Innovations and Inequities in Access to Medical Services*

Alex Hoagland†

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Abstract

Improving the return on health spending requires balancing tradeoffs between promoting novel treatments and ensuring equitable access to care. In addition to being costly, medical innovations may reduce availability of older services, an understudied source of inequity. I propose a framework to study this tradeoff, where innovations reduce other treatments' availability due to patient selection and reduced returns from specialization. Innovations lead some patients to lose access to care altogether, particularly those from high-risk groups. I apply the model to minimally-invasive valve replacement surgeries in the U.S., showing that innovation reduced local surgical volumes, particularly for patients of marginalized groups.

Keywords: Innovation Diffusion, Health Inequities

JEL codes: I12, I14, O30, D63

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†University of Toronto, Institute of Health Policy, Management, and Evaluation, 155 College St, Toronto, Ontario, Canada, M5T 3M6. Email: alexander.hoagland@utoronto.ca. Website: alex-hoagland.github.io.

1 Introduction

Improving the quality of medical treatments has immense economic and social value, through both economic returns from improved health states and insurance value from reduced population risk (Murphy and Topel, 2006; Lakdawalla et al., 2017). Funding, 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—may not be accessible to lower-income individuals during the early years following adoption, generating well-documented financial barriers to accessing care (Arcaya and Figueroa, 2017). In addition, medical innovation may place stricter limits on which patients can receive other interventions that physicians now provide less frequently. These scarcity-driven inequities are less well-understood and may be driven by a confluence of two mechanisms. First, physicians are capacity constrained in the services they can perform, so adopting innovative treatments mechanically reduces their availability for performing other procedures. Second, if physicians benefit from returns to specialization, this reduced availability may be compounded by a loss of skill, leading physicians to reduce their volume of older techniques by more than the take-up of the new treatment. The result is that patients may be crowded-out of access to specialist interventions altogether.[1] Achieving equitable expansion of health innovations requires a careful understanding of these tradeoffs.

I present a model of physician decision-making to characterize these effects. Physicians select one of three treatments for their patients: two surgical interventions (a high-intensity and a low-intensity procedure), and standard maintenance care. The model incorporates technological spillovers in the style of Chandra and Staiger (2007), meaning returns to a treatment increase with the relative volume of that procedure (e.g., physician learning-by-doing). The model allows me to consider how physician decision-making responds to innovations which increase the average return of the high-intensity procedure along two margins. First, innovation results in increased take-up of the high-intensity treatment among intermediate-risk patients, leading to a mechanical decrease in the relative use of other interventions. Second, and more surprising, this expansion generates a flow of high-risk patients out of receiving interventions altogether due to reduced returns from intervention. This results in a set of

[1] These inequities may be further exacerbated by incorrect perceptions of patient risk, either on the part of the physician, the patient, or the health system more generally (Arkfeld, 2021).

patients who lose access to surgical interventions entirely because of the innovation.

The model's central insight is that this crowd-out for high-risk patients may be in- equitably borne across a patient distribution. Inequitable crowd-out may arise directly—because patients of different groups are assigned different surgical appropriateness— or indirectly—because risk is imperfectly observed across groups, with some incorrectly assigned higher surgical risk. These inequities may further compound cost-based inequities in accessing novel technologies or even their more cost-effective substitutes.

I empirically test the model predictions using the development and dissemination of transcatheter aortic valve replacement (TAVR) surgeries used to treat aortic stenosis (AS) in elderly patients in the US. These minimally invasive surgeries expanded both the supply and demand of AS treatments: TAVR is appropriate even for patients who were previously deemed too high-risk for surgery and can be performed by interventional cardiologists (IVCs) instead of cardiothoracic surgeons alone. Hence, TAVR's dissemination disrupted local IVC markets.

I estimate how TAVR adoption in local markets led interventional cardiologists to change their provision of other surgical interventions, focusing on other percutaneous coronary interventions (PCIs) such as angioplasties. Adopting IVCs quickly specialized in TAVR, dedicating up to 20% of their time to the procedure within three years and expanding the scope of screening patients for surgeries. This resulted in older, higher-risk patients receiving valve replacement surgeries. However, I observe a corresponding *decrease* in total surgical volume, caused by a larger reduction in the number of PCIs performed locally than the increase in valve replacements. The observed results validate the predictions of my model: the observed crowd-out is concentrated among higher-risk patients on the margin of receiving care at all. Finally, I show that this shift was inequitably borne by areas with higher levels of health deprivation, including local markets with a greater representation of nonwhite patients.

The model presented in this paper is the first to provide a framework for considering the equity impacts of health innovations and contributes to both the literature on health innovations and health disparities. Recent work has suggested that changes in the allocation of high-value medical services may reduce racial disparities in care, particularly when those reallocations reduce geographic variation in the provision of services (Chandra et al., 2020). The theoretical framework presented in this paper highlights that while innovations may reduce disparities in the populations directly affected by the innovation, other disruptions in the supply of services also need to be considered.

Health disparities have been increasing 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 novel technologies may still exacerbate inequities

even when cost-based inequities are eliminated. The paper also underscores that inequities may spill over into access for other specialty services (Arcaya and Figueroa, 2017). In that regard, my work is related to the spillover effects of health services (Fadlon and Nielsen, 2019; Hoagland, 2022).

I describe my setting and data in Section 2 before presenting my model in Section 3. The model suggests several empirically testable implications; I outline the empirical methods used for these tests in Section 4 and the results of these analyses in Section 5 before concluding in Section 6.

2 Setting and Data

2.1 The Adoption of TAVR

TAVR is a minimally-invasive alternative to surgical aortic valve replacement (SAVR), involving the transfemoral placement of either a balloon-expandable valve or a self-expanding valve instead of an open surgical approach. Numerous randomized trials of TAVR have indicated that the procedure is noninferior among patients at intermediate or high risk for mortality from typical surgery (Smith et al., 2011; Adams et al., 2014; Leon et al., 2016) and even among low-risk patients (Mack et al., 2019; Popma et al., 2019). Hence, the first TAVR device (Edwards-SAPIEN) received approval from the United States' Food and Drug Administration's Center for Devices and Radiological Health for patients with severe surgical risk in November 2011 (Dvir et al., 2012)); the procedure's use has been expanded over time to a wider pool of patient risk levels as comparison trials continued to show its noninferiority (Nishimura et al., 2014; Falk et al., 2017). As of 2017, more surgical interventions are performed percutaneously than using the traditional open methods (D'Agostino et al., 2018).

The adoption of TAVR is an ideal setting to study the tradeoffs between innovations and inequities for two reasons. First, this innovation was market-expanding: the median number of surgical interventions treating advanced AS in the U.S. increased by roughly 1/3 following the adoption of TAVR, with the number of providers supplying these interventions nearly doubling.[2] This increase in the total addressable market provided strong incentives for physicians to change practice styles, similar to the rapid expansion of PCIs as an alternative to coronary artery bypass graft (CABG) surgery (Cutler and Huckman, 2003).

Second, TAVR disrupted the supply of surgeries: whereas SAVR could be performed only by cardiothoracic surgeons, TAVR procedures are performed by a team of surgeons

[2]See Appendix Table A.1 and Figure A.2 for details on TAVR's expansion.

and IVCs (Adams et al., 2014). Importantly, these two types of cardiac specialists receive differentiated training. Importantly, these two types of specialists receive differentiated training. Specifically, as noted by Huckman and Stern (2022), after completing residency, IVCs complete three additional years of cardiology fellowship and an additional year of an interventional cardiologist-specific fellowship; meanwhile, cardiac surgeons complete six to seven years of cardiothoracic surgery fellowships. These unique training paths allow surgeons to hyper-specialize in different approaches (e.g., open or percutaneous surgical methods) at the expense of losing other skills.

2.2 Data

I assess the impact of TAVR adoption on treatment decisions for traditional Medicare patients seeking cardiology care using Medicare fee-for-service (FFS) claims data from 2010 to 2017.[3] I observe 100% of cardiology inpatient procedures performed on Medicare patients and important information about patient risk and demographics. I also observe surgeon information, including specialization. By 2017—when TAVR surpassed SAVR as the most popular intervention—IVCs were involved in over 1/5 of these procedures.3 My main sample includes 9,858,536 Medicare patients with AS, including those who ultimately received intervention and those who did not.

Appendix Table A.2 presents relevant summary information for my sample. I observe demographic information, including a proxy for income by zip codes. I also construct relevant clinical information, including estimated surgical risk (see Section 4.1), surgical histories, and other patient risk factors using the methodology of Ellis et al. (2022).

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 (e.g., PCIs, $s = 1$), and high-intensity surgical interventions (e.g., valve replacement, $s = 2$).

The patient-specific appropriateness of each procedure depends on a patient risk index θ_{is} for patient i. When observed perfectly, θ_{is} captures both diagnostic severity and the relative risk of each intervention—hence, individuals with lower θ_{is} are more likely to receive intensive treatments. In practice, θ_{is} is not observable; instead, physicians and patients proxy this risk based on a set of observable characteristics Z_{is}; I discuss this in Section 4.3.

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

The expected utility of each procedure for a patient with characteristics $\{Z_{is}\}_s$ 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 style of Chandra and Staiger (2007), captured in the second term; that is, if $\alpha_s > 0$, increased investment in a procedure improves its average outcome 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 the statement that the magnitude of the marginal utility of treatment with respect to risk is greater for more intensive interventions.[4] Patients hence make choices only along one of two margins: a choice between valve replacement and valve support surgeries, or a choice between PCIs and maintenance care. I therefore represent surgical risk as a single measure across treatments, θ_i.

A patient thus chooses the most 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:

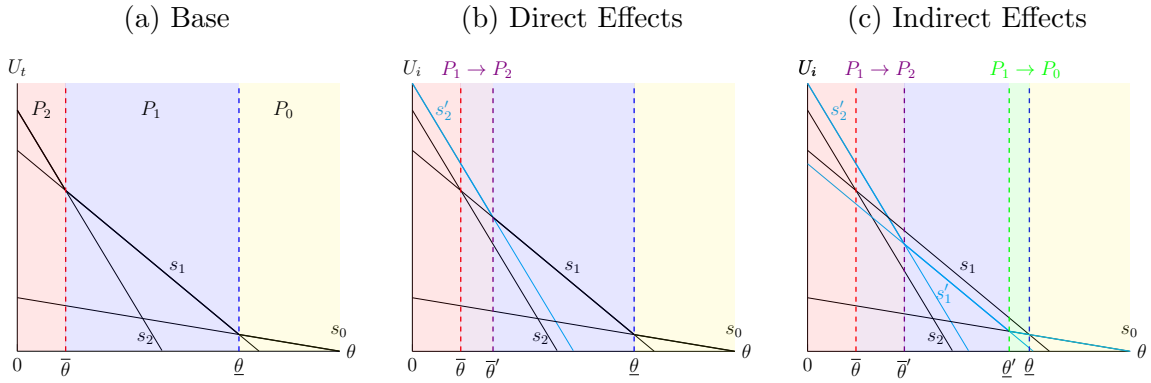
$$P_1 = \int_Z \Pr\{\beta_{10} Z + \alpha_{10} P_1 + \alpha_0 P_2 - \alpha_0 > \varepsilon_{10}\} f(Z) dZ \tag{4}$$

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

[4] Or $|\partial U_{i2}/\partial \theta_2| > |\partial U_{i1}/\partial \theta_1| > |\partial U_{i0}/\partial \theta_0|$. Note that in the case where θ_{is} perfectly captures patient appropriateness for treatment, this assumption is not a special case.

The equilibrium can be conceptualized in a simple single-crossing framework. Given any initial allocation, differences in expected utility will cause some patients to shift from high-intensity to lower-intensity care. This flow decreases the survival returns from a procedure, amplifying the exit of patients until only the most appropriate ones receive high-intensity interventions. A similar mechanism determines the allocation of low-intensity care for patients whose risk does not justify high-intensity treatments but who still warrant intervention.

Figure 1. Treatment Decisions Based on Patient Risk



Notes: Graphical illustration of the selection of patients into treatment based on risk, and how innovations disrupt this. Panel (a) presents the production possibilities frontier for all levels of θ in the non-innovation case, which defines distinct treatment regions: high-intensity treatments (red, defined as P_2); low-intensity treatments (blue, defined as P_1); and maintenance care (yellow, defined as P_0). Panel (b) presents direct effects of innovations, which change the tradeoff between high- and low-intensity interventions (captured in purple and the change in $\overline{\theta}$ to $\overline{\theta}'$). Panel (c) highlights the indirect effects, where spillover externalities result in a larger share of patients in P_2 and movement from s_1 to s_0 (captured in green and the change in $\underline{\theta}$ to $\underline{\theta}$').

Figure 1, panel (a) illustrates the allocation of patients to treatments given perfectly observed risk. The figure plots patient utility $U_s(\theta)$ for each of the three possible choices of treatment. Each utility is declining in risk; however, by assumption, these declines are faster for more intensive treatments. This creates three well-defined treatment regions, where patients with the lowest risk select the high-intensity intervention s_2, patients with moderate risk select s_1, and the highest risk patients choose maintenance care s_0. These regions are defined by threshold 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

The model allows a direct comparison of how innovations affecting one treatment may modify others' availability. Consider an innovation in valve replacement technology ($s = 2$) reflected in the adoption of TAVR. This innovation can be characterized as a uniform cost reduction

across θ without affecting survival utility, as TAVR is a noninferior risk-reducing procedure. Hence, I model TAVR as an outward shift in the expected utility U_1 by a fixed τ.[5]

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 a greater share of patients, who switch from the low-intensity intervention (shown in purple). However, this flow also generates spillover externalities as physician skills change; this results in further utility increases for s_2 and corresponding decreases in utility of other interventions. Panel (c) introduces these indirect effects as two separate flows out of s_1, some into s_2 and others into s_0 (shown in green) due to lower returns from s_1. These changes continue as discussed above until a new equilibrium is reached, with new risk thresholds $(\overline{\theta}', \underline{\theta}')$.

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

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

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

Based on this system, the comparative statics measuring how risk thresholds change in response to changes in τ are

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

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

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—meaning that 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 in Equation 11 represent the reductions in

[5] In general, τ need not be constant; the results in this section do not depend on this simplifying assumption.

productivity spillovers for both s_0 and s_1 associated with changing risk thresholds, while the right side captures the differences in the marginal utility of each treatment. Hence, crowd out occurs when the relative change in the productivity spillovers between s_1 and s_0 is less than the difference in the magnitude of the marginal utilities between treatments. Given that changes in a treatment's effectiveness simply from provider specialization are estimated to be much smaller than the marginal returns of an effective treatment itself, this condition is likely to be met in many cases (Chandra and Staiger, 2007).[6]

3.2 Exacerbating Inequities

Any loss in efficient access to specialty care may be considered an inequitable distortion in the market. More importantly, however, this loss in access to care may differ substantially across different patient groups, particularly those with different underlying risks and medical need. These inequities may be further compounded when patient risk is not perfectly observed.

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 after its adoption. C is defined by the region of the true risk distribution $[\underline{\theta}, \underline{\theta}']$. However, suppose that clinicians do not observe θ directly but a proxy $\hat{\theta}$.[7] I assume that $\hat{\theta}$ is a linear combination of observable characteristics Z_{is} which correctly predicts θ except for an idiosyncratic, mean-zero error term ε:

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

Suppose that among the variables contained in Z_{is}, there is a binary variable d_{ig} equal to 1 if patient i is a member of a group g, and 0 otherwise. Hence, d_{ig} encompasses membership to demographic groups (e.g., a low-income indicator) or clinical indicators (e.g., patients with diabetes or smokers).[8] The coefficient γ_d captures a discrete shift in predicted risk based on membership in d. For ease of exposition, I assume throughout this section that d_{ig} is independent to all other, non-group covariates $Z_{is,-g} = Z_{is} \setminus d_{ig}$.

If group membership is informative for risk (e.g., γ_d is nonzero), patients in different groups will have different likelihoods of treatment crowd-out. Given the underlying distribution of θ and $Z_{is}\gamma$, we can identify the fraction of patients in C who belong to g using

[6] Descriptions of conditions under which innovations are market-expanding and more general outcomes are presented in the Appendix.

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

[8] Such indicators routinely inform patient risk calculations (van Ryn and Burke, 2000).

Bayes' rule:

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

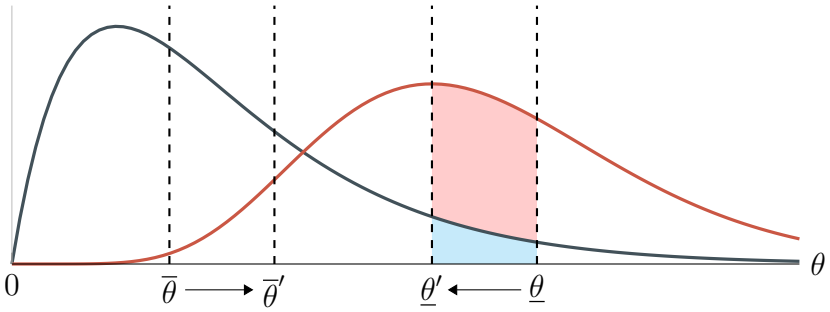
$$= \frac{s_g}{s_C} \left[Pr(Z_{it,-g}\gamma_{-g} + \gamma_g \in [\underline{\theta}, \underline{\theta}']] \right] \tag{14}$$

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

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

Here, s_g indicates the relative size of group g in the population, and $s_C = F(\underline{\theta}) - F(\underline{\theta}')$ is the relative size of C. In general, these two are not equal, meaning that C may over- or under-include members of g relative to the population. Although this difference arises from true (average) differences in patient risk, systematic differences in who accesses care may still have important differential long-term effects.

Figure 2. Inequities in Crowdout



Notes: Graph shows potential inequities associated with patients crowded out of 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) for each distribution.

Figure 2 presents the intuition of this result. The graph highlights the crowd-out region associated with an innovation, as well as the risk distributions for patients of two different 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 not correctly measured. Imperfect proxying may be the result of providers who incorrectly gauge risk across groups, but may also be the result of other factors such as patient beliefs or biased health system measurements.[9] However it arises, measurement error distorts the likelihood that members of g are represented

[9] E.g., risk scores; see Obermeyer et al. (2019).

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" $\hat{\gamma}_g$, defined as

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

where ν is an idiosyncratic error in group risk measurement.[10] I define the inequity resulting from the presence of ν as the change in the representation of members of group g in C, relative to the initial representation $s_{C,g}$ (Equation 16). That is, the increased likelihood for a member of g being represented in C is

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

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

Importantly, notice that

$$\frac{\partial I}{\partial \nu} = \frac{1}{s_{C,g}} \left[f_{X_{-g}\gamma_{-g}}(\underline{\theta} - \gamma_d - \nu) - f_{X_{-g}\gamma_{-g}}(\underline{\theta}' - \gamma_d - \nu) \right]. \tag{20}$$

That is, ν affects the relative crowd-out of members of group g in proportion to the initial composition of g in C and the relative comparison points used in assessing the risk of non-members. Appendix Figure A.1 presents the intuition behind these inequities. Intuitively, measurement error results in patients of a specific group being misplaced along a risk distribution. For example, if surgical risk is systematically over-estimated for members of g, then members of g may be more likely to be in the crowd-out region of an innovation. This ultimately results in an over-representation of group members among those who lose access to specialty interventions after an innovation.

3.3 Empirical Implications

The model predicts that innovations may exacerbate health inequities through two steps. First, technological spillovers from interventions may create "crowd-out regions" that shift high-risk patients out of care altogether. Second, these affected patients may be systematically different from the overall population, an inequity which is exacerbated if risk is incorrectly proxied.

[10] Note ν does not represent classical measurement error, nor is it necessarily centered around 0. In the simplest model, ν is common across provider-patient assessments; however, the model could easily generalize ν to either vary across providers or patients, as appropriate for the context.

Three empirical implications arise from this model. First, I can test for the direct and indirect effects of innovation by assessing how adopting physicians substitute patients along both intensive and extensive margins. Given sufficient data on patient risk, I can also test which patients are affected along each margin and identify the existence and magnitude of crowd-out regions generated by TAVR. In addition to crowd-out heterogeneity across risk, I can empirically test the prediction that crowded-out patients will be (potentially inequitably) distributed across members of different groups. This differential access to specialized medical interventions may be informed both by true and perceived differences in risk across groups; however, given the long-term effects of inequities in accessing care, even identifying aggregate differences sheds important light on potential equity tradeoffs associated with innovation. Finally, I use the identified model parameters—including treatment risk thresholds and the distribution of patient demographics—to present suggestive evidence on imperfect risk proxying across patient groups.

4 Methods

To test these implications, I assess the effects of TAVR's adoption on access to cardiac medicine within a local market. The model abstracts away from many features complicating physician decision-making; however, I can test its basic insights on physician substitution of techniques across patients based on their observed risk.

I assess the role of TAVR's adoption on utilization of PCIs, such as angioplasties and valvuloplasties.[11] Due to the high comorbidity of CAD with AS, revascularization surgeries were frequently performed when a patient's risk made them unfit to receive a valve replacement through SAVR. Hence, TAVR's adoption may affect both margins of treatment for patients seeking PCIs from interventional cardiologists.[12]

4.1 Estimating Patient Risk

A patient's risk for cardiac surgery is typically based on risk models constructed by The Society of Thoracic Surgeons (STS), which account for pre-operative factors that may influence surgical outcomes and predict risks for surgical mortality, stroke, infection, and length of stay, among others (O'Brien et al., 2009).

I model patient risk θ using the STS Predicted Risk of Mortality model (STS-PROM).

[11] See Appendix Table A.3 for the procedure and diagnosis codes used to identify relevant services.

[12] There is new evidence that PCIs can be performed together with TAVR (Bajaj et al., 2017; Søndergaard et al., 2019); although this comes after my sample, it should be considered in future assessments of this tradeoff.

This predicts the likelihood of 30-day surgical mortality following a cardiac surgery using logistic regression and covariates spanning demographics, health conditions, and time trends (see Appendix Table A.4 for the full specification). The STS-PROM model is generally used to classify patients into one of three risk categories: low risk (score $\leq 3\%$), moderate risk (score between 3% and 8%), and high risk (score $\geq 8\%$). Open surgical interventions are generally limited to low-risk patients, while PCI interventions have slightly more risk tolerance.[13]

The empirical distribution of predicted risk closely matches the predictions of the population STS-PROM model (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 IVC treatment decisions, I use a "stacked" regression design to avoid bias from naive staggered adoption designs with heterogeneous treatment effects (Goodman-Bacon et al., 2019; de Chaisemartin and D'Haultfoeuille, 2019).[14] I identify adoption-quarter cohorts $r \in \{1, ..., N^1\}$ and stack them into a single estimation with cohort-specific time and group fixed effects (Cengiz et al., 2019):

$$\Pr(\text{Treatment}_{is,r}) = \alpha_{s,r} + \tau_{t,r} + \sum_{k=-T}^{T} \gamma_k \mathbb{1}\{t - E_{ist,r} = k\} + \epsilon_{ist,r}. \tag{21}$$

The outcomes of interest are treatment decisions for patients (i) seen at time t (measured in quarters) by surgeons (s) who first adopted TAVR in cohort r. I cluster standard errors at the local health market level and weight markets based on average total surgical volume.[15]

In addition to market-level responses, the model's predictions require estimating potentially heterogeneous treatment effects across patient risk levels, as TAVR's adoption may change treatment decisions for patients at both margins of receiving PCIs. I therefore estimate potentially heterogeneous treatment effects across patient risk. I use two estimators proposed by Xie et al. (2012), which allow treatment effects to be correlated with individuals' treatment probabilities (in this case, surgical risk). These include a parametric estimator as-

[13] There is recent evidence questioning the STS-PROM model as the basis for physician decision-making (Catalano et al., 2020; Khan et al., 2019); however, given that this is still the model most commonly used by practitioners to approximate θ, I incorporate it here.

[14] My results are robust across other novel specifications, as illustrated in the Appendix (Callaway and Sant'Anna, 2018; Sant'Anna and Zhao, 2020).

[15] The local market is defined as the commuting zone using relevant U.S. Census data.

sessing treatment effects across bins of patient risk, and a nonparametric matching estimator which estimates treatment effects as a function of propensity scores (risk).

4.3 Inequities in Post-Innovation Access

Finally, I identify how crowd-out inequitably differentially affects disadvantaged markets. I assess inequities across three dimensions: the racial makeup of a commuting zone (measured as the fraction of cardiac patients identifying as non-white), a commuting zone's Area Deprivation Index (ADI) score (averaged over the 9-digit zip codes making up the commuting zone), and a region's socioeconomic status (proxied by the fraction of cardiac patients who are dually-eligible for Medicaid). ADI scores rank regions by socioeconomic disadvantage based on factors such as income, education, employment, and housing quality (Kind and Buckingham, 2018). For each measure, I estimate heterogeneous treatment effects of TAVR's adoption across ventiles of commuting zones; this allows me to assess how areas that are more disadvantaged are differentially affected by TAVR's adoption.

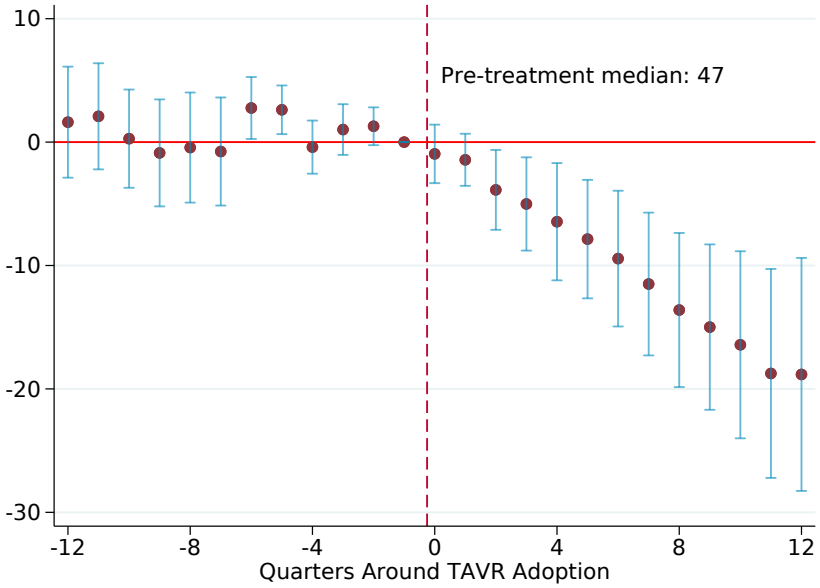
If patient risk is perfectly perceived, the share of crowded-out low-income patients is proportional to the predicted effect of being low-income on patient risk in the STS-PROM model. Hence, I provide suggestive evidence of systematic risk misevaluation by comparing the size of this share empirically observed in the data to its predicted size based only on STS-PROM regression coefficients (the parameter ν in Equation 19). Patient income significantly predicts surgical risk in the STS-PROM model: low-income patients have an expected increase in risk of approximately 0.4% (11% of average risk).

5 Results

TAVR's adoption expanded surgeries to older, higher-risk patients. I observe the average likelihood of high-intensity heart surgery double within the first three years of adoption, from a baseline of 0.03% to 0.06% (Appendix Figure A.4). Following adoption, surgical patients are estimated to be 4 years older and roughly 0.2% riskier (up 0.0044 percentage points from a baseline of 2.2%; see Appendix Figure A.5).

Figure 3 presents the dynamic effects of adopting TAVR on a commuting zone's procedure volume among IVCs. The figure shows a marked decline in overall procedure volume, including both valve replacement surgeries and percutaneous procedures: the median commuting zone performs almost 50 procedures per quarter before adoption, but within three years of adoption, volume drops by an average of 40%. Overall reductions are the result of a larger drop in PCI provision than TAVR takeup, leaving fewer patients receiving surgical

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



Notes: Figure shows estimated impact of TAVR adoption on the total volume of surgical interventions performed by IVCs, including all SAVR, TAVR, and PCI procedures. Interventional cardiologists who perform fewer than 10 inpatient surgeries per quarter are dropped from estimation, and standard errors are clustered at the commuting zone level.

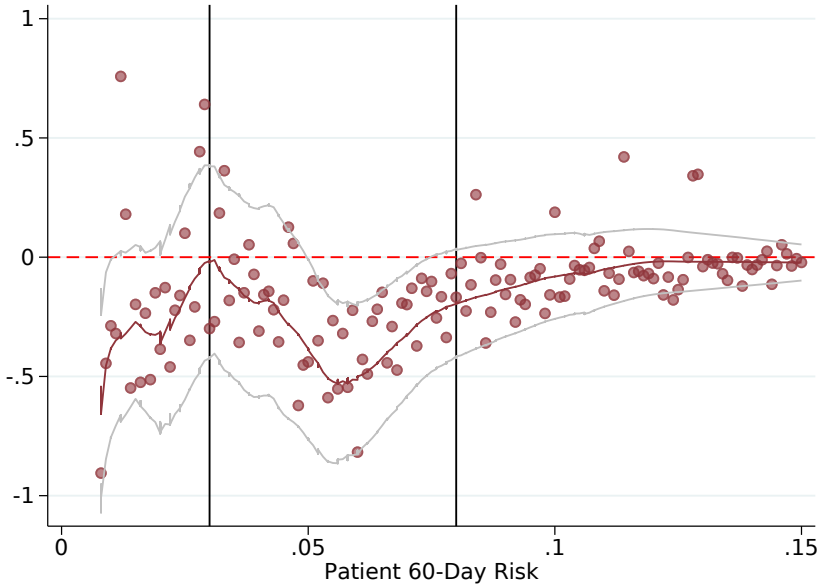
treatments overall (Appendix Figure A.6).[16]

These findings corroborate the model's predictions that patients will be crowded out from access to any surgical care. In addition, I find evidence that this crowd-out is concentrated among patients whose surgical risk leaves them a marginal candidate for low-intensity surgery (PCI). While TAVR increased the conditional risk of patients receiving valve replacement surgery, there is not a corresponding decrease in the conditional risk of PCI patients, suggesting that the composition of PCI patients changed along both risk margins (Appendix Figure A.7). To assess this, I estimate how TAVR's adoption may have differentially affected the number of surgical procedures performed in a market across risk thresholds.

Figure 4 shows the results across the distribution of 60-day patient risk. I bin patients based on their estimated surgical risk, and estimate the effect of TAVR's adoption on IVC surgical volumes at the market level within each bin. The figure reports estimated treatment effects, as well as the smoothed results using a local linear regression weighted by the total number of patients in each bin. This exercise therefore highlights which patients experience the largest reductions in access to surgery based on their predicted risk.

[16] Appendix Figure A.9 shows that in markets adopting TAVR, the fraction of IVCs screening patients for aortic stenosis (and subsequently, appropriateness for valve replacement surgery) increases by roughly 1/3 (one percentage point). This is in line with recent findings (Mullainathan and Obermeyer, 2021).

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



Notes: Figure shows estimated heterogeneous treatment effects of TAVR's adoption on total surgical volume for patients in different risk bins. Risk is measured according to the STS-PROM model (60-day mortality), with bins of 0.2 percentage points created. Within each bin, Equation 21 is estimated, capturing the effect of TAVR adoption on total surgical volume in each bin (including TAVR, SAVR, and PCI). Estimated effects are smoothed nonparametrically using a local linear regression, weighted by the total number of patients in each risk bin. Interventional cardiologists who perform fewer than 10 inpatient surgeries per quarter are dropped from estimation. Vertical lines indicate STS-PROM delineation between low-risk patients (3%) and high-risk patients (8%).

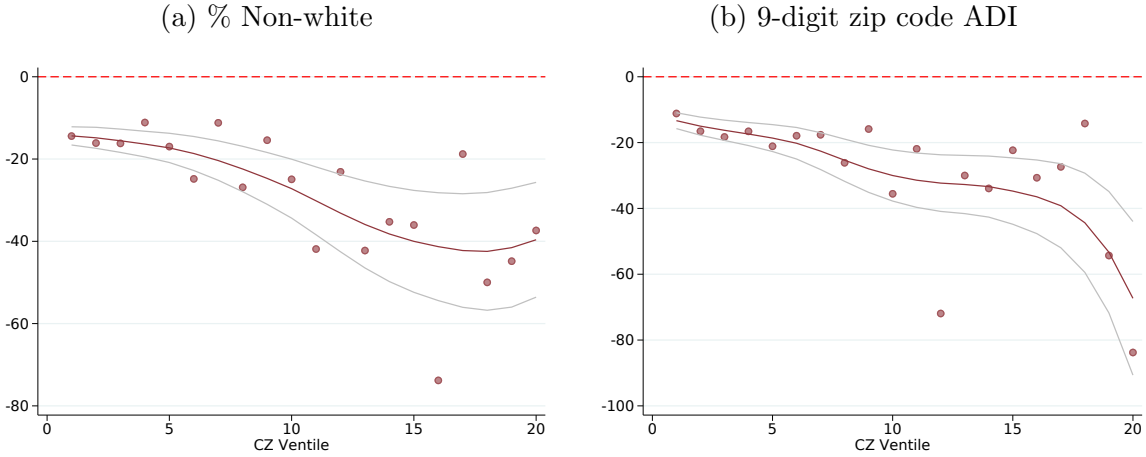
As predicted by the model, TAVR's adoption led to the largest reductions in surgical volumes for patients on the margin between medium- and high-risk (in the model, patients who were marginally induced into either low-intensity treatments or no treatment at all). Specifically, I observe that patients whose risk is between 5% and 8% experience the largest declines in access to care; among this group, commuting zones adopting TAVR perform about 0.5 surgeries fewer *per patient* in each bin. These results suggest that TAVR induced low-risk patients to switch into surgery and higher-risk patients to switch out of specialty care altogether.

5.1 Inequities in Access to Surgical Care

My results indicate that TAVR's adoption resulted in lower access to cardiac surgeries for higher-risk patients. As predicted by the model, these effects may differentially affect patients of different groups, to the extent that groups exhibit heterogeneity in surgical risk assignment. I therefore examine how TAVR's adoption differentially impacted markets in ways that may

generate health inequities.

Figure 5. Heterogneous Effects of TAVR's Adoption on Local Surgical Access



Notes: Figures show heterogeneous effects of TAVR adoption on access to surgical care (total surgical volume) by a commuting zone's racial makeup and area disadvantage index (ADI). CZs are binned by ventiles according to disadvantage, measured in panel (a) as the fraction of nonwhite patients, and in panel (b) as the average ADI at the patient 9-digit zip code level. Within each bin, Equation 21 is estimated, capturing the effect of TAVR adoption on total surgical volume, including TAVR, SAVR, and PCI. Estimated effects are smoothed nonparametrically using a local linear regression. CZs with fewer than 10 inpatient surgeries per quarter are dropped from estimation.

Figure 5 presents the results. In each panel, I sort commuting zones into ventiles based on a commonly used measure 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 as that experienced by 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).[17] These results provide strong evidence that the local adoption of a highly innovative technique may generate inequitable loss in access to other services by the most vulnerable patient groups.[18]

Finally, I explore the hypothesis that surgical crowd-out is exacerbated by limited productivity spillovers, reducing the returns to low-intensity procedures such as PCIs. To do

[17] I also perform this exercise stratifying markets on dual eligibility, and find little evidence of inequities borne by dually-eligible Medicare patients.

[18] The estimates shown in Figure 5 aggregate differences in true underlying risk and compounding inequities from incorrect risk assignment. As a simple, back-of-the-envelope calculation, consider that the change in the risk threshold for PCI interventions went from a baseline of 8% to about 6% (Figure 4). Nonwhite patients would have to be twice as likely to be in this risk band to generate Figure 5; however, in the data, nonwhite and white patients are equally likely to be in this crowd-out region. This suggests that roughly half of the observed inequities arise from "true" risk differences (nonwhite individuals have an increased risk of surgical mortality of 1.1%; see Appendix A.4) and half from misperceptions of patient risk based on race.

this, I assess the effect of TAVR's adoption on risk-adjusted surgical outcomes for PCIs in a market, including both readmission rates and surgical mortality. I find little evidence that TAVR's adoption affected either of these in the long term (Appendix Figure A.8); there is some evidence that the likelihood of readmission increased by about 10% immediately following TAVR's adoption, but this effect is neither estimated precisely nor persistent over time. These results, however, do not adjust for the dynamics explained in Section 3; future work may further highlight whether and how innovation adoption may affect overall surgical quality.

6 Conclusion

I present a theoretical framework to consider the equity implications of expanding access to novel medical technologies. The model highlights a tension between increased access to an innovation and overall access to specialized health services, arising from both surgical capacity constraints and externalities from physician specialization. Increased provider investment in an innovative treatment area may generate a flow of patients out of surgical interventions altogether due to the diminished returns of low-intensity procedures. Importantly, the composition of these patients may differ systematically from the patient population.

The model is useful in assessing how TAVR's adoption changed the market for cardiac surgeries. The innovation expanded valve replacements for lower-risk patients, but overall fewer surgeries were performed, and some high-risk patients were less likely to receive surgery at all. This crowding-out disproportionately affected low-income patients, potentially exacerbating socioeconomic disparities in healthcare access.

This application highlights the value of the theoretical framework in considering the general equilibrium effects of innovation diffusion on equitable access to healthcare. Taken together, both the model and the empirical exercise suggest there is room for considering equity implications and potential downstream effects of an innovation at the time of adoption, particularly by large fee-setting regulators such as CMS.

Future work can build on the tension highlighted in this paper in several directions. New research may generalize the model to include multiple dimensions of patient risk or consider longer-term consequences of losing access to specialty care. These generalizations may lend themselves well to empirical applications which identify health disparities (Mullainathan and Obermeyer, 2021). Additionally, future work may identify the extent to which physician selection into innovation adoption affects long-run market outcomes, including equitable access to health services (Huckman and Stern, 2022). Finally, while this project highlighted socioeconomic and geographic disparities exacerbated by medical innovations, this framework

can be extended to many other inequities and structural forces which worsen health outcomes for marginalized groups. These include more direct examinations of discrimination at the point of care, as well as systematic gaps in seeking out specialty services due to barriers or eroded trust in the healthcare system (Webb Hooper et al., 2019).

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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.

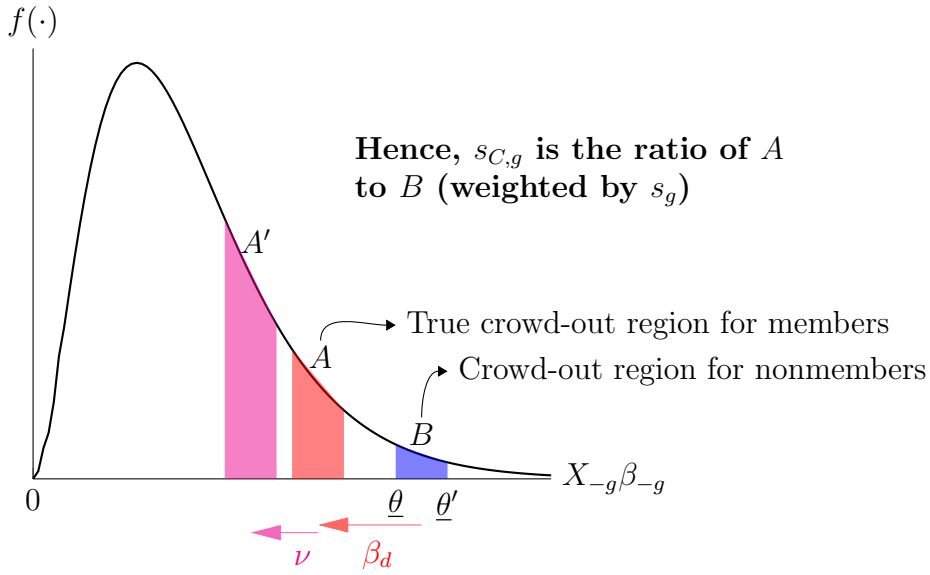
	30-Day Mortality		60-Day Mortality		90-Day Mortality	
	ME	95% CI	ME	95% CI	ME	95% CI
Panel A: Patient Demographics						
Patient age	-0.000	[-0.001,-0.000]	-0.000	[-0.000,-0.000]	0.000	[-0.000,0.000]
Female	0.007	[0.006,0.008]	0.006	[0.004,0.007]	0.004	[0.002,0.006]
Black	0.011	[0.008,0.014]	0.009	[0.006,0.013]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

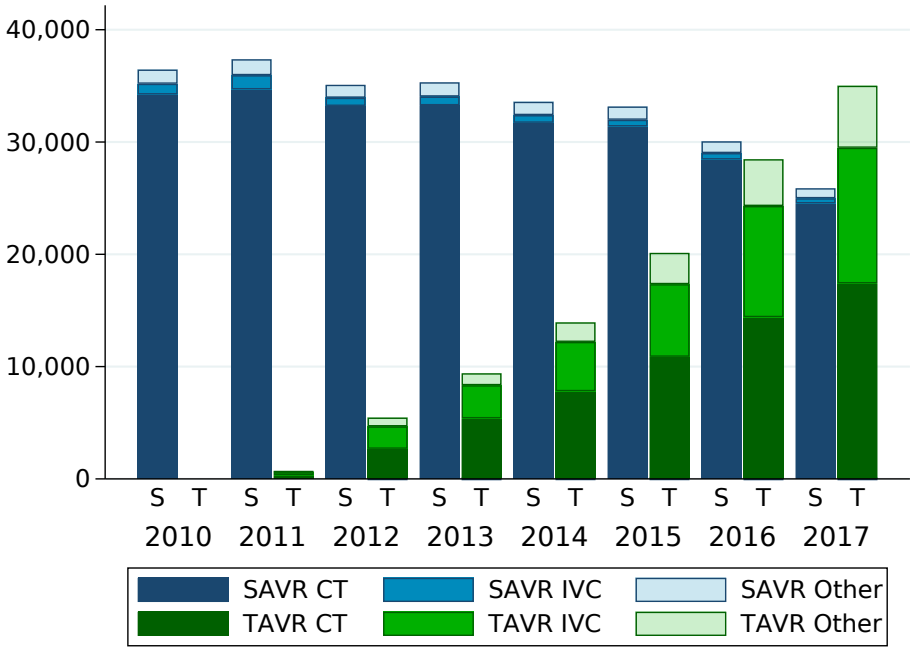
A.2 Figures

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.

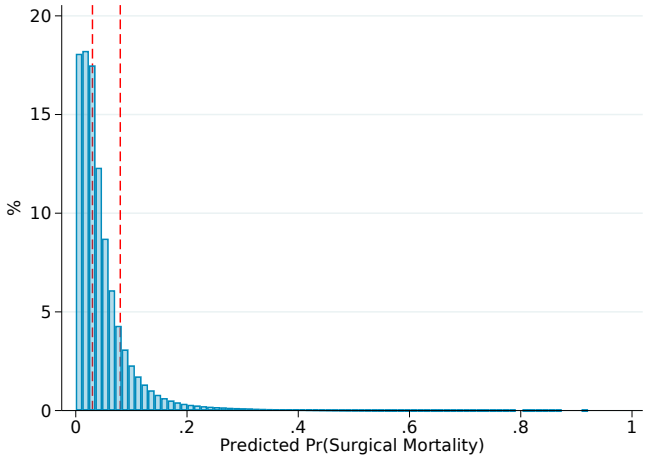
Figure A.2. Timeline of TAVR Adoption



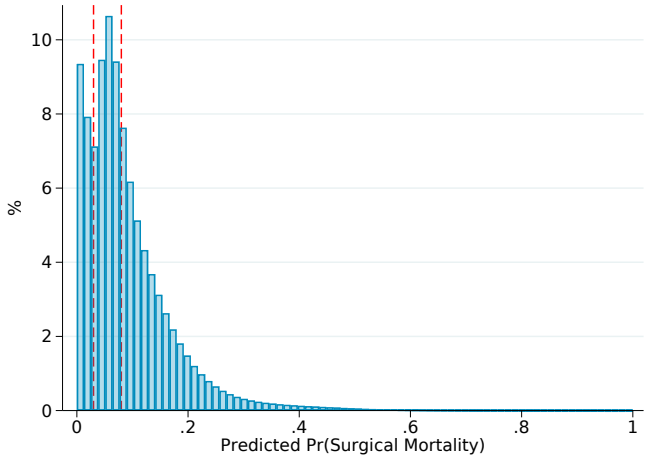
Notes: Figure shows diffusion of TAVR procedures among different cardiac surgeon specialties over time. Total volume of surgical valve replacements (SAVR and TAVR, labelled as "S" and "T" on the x-axis) for the full U.S. Medicare population are shown, with a breakdown of surgeon specialty. Cardiothoracic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

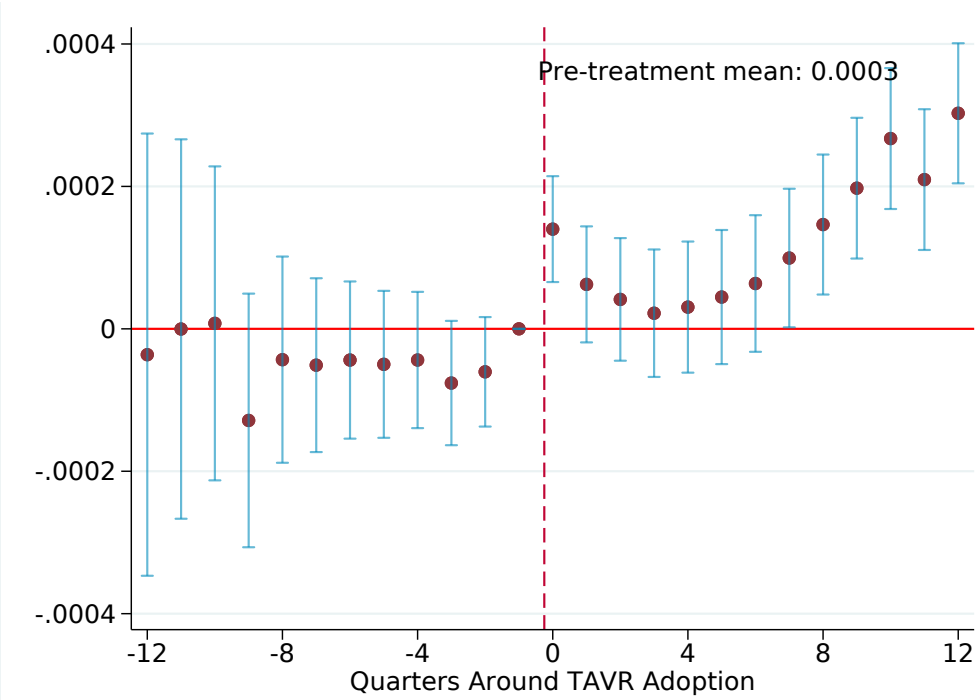


(b) Pr(90-Day Mortality)



Notes: Figure shows predicted surgical risk from TAVR and SAVR, estimated using the STS-PROM model presented in Table A.4.

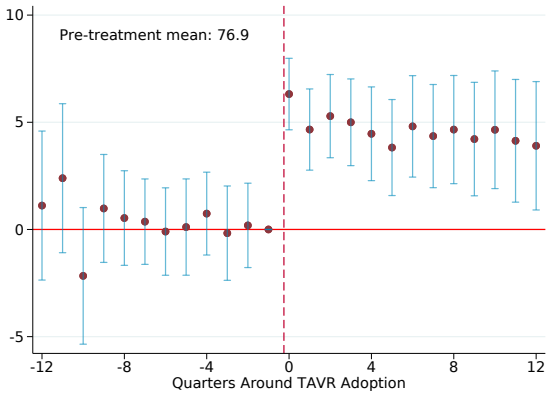
Figure A.4. TAVR Adoption Increases Individual Probability of SAVR/TAVR Surgery



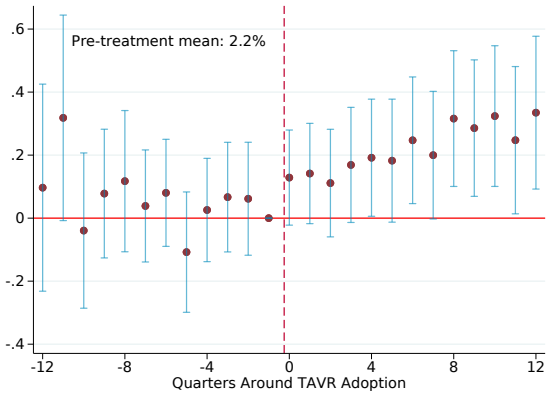
Notes: Figure shows estimated likelihood of an individual patient receiving valve replacement surgery (TAVR or SAVR) following TAVR adoption in their market. Surgical candidates are identified using the diagnostic codes associated with TAVR, SAVR, or PCI procedures in the Medicare data. Standard errors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



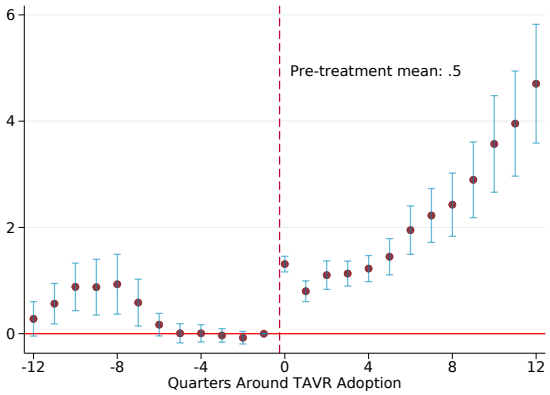
(b) $\sinh^{-1}$(30-Day Patient Risk)



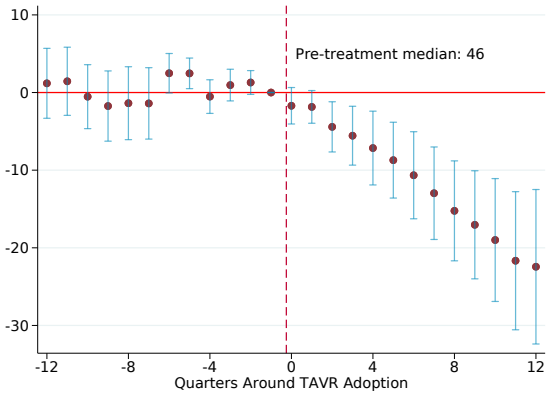
Note: Figures show effect of TAVR adoption at the CZ level on estimated age and risk for patients receiving high-intensity heart surgeries (TAVR and SAVR). Panel (a) shows the effects on patient age, while panel (b) shows effects on the inverse hyperbolic sine of 30-day STS-PROM risk score (hence, coefficients 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. IVC Surgical Volume Responses to TAVR Adoption, Commuting Zone Level

(a) SAVR/TAVR Surgeries

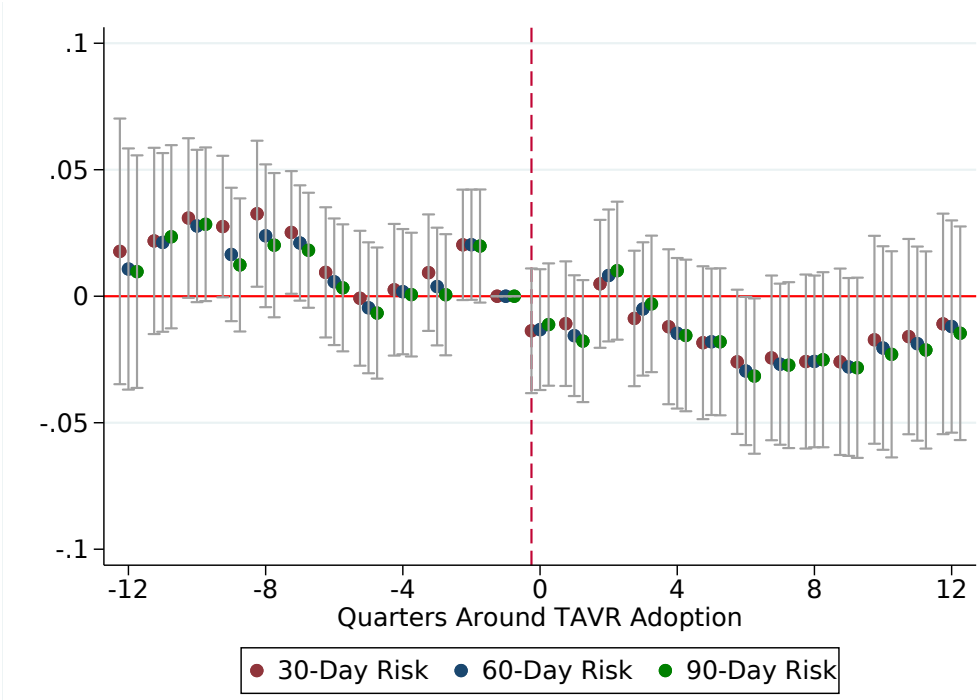


(b) PCIs



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. Interventional cardiologists who perform fewer than 10 inpatient surgeries per quarter are dropped from estimation, and standard errors are clustered at the commuting zone level.

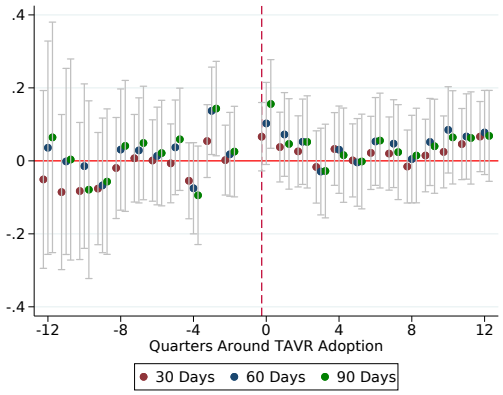
Figure A.7. Effect of TAVR Adoption on Average Risk of PCI Patients



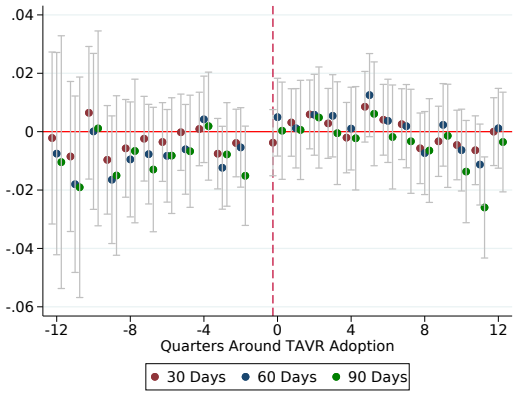
Note: Figure shows effect of TAVR adoption at the CZ level on estimated mortality risk (STS-PROM) for patients receiving low-intensity treatments (PCI). Figure shows results for 30-, 60-, and 90-day predicted risk. Regressions are estimated as in Equation 21, with standard errors clustered at the CZ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

Figure A.8. Effect of TAVR Adoption on PCI Surgical Outcomes

(a) Readmission

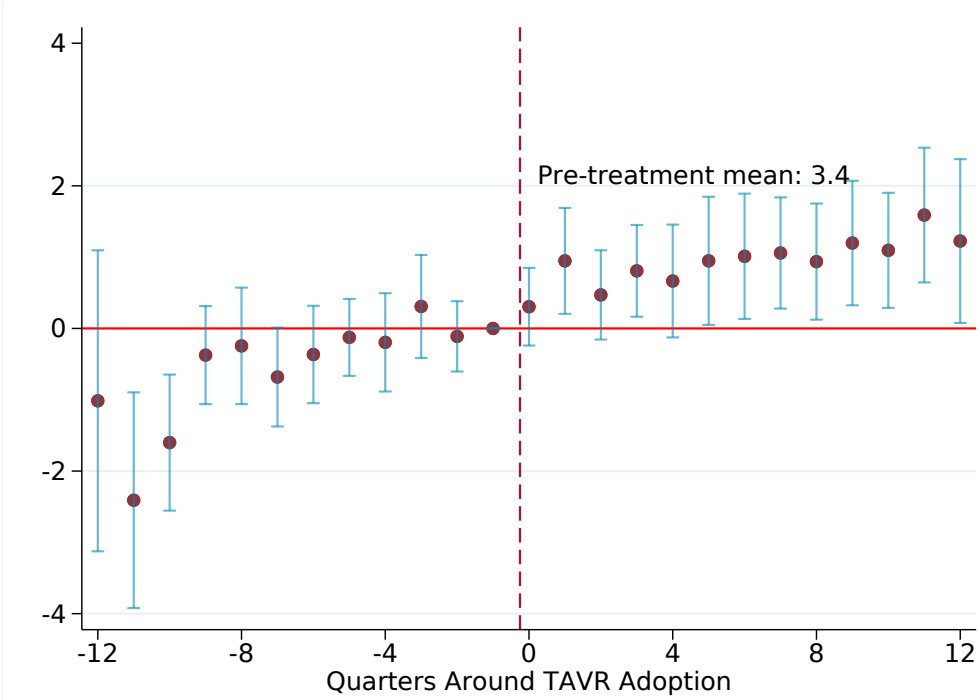


(b) Mortality



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.

Figure A.9. 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.