenous at the market level, or that interventional cardiologists did not adopt TAVR due to underlying changes in the expected volume of patients seeking valve support (not valve replacement) surgeries. This can be examined directly by assessing differential pre-trends between adopting and non-adopting markets for indications that volumes were changing before adoption.

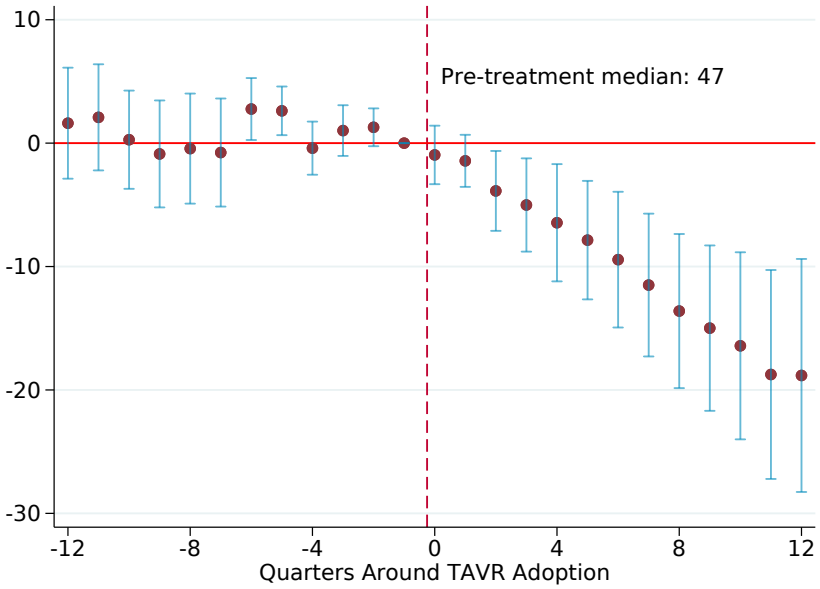
4.3 Heterogeneity & Inequities in Post-Innovation Access

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. Where applicable, I adjust these results for multiple inferences using sharpened false discovery rate control methods (Anderson, 2008), allowing for a direct comparison of adoption effects across patients of differing surgical risk and markets of differing disadvantage.

5 Results

TAVR's adoption expanded surgeries to older, higher-risk patients. I observe the average likelihood of valve replacements double within three years of adoption, with patients estimated to be 4 years older and roughly 0.2% riskier (Appendix Figures A.4, A.5).

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



Notes: Estimated impact of TAVR adoption on total volume of surgical interventions performed by IVCs, including all SAVRs, TAVRs, and PCIs. Markets with fewer than 10 sugeries per quarter are dropped from estimation. Standard errors are clustered by commuting zone.

Figure 3 presents the dynamic effects of TAVR adoption on interventional cardiology procedures at the commuting zone level (Equation 21).[15] The figure shows a marked decline in total surgical volume: the median commuting zone performs 47 procedures annually pre-adoption, but within two years, volume drops by 40%. This decline is driven by reductions in valve supports, which swamp takeup of valve replacements (Appendix Figure A.7).[16]

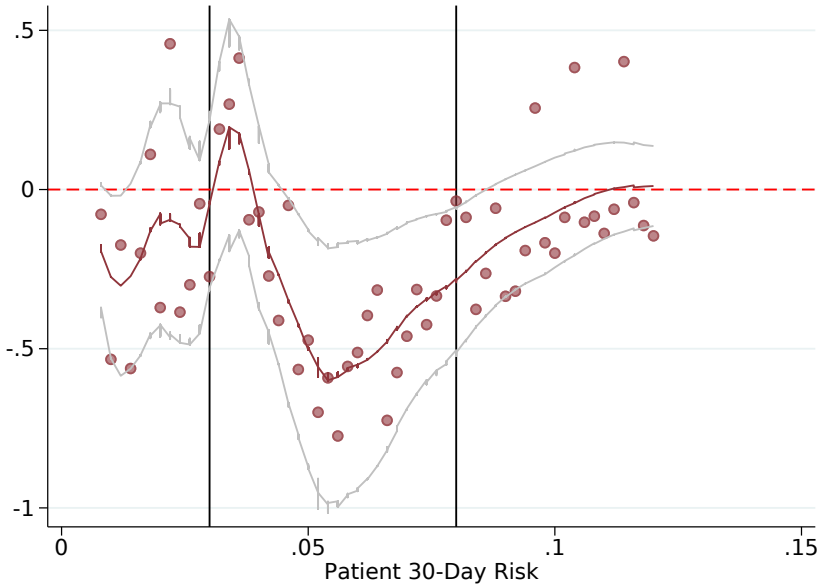
These findings corroborate the model's predictions that patients will be crowded out from access to surgical care. Next, I isolate which patients are losing access to treatments, particularly across patient risk. I first examine the effect of TAVR adoption on the average predicted risk of patients in each treatment group. I find that TAVR caused the conditional

[15]Results are robust to performing estimation at the individual organization level (Appendix Figure A.6).

[16]The Appendix provides additional results. Figure A.8 shows post-adoption, interventional cardiologists are roughly 33% more likely to screen patients for appropriateness for SAVR/TAVR, suggesting physicians adapt their diagnostic screening strategies in response to technology (Mullainathan and Obermeyer, 2021). I also show that while the overall availability of PCIs declines post-adoption, urgent PCI procedures are not delayed (Figure A.9).

risk of SAVR/TAVR patients to increase, but do not observe a corresponding change in the risk composition of PCI patients (Appendix Figure A.10). This suggests that the composition of PCI patients changed along both margins. I investigate this further, estimating treatment effects separately across bins of patient risk to identify the crowd-out region.

Figure 4. Heterogeneous Effects of TAVR Adoption on Surgical Volumes by Patient Risk



Notes: Estimated heterogeneous treatment effects of adoption on total surgical volume for patients by risk bin (width=0.2pp). Each point is a bin-specific difference-in-differences coefficient. 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 Appendix Figure A.11 for non-smoothed version. Vertical lines indicate STS-PROM delineation between low- and high-risk patients.

Figure 4 shows the results across the distribution of 30-day risk.[17] 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.[18] The figure therefore identifies which patients experienced the largest declines in access to surgeries following TAVR's adoption in their market. The findings corroborate the model predictions that patients whose risk placed them on the margin between low-intensity surgery (PCIs) and maintenance care were 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%. Patients in this group lost access to surgeries at a rate of 0.5 surgeries per quarter per bin, corresponding to the 15 surgeries at

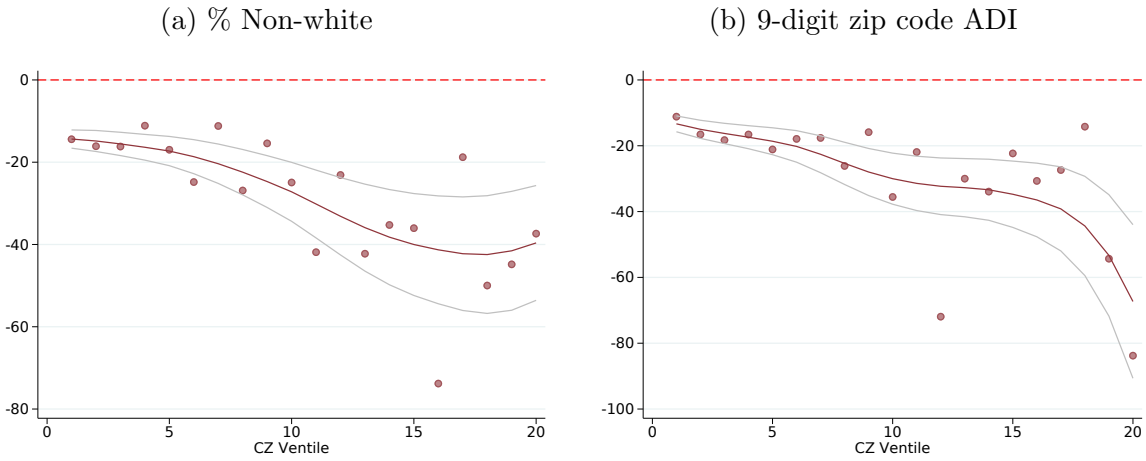
[17] Results are similar across 60- and 90-day risk.
[18] Appendix Figure A.11 presents a version without smoothing.

the commuting zone-quarter level presented in Figure 3.

5.1 Inequities in Access to Surgical Care

The results suggest TAVR induced some relatively low-risk patients to switch into TAVR/SAVR, but also drove higher-risk patients out of receiving any surgery. 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.

Figure 5. Inequities in TAVR's Effects on Local Access to Valve Surgeries



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; 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.12 for results for dually-eligible patients.

Figure 5 presents the results. I sort commuting zones into ventiles based on commonly used measures for health equity: in panel (a), the share of nonwhite patients, and in panel (b), the average ADI, measuring an area's overall economic disadvantage. In both panels, a clear gradient emerges; 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 (measured by the ADI).[19] 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.[20]

[19]I also stratify markets by dual eligibility, finding little evidence of inequities along this dimension (Appendix Figure A.12).

[20]Estimates in Figure 5 aggregate differences in true underlying risk and the impacts of incorrect risk

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 PCIs were over-used in some markets, the results in Figure 5 may not be welfare-decreasing (Chandra and Staiger, 2020). I therefore explore two patient outcomes in Appendix Figure A.13: the rate at which PCIs were accessed only following acute cardiac events, and post-surgical 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.[21]

I also investigate post-surgical outcomes, measured as the rate at which PCI recipients experience cardiac events within a year post-surgery. Appendix Figure A.13 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.[22]

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, some patients may forego surgical care altogether. 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.

assignment. As a back-of-the-envelope calculation, assume the change in the risk threshold for PCIs went from 8% to 4.5% post-adoption (Figure 4). Nonwhite patients would have to be twice as likely to be in this interval to generate Figure 5; however, in the data, nonwhite and white patients are equally prevalent. This suggests that roughly half of observed inequities arise from "true" risk differences (nonwhite individuals have $\gamma_d = 1.1\%$ according to Appendix A.4) and half from misperceptions of patient risk based on race.

[21] 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.

[22] Finally, I examined the effect of TAVR's adoption on risk-adjusted PCI surgical outcome (readmission and mortality); I find little evidence of an effect for either (Appendix Figure A.14).

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 procedures—can limit inequitable spillover effects. 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 relying less on demographic information or eliminating provider bias may generate large reductions in population-level differences in access. These potentially snowballing effects may make policies targeting equality across patient groups—for example, through equity-minded artificial intelligence models—particularly appealing to regulators (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).

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.[23] 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).

[23] Wait times for SAVR/TAVR have increased in other countries, leading to higher rates of heart failure for those with severe AS (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 AS treatments may have occurred.

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A Appendix

A.1 Tables

	All Surgeries (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 surgical type performed by the type of medical professional in a given year. Sample is limited to all aortic valve replacement surgeries (TAVR/SAVR) procedures. Totals do not add up to 100% because some procedures are performed by a team comprised of both CT surgeons and IV 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".

	All	PCI	SAVR	TAVR
Age	73.6	73.4	74.6	81.4
	(0.003)	(0.006)	(0.016)	(0.023)
Female	0.50	0.45	0.38	0.47
	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Black	0.11	0.10	0.05	0.04
	(0.0001)	(0.0002)	(0.0004)	(0.0006)
Hispanic	0.02	0.02	0.01	0.01
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Other Minority Race	0.04	0.04	0.03	0.02
	(0.0001)	(0.0001)	(0.0003)	(0.0004)
Average 5-Zip Income	$65,456	$64,677	$67,389	$70,519
	(5.03)	(9.68)	(34.38)	(55.66)
ADI	51.7	53.2	48.2	46.1
	(0.008)	(0.015)	(0.051)	(0.076)
Dual Eligible	0.25	0.23	0.12	0.11
	(0.0001)	(0.0002)	(0.0006)	(0.0009)
# of Chronic Conditions	5.7	6.5	6.0	7.4
	(0.001)	(0.002)	(0.005)	(0.007)
Predicted STS-PROM Risk: 30-day	0.050	0.058	0.053	0.045
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Predicted STS-PROM Risk: 60-day	0.069	0.071	0.072	0.065
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Predicted STS-PROM Risk: 90-day	0.081	0.080	0.084	0.077
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
N	11,581,620	3,038,436	263,387	112,424

Notes: Table shows summary statistics for patients in analytical sample, 2010–2017. Patients are grouped based on if they ever had a PCI, SAVR, or TAVR surgery (groups may not be mutually exclusive). Income is averaged at the 5-digit zip code level (reported in 2021 USD). The Area Deprivation Index (ADI) ranks 9-digit zip codes by socioeconomic disadvantage nationally; higher ADI indicates greater disadvantage (Kind and Buckingham, 2018). Predicted patient risk (STS-PROM) is predicted as described in Table A.4.

Table A.2. Summary Statistics: Patients

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.3. Definitions of Interventional Cardiology Procedures

Notes: Table shows inpatient hospital procedure codes (ICD-9-PCS and ICD-10-PCS) used to identify valve replacement surgeries (TAVR and SAVR) and interventional cardiology procedures (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.

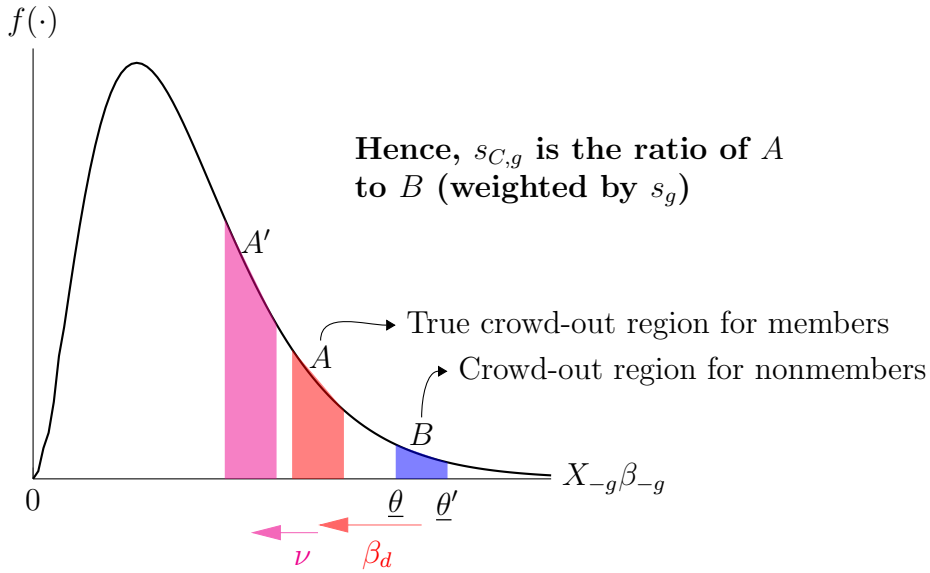
	30-Day Mortality		60-Day Mortality		90-Day Mortality	
	ME	95% CI	ME	95% CI	ME	95% CI
Panel A: Patient Demographics						
Patient age	-0.000	[-0.001,-0.000]	-0.000	[-0.000,-0.000]	0.000	[-0.000,0.000]
Female	0.007	[0.006,0.008]	0.006	[0.004,0.007]	0.004	[0.002,0.006]
Black	0.011	[0.008,0.014]	0.009	[0.006,0.013]	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.4. 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.

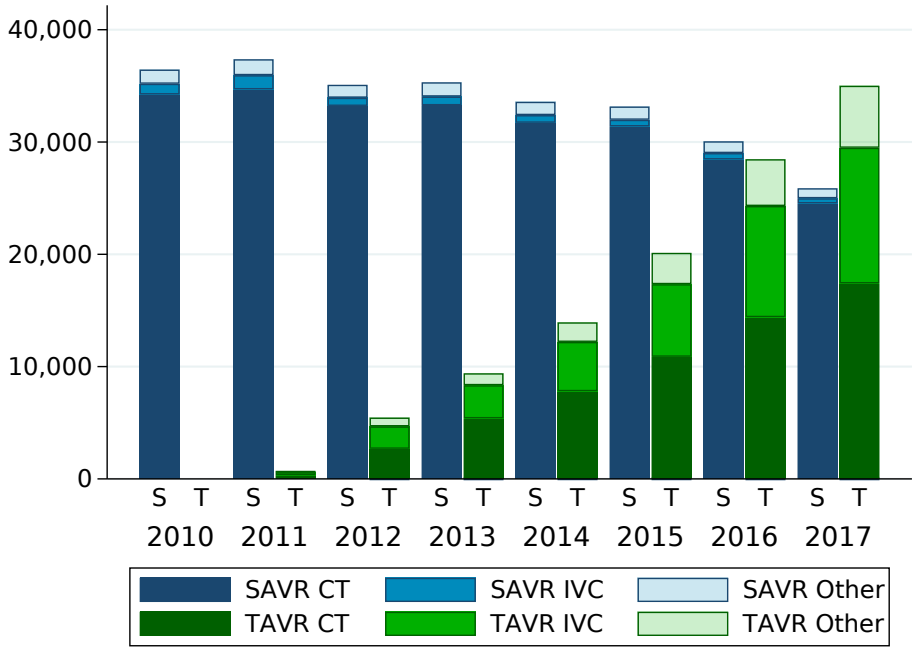
A.2 Figures

Figure A.1. 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.

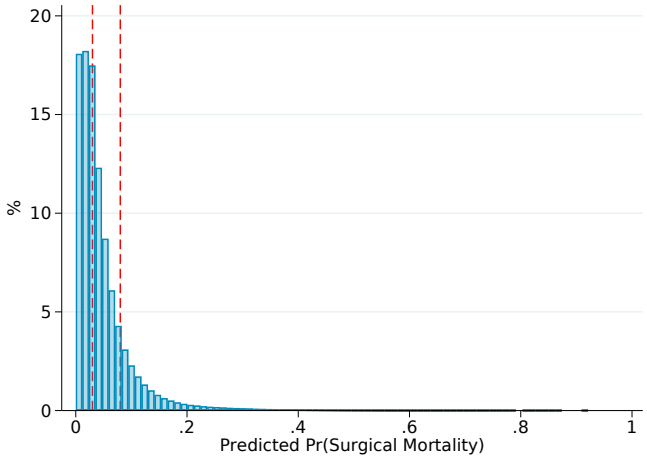
Figure A.2. Timeline of TAVR Adoption



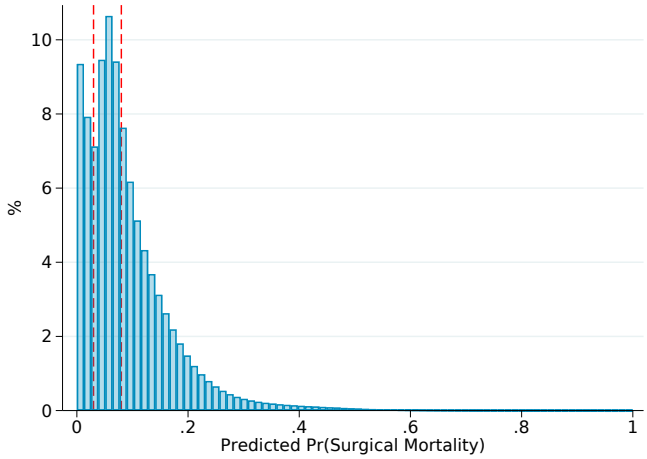
Notes: Figure shows diffusion of TAVR procedures among different cardiac surgeon specialties over time. Total volume of surgical valve replacements (SAVR and TAVR, labelled as "S" and "T" on the x-axis) for the full U.S. Medicare population are shown, with a breakdown of surgeon specialty. Cardiothoracic 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.3. Predicted Patient Risk of Surgical Mortality (STS-PROM)

(a) Pr(30-Day Mortality)

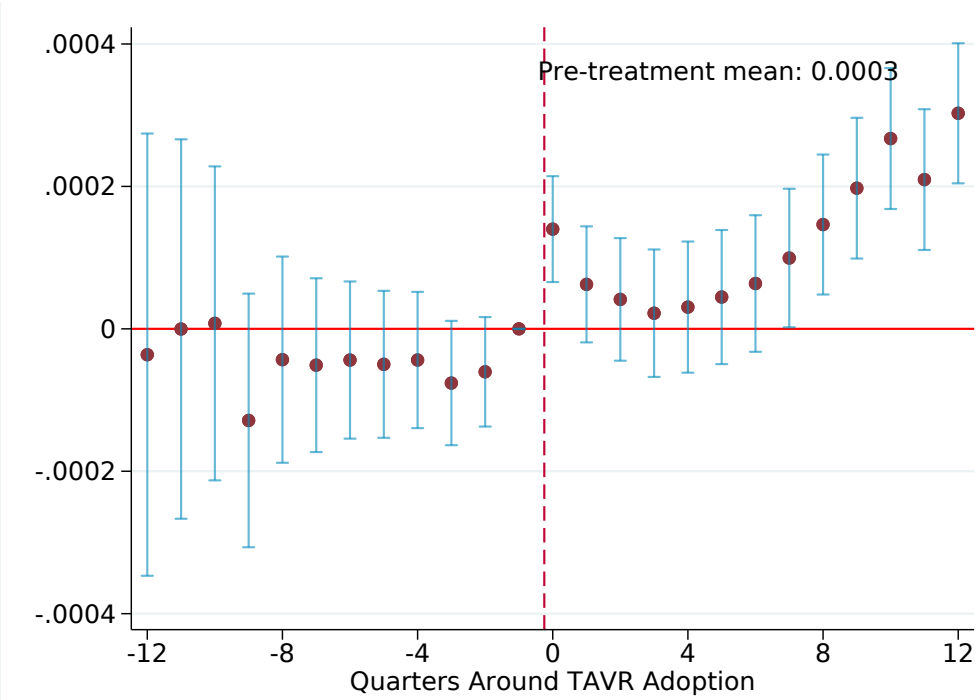


(b) Pr(90-Day Mortality)



Notes: Figure shows predicted surgical risk from TAVR and SAVR, estimated using the STS-PROM model presented in Table A.4. The current STS-PROM model classifies a similar population as 33% low-risk, 42% intermediate-risk, and 25% high-risk (Kumar et al., 2018).

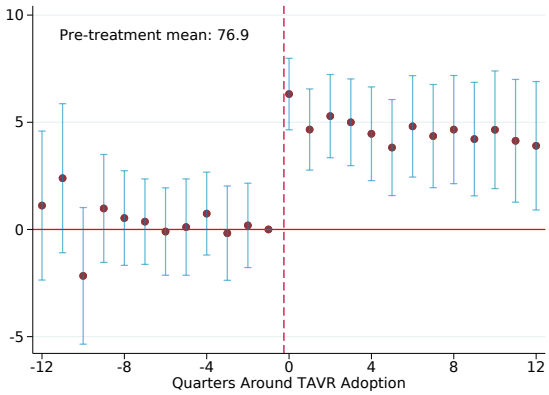
Figure A.4. TAVR Adoption Increases Individual Probability of SAVR/TAVR Surgery



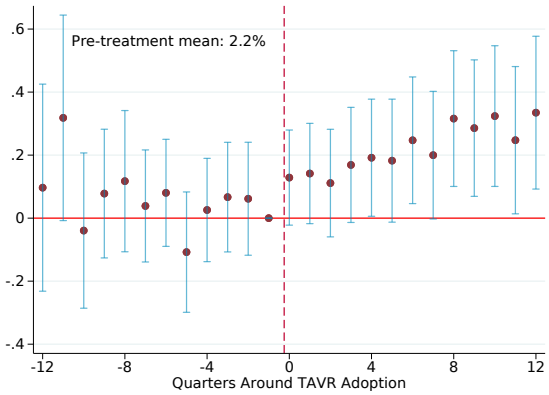
Notes: Figure shows estimated likelihood of an individual patient receiving valve replacement surgery (TAVR or SAVR) following TAVR adoption in their market. Surgical candidates are identified using the diagnostic codes associated with TAVR, SAVR, or PCI procedures in the Medicare data. Standard errors are clustered at the commuting zone level.

Figure A.5. Effect of TAVR Adoption on Average Age/Risk of TAVR/SAVR Patients

(a) Patient Age

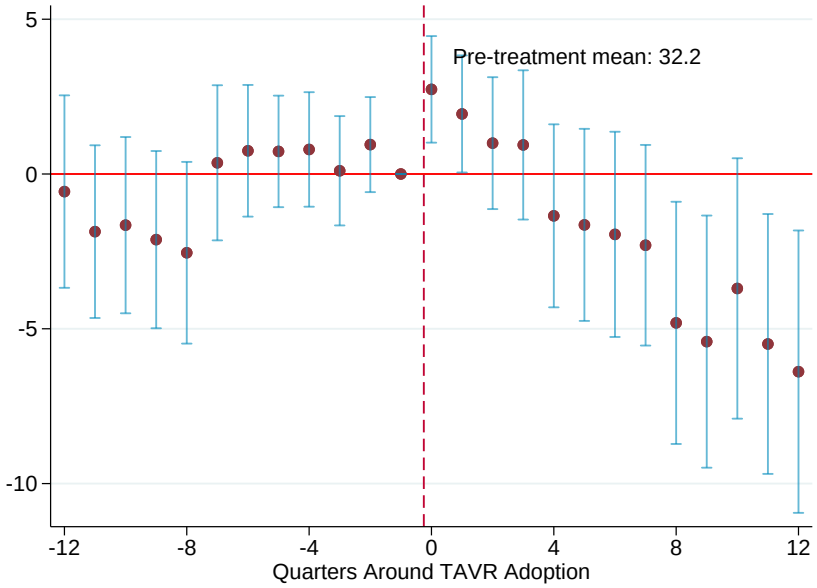


(b) $\sinh^{-1}$(30-Day Patient Risk)



Note: Figures show effect of TAVR adoption at the CZ level on estimated age and risk for patients receiving high-intensity heart surgeries (TAVR and SAVR). Panel (a) shows the effects on patient age, while panel (b) shows effects on the inverse hyperbolic sine of 30-day STS-PROM risk score (hence, coefficients are roughly interpretable as percentage changes; see (Bellemare and Wichman, 2020)). Regressions are estimated as in Equation 21, with standard errors clustered at the CZ level.

Figure A.6. Effect of TAVR Adoption on Total IVC Surgical Volumes, Individual Organization Level

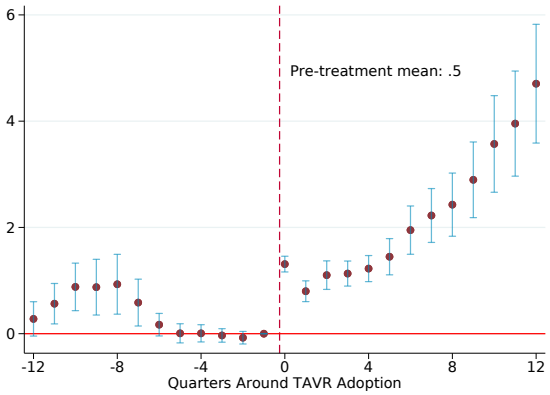


Notes: Figure shows estimated impact of TAVR adoption on the total volume of surgical interventions performed by IVCs within an individual organization (e.g., a hospital or independent catheterization lab). Organizations are identified using organization NPIs. All organizations in markets with fewer than 10 inpatient surgeries total per quarter are dropped from estimation, and standard errors are clustered at the commuting zone level.

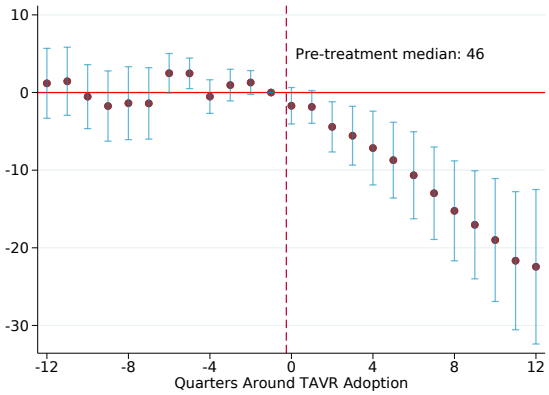
Figure A.6 shows that results presented in Section 5 are robust whether estimation is performed at the market (commuting zone) or individual agent (organization) level. Estimation is done using the organization NPI number to identify individual organizations (e.g., hospitals). Following an organization's adoption of TAVR, total surgical availability increases in the very short run, but then decrease by about 15% (5 surgeries) per quarter by the second year following adoption.

Figure A.7. IVC Surgical Volume Responses to TAVR Adoption, Commuting Zone Level

(a) SAVR/TAVR Surgeries

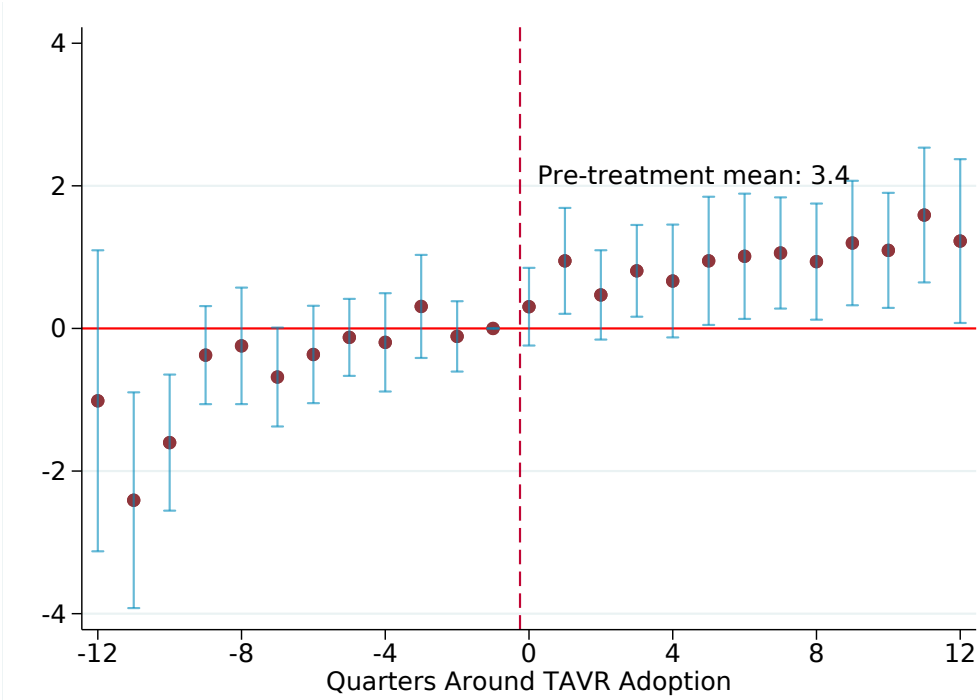


(b) PCIs



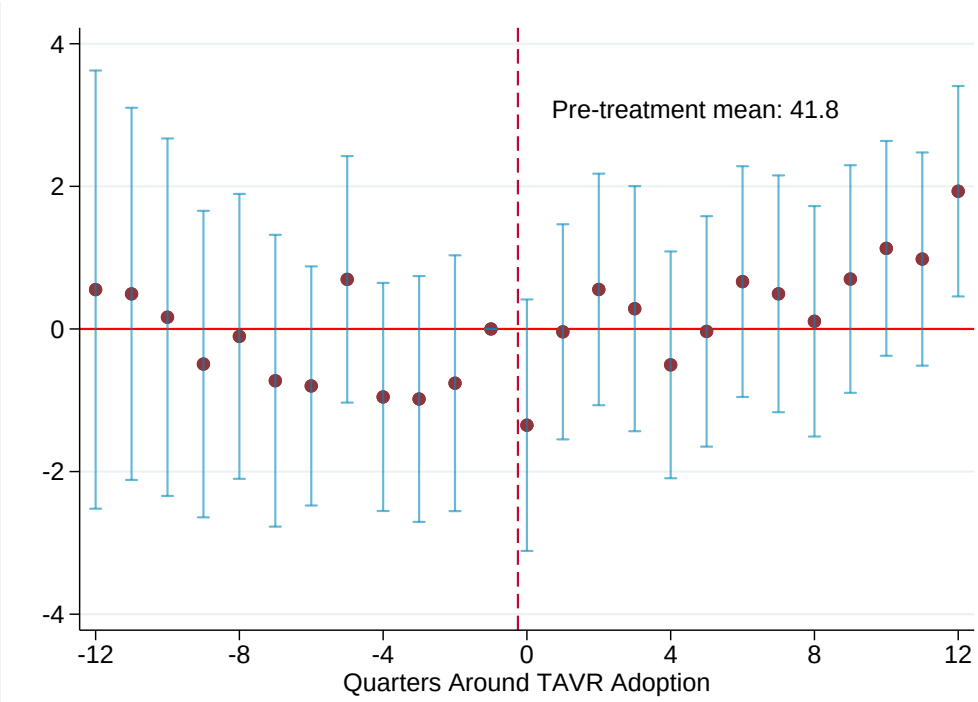
Notes: Figure shows estimated impact of TAVR adoption on the total volume of surgical interventions performed by IVCs. Panel (a) shows the effect on all SAVR/TAVR surgeries, and panel (b) shows the effect on PCI procedures. Markets with fewer than 10 inpatient surgeries per quarter are dropped from estimation, and standard errors are clustered at the commuting zone level.

Figure A.8. Effect of TAVR Adoption on Screening for Surgical Viability



Note: Figure shows effect of TAVR adoption at the CZ level on the fraction of IVCs performing Computed Tomography Angiography (CTA) screening to diagnose aortic stenosis and discuss valve replacement surgeries (CPT code 71275). Regressions are estimated as in Equation 21, with standard errors clustered at the CZ level.

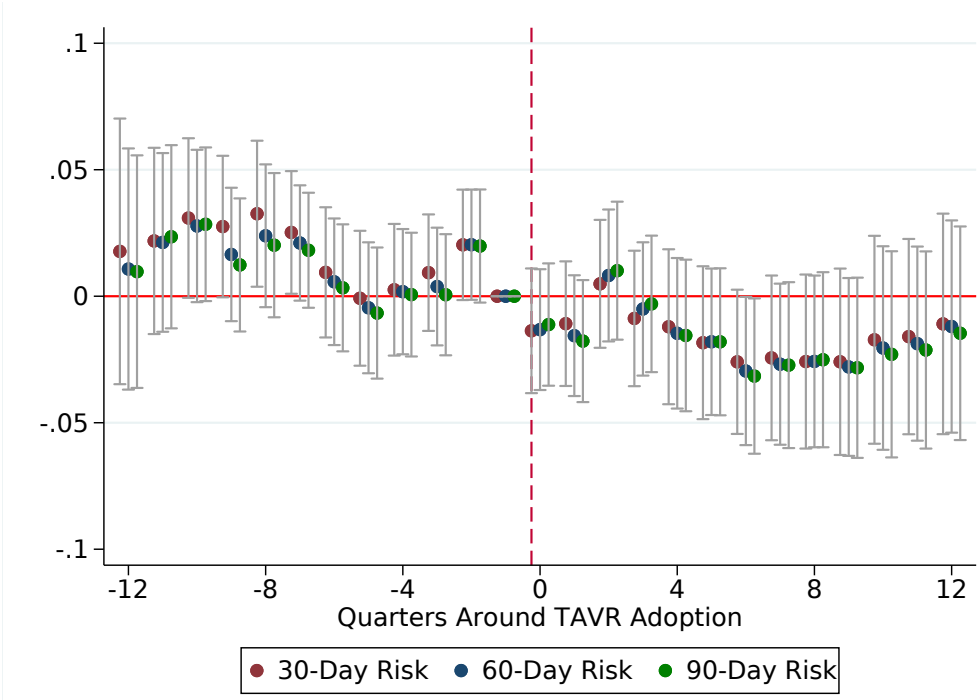
Figure A.9. Effects of TAVR Adoption on Acute Angiography for Heart Attack (NSTEMI) Patients



Note: Figure shows estimated treatment effects of TAVR's adoption using a stacked DD regression design 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 10 NSTEMI patients per quarter are dropped from estimation.

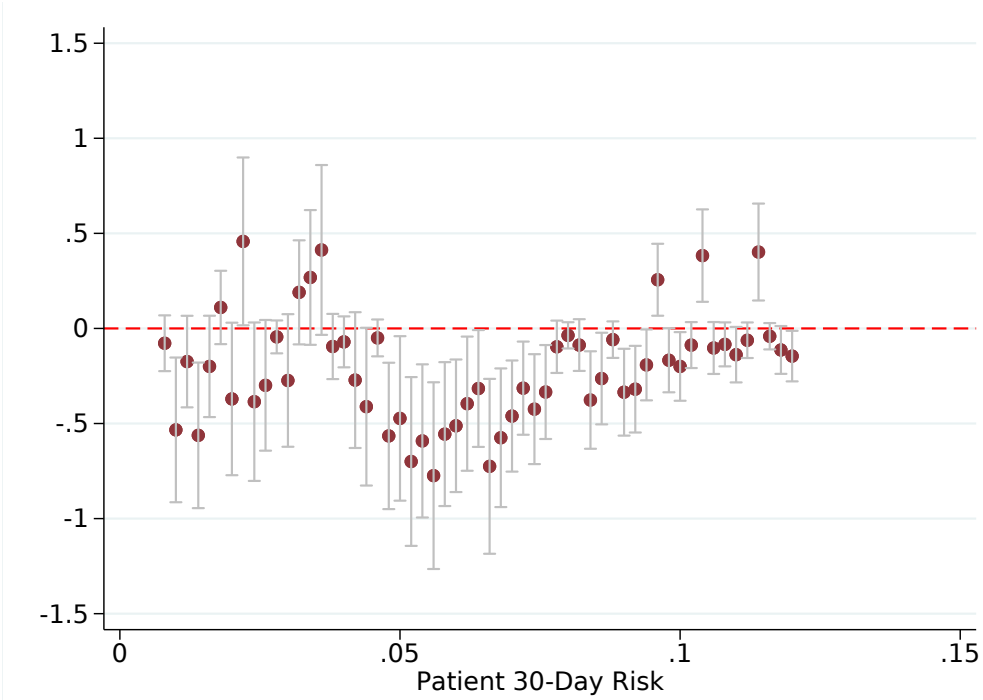
Figure A.9 considers the case of urgently required PCIs, using the case of Non-ST-Elevation Myocardial Infarctions (NSTEMIs). These are less severe heart attacks that typically require angioplasty to reduce patient risk of future, more serious, heart attacks or strokes. The American and European Society 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.10. Effect of TAVR Adoption on Average Risk of PCI Patients



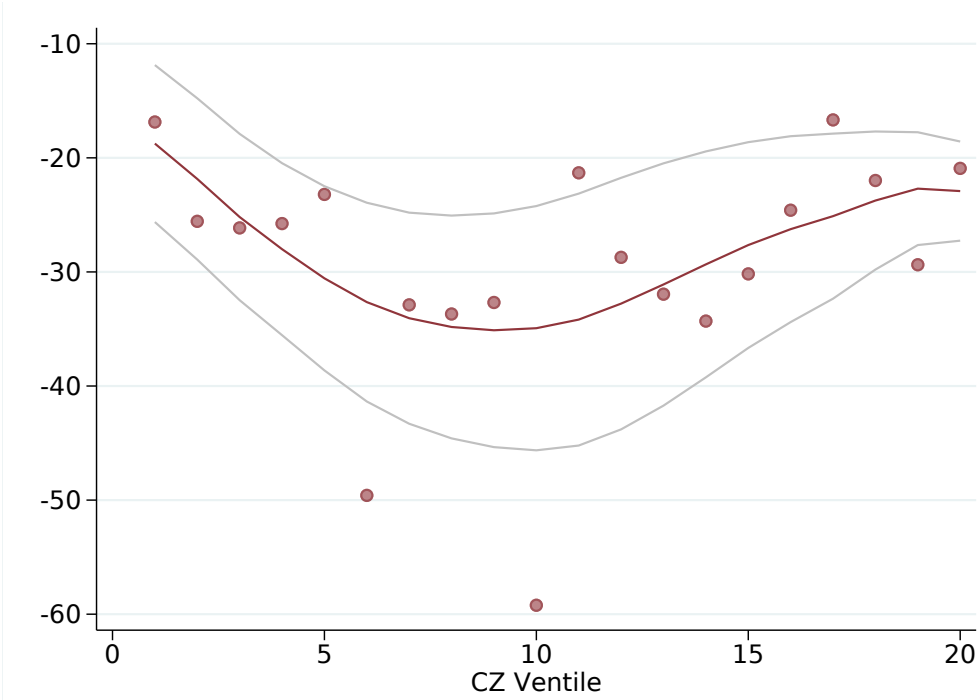
Note: Figure shows effect of TAVR adoption at the CZ level on estimated mortality risk (STS-PROM) for patients receiving low-intensity treatments (PCI). Figure shows results for 30-, 60-, and 90-day predicted risk. Regressions are estimated as in Equation 21, with standard errors clustered at the CZ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

Figure A.11. Heterogeneous Effects of TAVR Adoption on Surgical 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.

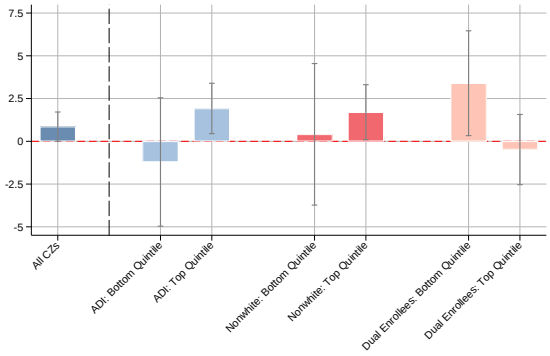
Figure A.12. Potential Inequitable Effects of TAVR Adoption on Surgical Volumes: Dual-Medicaid Eligibility



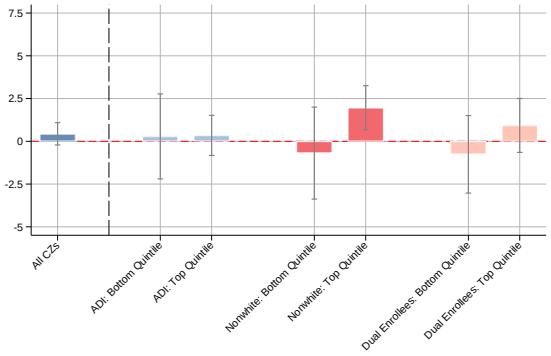
Note: Figure show heterogeneous effects of TAVR adoption on total volumes of valve replacements in a commuting zone. CZs are binned by ventiles according to the fraction of patients in a market who are dually-eligible for Medicaid. Each point represents a difference-in-differences coefficient; effects are smoothed nonparametrically using local linear regression weighted by patient volume. 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. Compare with Figure 5.

Figure A.13. Incidence of Cardiac Events Prior to or Following PCI Surgery

(a) Hospitalization Preceding PCI



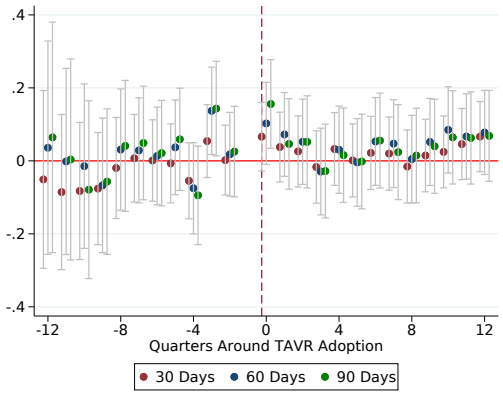
(b) Hospitalization Following PCI



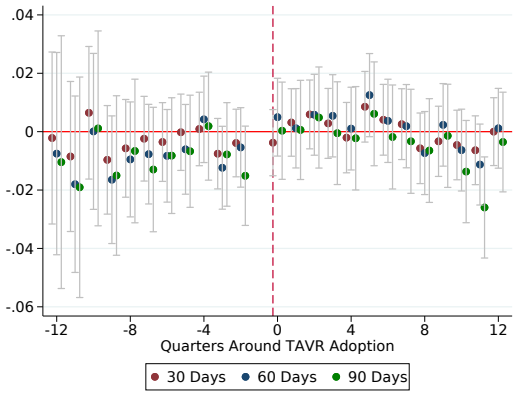
Notes: Figure shows difference-in-differences coefficients estimating the effect of local TAVR adoption on the percentage of PCI patients who either (a) had their surgery precipitated by a hospitalization (less than a year prior to surgery) or (b) experienced a cardiac event within a year following their surgery. 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.

Figure A.14. Effect of TAVR Adoption on PCI Surgical Outcomes

(a) Readmission



(b) Mortality



Note: Figures show effect of TAVR adoption at the CZ level on readmissions (panel A) and mortality (panel B) following PCI procedures. Regressions are estimated as in Equation 21, with standard errors clustered at the CZ level.