The Cost of Clarity:

Trade-offs to Public Investments in Rural Diagnostic Care

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Abstract

Rural hospitals face persistent financial constraints that limit investment in advanced medical technologies, creating disparities in health care quality between rural and urban areas. This paper examines the cost-access trade-off associated with deploying expensive diagnostic equipment in rural markets by studying the diffusion of 3D-mammography (3DM) technology for breast cancer screening in Georgia. I exploit quasi-exogenous variation in rural 3DM supply generated by a state subsidy program that increased adoption rates by 20 percentage points. Using patient-level screening records from 2016–2019, I find that 3DM adoption triples local utilization of the technology, primarily through substitution from 2D-mammography. Distance significantly affects technology choice: being one mile further from the nearest 3DM provider reduces the probability of receiving a 3D-screening by 0.08 percentage points, though this sensitivity varies with patient risk factors and socioeconomic status. I estimate a structural model of screening demand to quantify welfare effects, finding that rural 3DM investments generated \$0.95 in total surplus per dollar invested. However, counterfactual simulations reveal substantial heterogeneity across hospitals. Targeting investments toward more remote hospitals with sufficient local populations maximizes social returns by reducing socially redundant business stealing while ensuring technology deployment at economically viable scale.

1 Introduction

Rural hospitals face persistent financial constraints that hinder investment in physical capital. Declining cash flows have eroded profit margins, making it difficult for rural hospitals to acquire medical technologies that are commonplace in better-resourced urban facilities (Joynt et al., 2011; Adler-Milstein et al., 2015; Horwitz et al., 2018). This technology gap contributes to disparities in health care quality, particularly in capital-intensive service lines like radiology, where reliance on outdated equipment can impede the delivery of high-quality care (AHRQ, 2024). As a result, many patients who live in rural areas face a choice between local, low-quality diagnostic care versus high-quality diagnostic care that requires travel.

The widening technology gap between rural and urban hospitals has prompted calls for increased public investment in rural health care infrastructure (Deryugina and Molitor, 2021). Empirical evidence shows that distance is an important factor in hospital choice, suggesting that funding technology adoption at rural hospitals will increase local utilization of high-quality diagnostic care (Scoggins et al., 2012; Syed et al., 2013). However, given the unique features of rural health care markets, publicly funded efforts to close technology gaps may not be cost-effective. Because the fixed costs of adoption are large, small rural hospitals may lack the patient volume needed to deliver upgraded services at a reasonable unit cost. Moreover, distance may not be a meaningful barrier to access for all patients in rural markets. If willingness to travel for high-quality screenings is a function of underlying health risks, deploying advanced diagnostic tools at local hospitals may be socially redundant. These conflicting forces create a trade-off between expanding access and maintaining cost-efficiency in rural health care markets.

This paper evaluates the cost-access trade-off in the market for breast cancer screening. As the second leading cause of death for women in the United States, biennial screenings for breast cancer are recommended for all women ages 50–74 USPSTF (2016). Traditionally these have been performed with 2D-mammography (2DM). However, recent technological advances have brought a new tool to this market. Approved by the FDA in 2011, 3D-mammography (3DM) offers clear clinical advantages over traditional 2D-screenings. By the end of 2017, 3DM supplanted 2DM as the predominant mode of screening for women in the United States. However, the diffusion of this technology has been slower in rural markets where hospitals are less likely to house expensive 3D-scanners (Richman et al., 2019).

To quantify the trade-off between access and cost in this setting, I use quasi-exogenous variation in the supply of 3DM at rural Georgia hospitals to estimate a model of individual screening decisions. The model recovers patients' preferences over screening technologies and the disutility of travel. These estimates provide insight into how rural 3DM adoption affects the allocation of patients across hospitals and screening services allowing me to assess the degree of substitution from 2D to 3D-screenings versus substitution from regional to local providers. I use a revealed preference approach to construct back-of-the-envelope welfare calculations in which the benefits of increased access are weighed against the fixed cost of technology adoption. Finally, I use the estimated structural parameters to simulate counterfactuals that alter the distribution of rural 3DM supply. These analyses explore the effect of alternative allocation rules which assign 3D-scanners to rural hospitals based on distance to incumbent 3DM providers and potential market size. By varying the location of 3DM across hospitals, I illustrate how the social returns to adoption vary across characteristic space providing insight into the features of rural markets where the cost-access trade-off binds.

My analysis centers on the market for breast cancer screenings in Georgia where a subsidy for rural hospitals lowered financial frictions to capital investment, facilitating 3DM adoption. To quantify the effect of the subsidy on Georgia's rural 3DM supply, I estimate an event-study model comparing adoption rates between subsidized Georgia hospitals and rural hospitals in other southern states. I find that the subsidy sharply increased 3DM investment estimating a 20 percentage point increase in the probability of 3DM adoption over the first three years of the policy.

This quasi-exogenous variation in the supply of 3DM at rural Georgia hospitals plays a key role in my analysis. Using patient-level screening records from 2016-2019, I exploit changes in geographic access to 3DM over time to measure the relationship between distance and technology choice. I estimate that local utilization of 3DM triples after it becomes available at the nearest hospital. I find that this increase is driven by substitution between screening technologies rather than an increase in overall breast cancer screening participation. I find that the non-monetary costs of travel have a strong effect on patients' choice of screening technology. Leveraging marginal changes in distance to 3DM, I estimate that being 10 miles farther from the nearest 3DM provider reduces the probability of 3D-screening by 8 percentage points. However, I find that the salience of travel cost varies with patient characteristics. Patients with higher underlying risk factors are willing to travel farther to access 3D-screenings. Conversely, minority groups of lower socioeconomic status are less likely to utilize 3DM as distance increases.

These reduced form estimates show a clear relationship between local access to 3DM and technology choice, but the mechanisms which drive this pattern are unclear. To investigate the underlying factors that affect patient choice, I estimate a structural model of demand for breast cancer screenings. Demand estimates show that while patients prefer higher quality 3D-screenings, they have stronger preferences for screenings at local providers where travel costs are lower. As a result there is sharp substitution toward local 3D-screenings in the post adoption period. The model predicts that in lieu of adoption, 60% of patients utilizing local 3DM would have received 2D-screenings.

Finally, I quantify the welfare effects of rural 3DM adoption by comparing patients' willingness to pay for local 3DM to the fixed cost of adoption. On net, I find that the observed adoptions increased total welfare. These back-of-the-envelope calculations suggest that every dollar invested in the rural 3DM supply generated $0.95 in total surplus. However, I document wide heterogeneity in these effects across hospitals. To disentangle this heterogeneity, I simulate counterfactuals which alter the set of rural 3DM suppliers based on market characteristics. I find that targeting 3DM investments at more remote hospitals, that are at least 12 miles from incumbents, reduces investment in markets where adoption is socially redundant due to business stealing. However, total surplus is improved by concentrating the rural 3DM supply at the set of hospitals that are at least 12 miles from incumbents with local populations above the 25th percentile of the distribution. This two-part allocation criteria helps to isolate the socially desirable set of rural 3DM suppliers by ensuring that the technology is not deployed in sparsely populated markets where local 3DM cannot be delivered at scale.

This paper contributes to several strands of research. First, it adds to the literature on rural health care access. Prior work underscores the essential role rural hospitals play in delivering critical services to isolated communities. For example, Gujral and Basu (2020) show that rural hospital closures increase local mortality rates for emergency patients by 8 percentage points, while Kozhimannil et al. (2020) document the substantial gaps in obstetric care caused by such closures. I extend this literature by focusing on access to higher-quality diagnostic care. In particular, I examine how proximity to advanced screening technologies shapes screening patterns in rural areas, a key factor in assessing whether current diagnostic networks meet the needs of these populations.

Second, I add new evidence to the broad literature studying the impacts of provider entry, service adoption, and technology diffusion in health care markets. Much of this literature draws on Mankiw and Whinston (1986), which theoretically shows that when fixed costs are present, the marginal entrant's effect on welfare depends on the size of the product diversity and business stealing effects relative to fixed cost. Horn et al. (2021) explore these effects in the context of robotic surgery. While they find evidence that the market for surgical interventions expands as more hospitals adopt this technology, adoption also leads to business stealing by changing the allocation of patients across hospitals. Similarly Rosenkranz (2021), studies the repeal of entry regulation for dialysis centers in North Carolina and finds that marginal centers reduce patients' distance to higher quality peritoneal dialysis, expanding the market for high-quality care. I contribute to this literature by focusing on medical technology diffusion in rural health care markets where 3DM adoption may substantially reduce local patients' distance to 3D-technology. Following adoption, I find that the degree of business stealing versus technology substitution is directly related to patients' pre-adoption distance to incumbent 3DM providers, suggesting that the impact of rural technology adoption is dependent on proximity to the existing network of care.

Finally, by studying 3DM adoption, this paper provides new insight into the impact of service adoption at rural hospital. Much of the literature in this area has focused on services that exhibit quality returns to scale (Cutler and Kolstad, 2010; Trogdon, 2009; Yang, 2023; Dingel et al., 2023). However, less evidence exists regarding the impact of rural service expansions in clinical settings without strong quality returns to scale. By studying the adoption of a high-cost medical technology with clear clinical advantages, this paper isolates the trade-off between duplicating fixed costs and improving geographic access to care. My results show that there are large potential welfare gains from increasing the supply of advanced diagnostic services at rural hospitals, but that these effects are tempered by reductions in cost-efficiencies, creating a risk of over-investment in small markets that cannot sustain sufficient demand for these services.

The remainder of the paper is organized as follows. Section 2 provides institutional details and introduces my data. Section 3 shows reduced form analysis of the effect of the policy on the rural 3DM supply and the impact of adoption on screening patterns. Section 4 outlines the model and the estimation strategy while section 5 presents results. Section 6 shows welfare and counterfactual analysis. Section 7 concludes.

2 Setting and Data

2.1 Technology Gaps in Rural health care Markets

Over time, rural hospitals have faced mounting financial challenges. Depopulation and increased competition from urban providers generated demand volatility, lowering profit margins. From 2008-2010, 60 percent of rural hospitals earned negative annual profits, and since 2013, 8 percent of rural hospitals have closed (Sheps Center, 2024). This financial fragility hampers investment in new technology as hospitals may lack the liquidity needed for capital investments (Hegland et al., 2022). Moreover, financial uncertainty raises borrowing costs as lenders view rural hospitals as risky investments. These factors deter rural hospitals from purchasing expensive diagnostic equipment. As a result, rural areas often lag in availability of high-quality care, such as advanced imaging (AHRQ, 2024).

A notable rural-urban technology gap exists in the market for breast cancer screenings. While urban hospitals have rapidly integrated 3DM, it is less likely to be offered at rural providers (FDA, 2025). This disparity is attributed to the fact that rural facilities often lack the liquidity required to finance the fixed cost of upgrading to this advanced technology. Compelling evidence for this gap is observed in Georgia, where in 2016, women in rural counties had to travel twice as far on average to access 3DM due to the sparsity of the technology among local providers. This paper centers on the mammography technology gap in rural Georgia. My analysis leverages variation in access to 3DM following a subsidy that spurred 3D-technology adoption at rural Georgia hospitals.

2.2 Georgia's Rural Hospital Tax Credit

In 2017, Georgia implemented the Rural Hospital Tax Credit (RHTC), an innovative funding mechanism that effectively turned private donations to rural hospitals into 100% state tax credits. Each eligible hospital (non-profit or public, in counties $<$ population cutoff) could receive up to $4 million annually; in practice, eligible hospitals received an average of $650,000 per year from 2017–2019. Table A1 shows eligibility for the program and the evolution of donations received from 2017-2019. In 2017, RHTC funds were only available to non-profit or public hospitals in counties with populations below 35,000. In 2018, the population limit was raised to 50,000 and the number of participating hospitals increased to 58.

Over this time frame, nearly every qualifying hospital received RHTC funds. The statewide cap on donations was raised by $50 million in 2018, which led to a sharp increase in total and average funds received. Importantly, these funds were unrestricted in use, effectively boosting liquidity at participating hospitals. Table A2 reports aggregate information on reported use of RHTC funds in 2018. On average, hospitals spent 80% of funds available and held the remaining 20% as cash reserves. The bottom half of Table A2 shows that on average $250,000 of subsidy funds were spent on medical equipment in 2018, roughly 30% of all spending. Within these spending reports, hospitals claim to have used RHTC funds to purchase a wide variety of equipment, but the most commonly reported equipment acquisition is of a 3DM unit. My analysis is consistent with these reports as I find that by the end of 2019, 22 of the 58 subsidized hospitals acquired a 3DM scanner.

2.3 Data

This analysis relies on two primary datasets. To measure changes in the supply of 3DM across Georgia, I use technology adoption records. To measure changes in mammography utilization patterns, I use screening records for the entire state of Georgia.

Technology Adoption Records: I use administrative data from the FDA's X-Ray Installer database, which records every new installation of radiology equipment at U.S. health care providers.

Each record contains the facility's name and location, the type of equipment installed, and the installation date. Importantly, the records indicate if the equipment is for mammography and whether it has 3D capability. I use these records to construct a panel of 3DM adoption at hospitals across the southeast from 2014-2019.

Breast Cancer Screening Data: I incorporate patient-level data to observe mammography utilization. This data comes from the health care Cost and Utilization Project (HCUP), which records outpatient discharge records for all hospitals and ambulatory surgery centers in Georgia.[1] Each of these records includes information on when a patient visits a given facility and which procedures were performed during the visit, which allows me to observe whether a patient received a 2D or 3D-screening. Each record lists a patient's home zip code and demographic information on race, age, and insurance type. Records also include a unique patient identifier, which allows each encounter to be connected to a patient's care history over time. I use HCUP data from 2016-2019 to measure changes in hospital mammography service offerings and patient treatment patterns over time. I use the CPT procedure codes listed in Table A4, and the service identification algorithm introduced by Richman et al. (2022) to identify the type of technology used in a screening encounter. In the HCUP data, I observe 22 subsidized rural hospitals that start offering 3DM between 2017 and 2019. This aligns exactly with the 22 new installations recorded in the FDA data for rural Georgia, giving confidence that the adoption events are measured consistently across data sources. My analysis focus exclusively on screening mammography encounters.

Supplementary Data: I use information on hospital size and financial health from Medicare Cost Reports. To measure the resource cost of 3DM adoption and utilization, I rely on data from the Center for Medicare and Medicaid Services Practice Expense Files. These files provide line item estimates of the expenses associated with mammography service lines which I use to measure the incremental cost of 3DM. Finally, I use the American Community Survey for information on zip code demographics.

3 Reduced Form Evidence

3.1 Descriptive Screening Patterns

This section explores regional differences in mammography screening patterns across Georgia. I begin by highlighting disparities in 3DM access and use in rural versus urban Georgia. Next, I identify key factors influencing 3DM utilization, focusing on patient characteristics, absolute distance,

[1] I do not observe screenings in office-based imaging centers. However, I validate my data coverage against aggregate claims counts from Medicare Claims data in Table A5. Subsetting my data to match the FFS population, I capture 87% of 3DM screenings and 76% of 2DM screenings at the state level.

and crucially, differential distance to 3DM, defined as the difference between a patient's nearest 2DM and 3DM providers.

First, I document differences in proximity to and utilization of 3DM between rural and urban zip-codes across Georgia. Table 1 shows that in 2016, the year before the subsidy, there were significant disparities between these groups. The average distance for rural women to 3DM services was 22.5 miles, nearly double that of non-rural women at 12.5 miles, a difference that persists across the 25th and 75th percentiles of the distribution. In contrast, there is a small difference in the distance to 2DM between the two groups which is not statistically distinguishable from zero. Furthermore, the share of rural women screened with 3DM is considerably lower at 12.1%, compared to 30.6% for non-rural women. While the 25th percentile for 3DM screening is small for both groups, there is a sharp gap at the 75th percentile where 45% of non-rural women screening with 3DM relative to 30% of rural women.

Table 1: Disparities in Rural 3DM Access (2016)

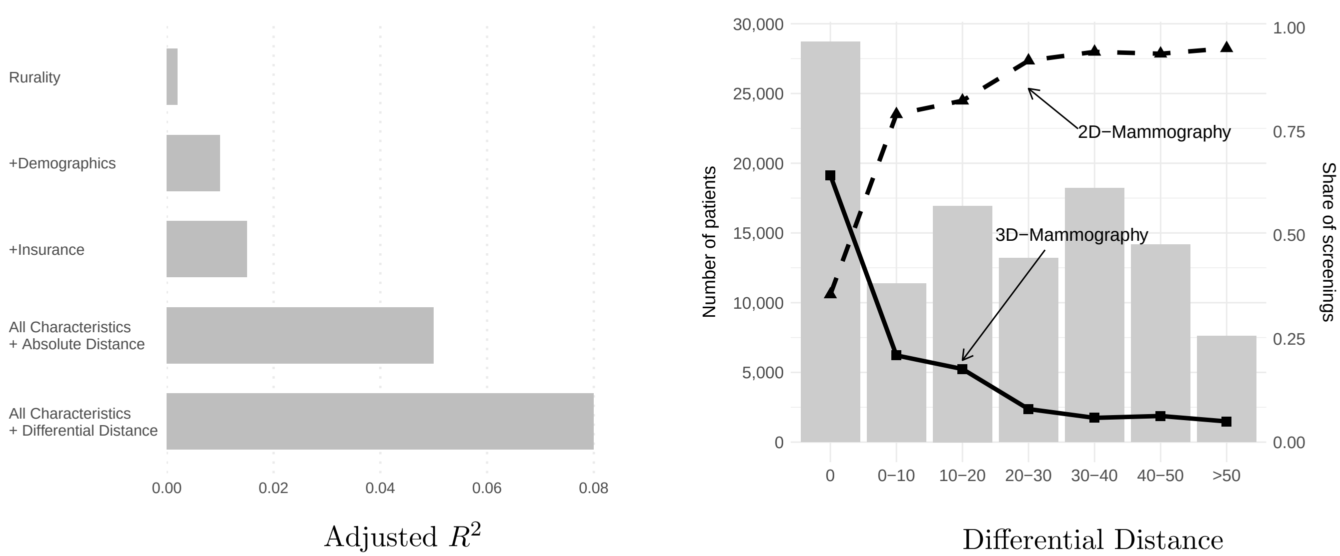
Sample Characteristics	Rural	Non-Rural	***p*-value**
Distance to 3DM (mi)			
Mean	22.5	12.5	0.000
25th %	13.5	8.5	
75th %	35.5	23.3	
Distance to 2DM (mi)			
Mean	14.6	11.1	0.450
25th %	8.9	8.2	
75th %	20.75	14.95	
Share Screened with 3D			
Mean	12.1%	30.6%	0.000
25th %	3.4%	5.1%	
75th %	30.0%	45.5%	

Notes: Table reports mean, 25th, and 75th percentiles of distance to nearest mammography provider and the share of screenings performed with 3DM. Sample includes all Georgia women screened in 2016. Distances are calculated at the zip code level using patient residence and provider location. P-values test for differences in rural versus non-rural means. Data source: HCUP screening records.

Next, I explore the factors influencing patient screening technology choice. Panel A of Figure 1 plots the adjusted R^2 for OLS regressions of technology choice on fixed effects for rurality, patient characteristics, insurance status, and absolute versus differential distance. Rurality alone explains little of the variation in screening decisions. Even after accounting for patient demographics and insurance type, the explained variation remained low. However, the inclusion of distance in the regression significantly increased the R-squared value. Notably, differential distance explained more of this variation than absolute distance, suggesting that the additional distance patients must travel to access 3DM is a crucial factor in their choice between 2DM and 3DM. This indicates that the comparative travel burden for advanced screening technologies plays a significant role in patient uptake.

Panel B of Figure 1 illustrates the probability of patient screening with 2D versus 3D mammography across differential-distance bins among the 2016 cross-section of patients in rural zip-codes. This figure shows that patients who face a higher differential distance to access 3DM are less likely to screen with that technology and are more likely to opt for 2DM services available at a closer provider. The 3DM trend has a non-linear slope, characterized by a sharp decrease between distance bin zero, where a patient's closest provider already offers 3DM, and distance bin ten. Suggesting that patients are less inclined to travel further for mammography services that are not offered by their nearest provider. These patterns point to differences in geographic proximity to 3DM as a primary factor contributing to differences in technology choice between rural and non-rural areas. However, from 2017–2019, rural areas across Georgia saw a marked reduction in barriers to 3DM access as many local hospitals adopted 3D-technology.

Figure 1: Cross-Sectional Variation in Technology Choice (2016)



Notes: The right figure shows the average probability of screening technology choice across bins of relative distance where relative distance is defined as the difference between the closest 2D and 3DM provider and is calculated at the zip code level. These probabilities are overlaid across the histogram of the number of patients by travel time. This figure is constructed using the sample of mammography screenings in rural Georgia in 2016.

This paper relies on variation in access to 3DM due to adoption of 3D-technology at rural Georgia hospitals. However, because a hospital's decision to invest in 3DM is endogenously determined, comparisons of screening outcomes over time may be biased by contemporaneous demand shocks. To mitigate this bias, my empirical analysis leverages supply-side variation created by a subsidy for rural Georgia hospitals. By lifting historic barriers to capital investment, these funds facilitated 3DM adoption at hospitals previously bound by financial constraints. Therefore, this policy provides a novel source of variation in the rural 3DM supply helping to isolate the effect of changes in access to technology on screening patterns.

3.2 Subsidized 3DM Adoption

In this section, I establish the effect of Georgia's Rural Hospital Tax Credit on hospitals' decision to upgrade from 2DM to 3DM.

Sample: For the analysis of the effect of subsidization on 3DM adoption, I compare the sample of all subsidized rural Georgia hospitals to a comparable set of control hospitals drawn from other states in the southeast.[2] Georgia did not expand Medicaid during this period, so I select controls from other non-expansion states to ensure comparability across my sample period. To select control hospitals, I identify the set of hospitals in each state that would be eligible to receive RHTC subsidies if an analogous program were to exist in their state. Table A3 shows 2016 summary statistics for both groups. Both are similar in size and baseline financial health suggesting this control group provides a reasonable counterfactual for Georgia hospitals in the absence of the subsidy.

Empirical Strategy: To quantify the effect of the RHTC subsidy on the probability of 3DM investment, I compare adoption rates before and after the subsidy between rural hospitals in Georgia, and a comparable group of rural hospitals in other southern states who are not exposed to the subsidy. The identifying assumption is that, absent the subsidy, Georgia's adoption trend would have followed a similar path to that of the control hospitals. I test this assumption by estimating the following event study model:

$$Y_{ht} = \sum_{k \neq -1} \beta_k \, GA_h \cdot D_{kt} + \lambda_t + \mu_h + \epsilon_{ht} \tag{1}$$

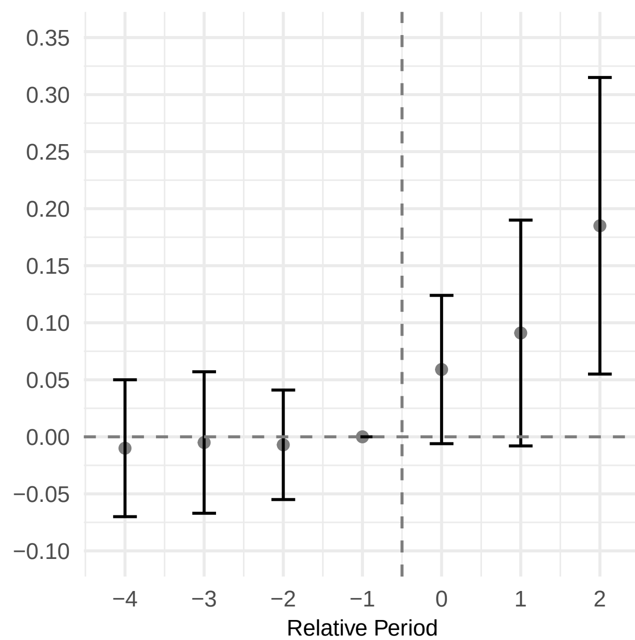
Where Y_{ht} is an indicator for whether hospital h adopted 3DM by year t, so that β_k shows the effect of subsidization on the cumulative probability of 3DM adoption at event time t, relative to the year before subsidy receipt, k=-1, which is normalized to zero. The model includes year fixed effects and hospital fixed effects. Since 9 of the 58 hospitals in my treated group do not receive

[2]Including: Alabama, Florida, Mississippi, North-Carolina, South Carolina, and Tennessee.

subsidy funds until 2018, I estimate this model using the imputation estimator proposed by Gardner (2022) which avoids the bad comparisons known to bias standard two-way fixed effects estimators.

Figure 2 plots the estimates of equation (1) for the primary sample, which compares rural hospitals in Georgia with those in other southern states. Crucially, I find no distinguishable difference in adoption trends between these groups across the pre-periods, thereby supporting the parallel trends assumption. Following the implementation of the subsidy in Georgia, I estimate a sharp increase in the annual probability of 3DM adoption. By relative period 2, I estimate that subsidization increased the cumulative probability of adoption by approximately 20 percentage points.

Figure 2: Effects of Subsidization on 3DM Adoption



Notes: This figure shows event study estimates for the 3DM investment outcome. This model is estimated using radiology equipment installation records from 2014-2019 for RHTC hospitals (N=58) and a group of rural hospitals in other southern states (N=95), creating a total of 918 hospital year observations. Relative year zero corresponds to 2017, the first year Georgia hospitals received subsidy funds. All estimates are normalized to relative year negative 1, the year before subsidy receipt. Standard errors are clustered at the hospital level. Source: FDA

I test the robustness of these results by estimating the triple difference specification presented in Equation 2. This model accounts for potential Georgia-specific factors that may be occurring concurrently with the implementation of the subsidy and could bias my estimated treatment effects. I address these potential confounding state-specific factors by comparing adoption rates among non-rural Georgia hospitals with those of non-rural hospitals located in control states. By differencing out adoption trends between these two non-rural groups this model is robust to time-varying state-specific confounders.

$$Y_{ht} = \beta_1(GA_h \cdot post_{ht} \cdot rural_h) + \beta_2(post_{ht} \cdot GA_h) + \beta_3(post_{ht} \cdot rural_h) + \lambda_t + \mu_h + \epsilon_{ht} \quad (2)$$

Table 2 presents the estimated effects from a standard difference-in-differences specification alongside the triple difference results. I find a significant 11 percentage point increase in the annual probability of 3DM adoption under the difference-in-differences specification that is significant at the 5% level. The triple difference estimate of 7.5 percentage points is significant at the 10% level. Though smaller in magnitude, the qualitative nature of these results suggests that the increased adoption of 3DM in rural Georgia hospitals is driven by the implemented subsidy. This increase in 3DM adoption at rural Georgia hospitals created plausibly exogenous variation in rural patients access to 3D-technology. In the next section, I exploit these time-varying changes in access to the nearest 3DM provider to quantify the effect of distance on screening technology choice.

Table 2: Effect of Subsidy on 3DM-Adoption

3D-Purchase	(DD)	(DDD)
Post x Subsidy	0.11**	0.075*
	(0.035)	(0.042)
Controls		
Hospital FE	Y	Y
Year FE	Y	Y
Hospital-Year Observations	918	3,627

Notes: Column 1 reports estimates from the difference in differences model estimated using the sample of rural hospitals in GA and control states. Column 2 reports estimates from the triple differences model estimated using the sample of rural and urban hospitals in GA and control states. Standard errors are clustered at the hospital level. Source: FDA

3.3 The Effect of Distance on Screening Technology Choice

In this section, I present reduced-form evidence of the effect of distance to 3DM on rural patients' screening patterns. I structure this analysis in three parts, first estimating the effect of gaining local access to 3DM on zip code level technology choice. I then exploit marginal changes in distance to 3DM to estimate the elasticity of 3DM-take-up with respect to distance. Finally, I document heterogeneity in the effect of distance across patients' observable characteristics including race, insurance type, and underlying risk of breast cancer.

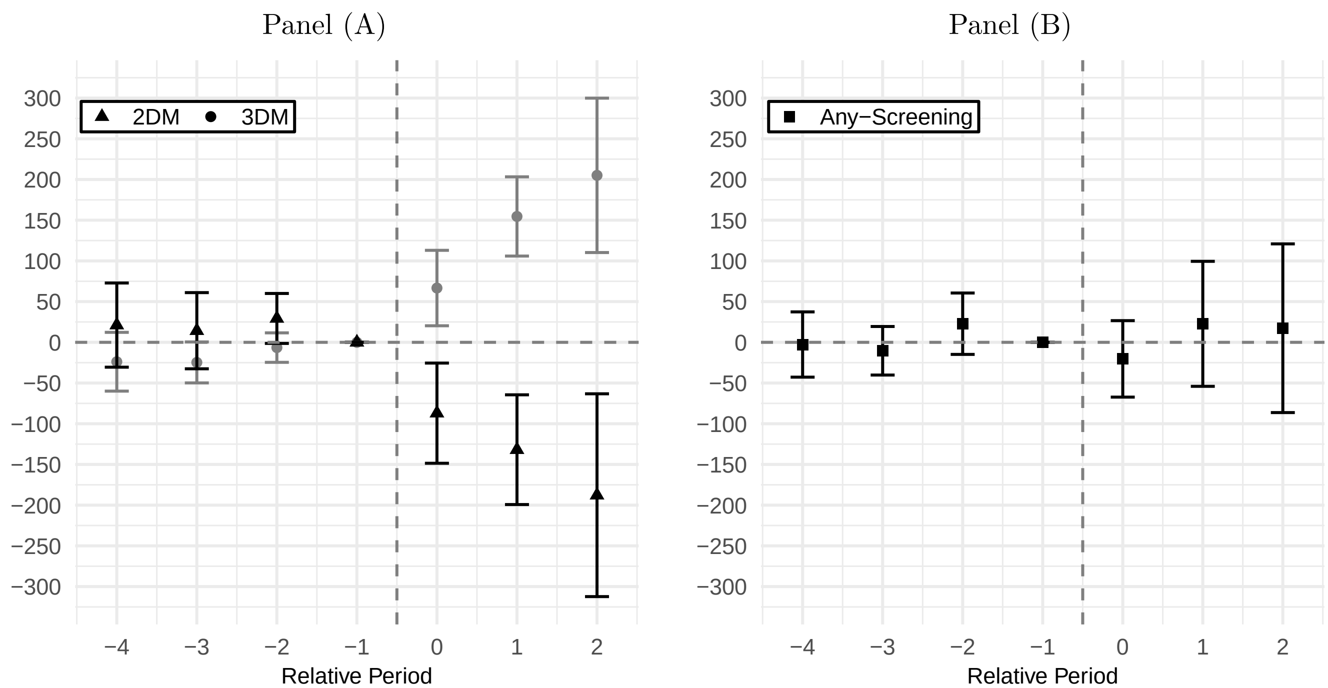
Gaining Local Access to 3DM: To quantify the relationship between local access and screening patterns, I use screening records from all rural Georgia zip-codes over the 5-year period from 2016–2019. My analysis exploits changes in patients' access to 3DM following its adoption at subsidized rural hospitals. I construct a time-varying zip code level measure of local access which is based on relative distance to 3DM. Specifically, I define local access as a binary indicator equal to one for zip code z in period t if 3DM is offered at z's nearest mammography provider. To precisely measure changes in access over time, I define calendar time periods in 6-month intervals. This leaves me with a sample of 216,544 screening observations across 136 rural zip-codes.

I estimate the event study model shown in Equation 3. This analysis centers around event period (e_z) in which 3DM becomes available at the provider nearest zip code z, following its adoption at a subsidized hospital. In my preferred specification, Equation 3 is estimated using the sample of zip-codes that are eventually treated or never treated, so that ϕ_ks are identified by variation within and across units over time. Formally, this analysis assumes that, conditional on observables, the counterfactual trends of zip-codes with different degrees of access to 3DM would have evolved in parallel. I evaluate the plausibility of this assumption by testing for differences in pre-trends across groups. I include zip code level controls for absolute distance to 3DM over time, the number of 3DM providers in z's commuting zone, and size of the screening eligible population. These controls help to account for potential bias resulting from changes in distance to 3DM over time in untreated zip-codes that never gain local access. However, any bias from these spillovers should depress my estimated treatment effects. Finally, to avoid bad comparisons resulting from staggered adoption of 3DM, I estimate the model presented in equation 3 using the Gardner imputation estimator where previously treated zip-codes are not included as comparison units.

$$Y_{zt} = \sum_{k \neq -1} \phi_k \cdot \mathbb{1}(t - e_z = k) + X_{zt} + \lambda_t + \mu_z + \epsilon_{zt} \tag{3}$$

Figure 3 presents event study estimates from model 3. ϕ_{ks} estimates span six-month time periods, from two years before to eighteen months after local adoption. Panel A illustrates the estimated effect of local 3DM access on zip code level screening volumes for both 2D and 3DM. The flat pre-trends for both outcomes provide plausible support for the identification assumption. Post-adoption estimates show a sharp increase in 3DM utilization across periods 0 through 3 for an average increase of 140 3D-scans per period. This rise in 3DM is mirrored by a decrease of similar magnitude in 2DM utilization suggesting that the local availability of 3DM prompts patients to substitute between screening technologies, rather than encouraging individuals who previously did not screen to begin screening. Estimates in Panel B, which show the effect of adoption on total breast cancer screening counts, are statistically indistinguishable from zero and small across the entire pre and post-period. Together, these outcomes show strong evidence that local access to 3DM primarily drives a shift in the choice of screening technology.

Figure 3: Effects of Gaining Local Access to 3DM on Screening Patterns



Notes: This figure shows estimates from model 3. Panel A shows estimated relative time coefficients for zip code screening volume across 2DM and 3DM. Respective means in relative period -1 are 2DM=168 and 3DM=49. Panel B shows estimates for overall screening counts. Each model is estimated using the sample of 216,544 screening observations across 136 rural zip-codes. Standard errors are clustered at the zip code level.

Marginal Changes in Distance to 3DM: Next, I exploit changes in rural patients' absolute distance to the nearest 3DM provider over time to estimate the elasticity of screening choice with respect to distance.

$$Y_{izt} = \rho\, d_{izt} + \lambda_t + \mu_z + X_i + County_i \cdot t + \epsilon_{zt} \tag{4}$$

Using the same sample of screening observations across 136 rural zip-codes from 2016–2019, I estimate the model presented in equation 4. Outcome variable Y_{izt} is an indicator for whether individual i chooses to screen with 3DM. My preferred specification controls for zip code and period fixed effects, though I also test the robustness of results to patient level controls and county-specific time-trends. Explanatory variable, d_{izt}, is a continuous measure of distance to the nearest 3DM provider in miles, so that ρ reflects the marginal effect of a change in distance to 3DM on the probability of screening with 3D-technology.

Table 3: Effect of Absolute Distance to 3DM on Technology Choice

	(1)	(2)	(3)
Panel A: Reduced Form—Dependent Variable: Screened with 3DM			
Distance to 3DM	-0.0058^{***}	-0.0059^{***}	-0.0063^{***}
	(0.0008)	(0.0009)	(0.0008)
N	216,544	216,544	216,544
Panel B: First Stage—Dependent Variable: Distance Traveled			
Distance to 3DM	0.6951^{***}	0.6851^{***}	0.6478^{***}
	(0.0938)	(0.0928)	(0.0953)
N	72,595	72,595	72,595
Mean outcome	27.730	27.730	27.730
F-stat	64.9	37.6	5.348
Panel C: Second Stage—Dependent Variable: Screened with 3DM			
Predicted Distance	-0.0084^{***}	-0.0086^{***}	-0.0096
to chosen provider	(0.0012)	(0.0013)	(0.0078)
Mean outcome	0.3352	0.3352	0.3352
Zip code FE:	X	X	X
Period FE:	X	X	X
Individual Controls:		X	X
County-Time-Trend:			X

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$,. This table displays the estimates from equation 4 quantifying the impact of distance to 3DM on 3DM utilization. Panel A reports the effect of distance to the closest 3DM provider in miles on the probability of 3DM screening. Panel B shows estimates of the relationship between minimum distance to 3DM and distance to the chosen 3D-screening provider. Panel C shows estimates from the second stage regression where predicted distance to the chosen 3DM providers is the explanatory variable. Each column includes period fixed effects. Column 1 includes zip code fixed effects, Column 2 adds patient level controls, Column 3 includes a linear time-trend at the county level. Standard errors are clustered at the zip code level, and bootstrapped using 500 iterations in Panel C.

To account for the fact that some women don't receive screenings at their nearest provider, I follow the approach of Gazze (2024) and supplement the results from equation 4 with a two-sample two-stage-least-squares (2SLS) model. This model is estimated using the sample of women who screen with 3DM, where first stage regresses distance to the chosen screening provider on distance to the nearest 3DM provider. I use estimates from the first stage to construct a measure of predicted miles traveled to 3DM for the full sample which is the explanatory variable in the second stage of estimation. This two-stage procedure scales the reduced form estimates of distance's effect on screening decisions by the share of compliers, that is, the individuals who change screening technology choice in response to a reduction in distance to 3DM. Standard errors for the second stage estimates are constructed via bootstrap.

Estimates in Panel A of Table 3 show that a one mile increase in distance to 3DM lowers the probability of 3D-take-up by -0.58 percentage points, equivalent to a 1.7% change in the mean outcome. This baseline estimated from column (1) is robust to alternative specifications including individual controls and time-varying trends. Panel B shows a strong first-stage relationship between minimum distance to 3DM and distance to the chosen provider for all specifications except column 3. This estimate implies that a one mile drop in distance to the nearest 3DM provider decreases the average distance traveled for 3D-screening by seven-tenths of a mile. Finally, I use the predicted distance estimate from the first-stage regression to estimate the scaled effect for the entire sample. Estimates in Panel C show that a one mile increase in predicted travel distance to 3DM reduces the probability of 3D-screening by -.084 percentage points. Together, these results show strong evidence that distance to 3D-technology is a key determinant in 3DM take-up.

Distance has a clear impact on screening decisions, but thus far, it is unclear whether these effects differ systematically across patient types. To quantify how changes in distance impact selection into 3D-screening, I estimate equation 4 on the sample of patients who choose to screen with 3DM, using patient characteristics as the outcome variable. These estimates measure changes in the average characteristics of rural 3DM screeners that result from marginal changes in distance to 3D-technology. Table 4 reports the results of this analysis across observable patient characteristics. Column 1 shows that women who opt into 3D-screenings at larger distances are more likely to have a family history of breast cancer, suggesting that patients' willingness to travel to access 3DM is positively related to underlying health risk. Column 2 tests for differences in willingness to travel to 3DM across age. Qualitatively, younger women are more likely to travel further to access 3D-screenings, but the estimated effect is not distinguishable from zero. In columns 3 and 4, I find that women screened with 3DM when travel costs are higher are less likely to be non-white or classified as Medicaid/Self-Pay. This suggests that lowering travel barriers to 3DM may have a larger effect on access for minority groups of lower socioeconomic status, but that the effects for women with observably higher health risk will be more muted.

Table 4: Changes in Mean Characteristics of 3DM Patients as Distance Varies

	Family History (1)	Age (2)	Non-White (3)	Medicaid/Self-Pay (4)
Distance to 3DM	0.003^{***}	-0.006	-0.002^{***}	-0.001^{***}
	(0.001)	(0.009)	(0.000)	(0.001)
Sample Mean	0.115	62.07	0.244	0.092

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$,. This table shows the effect of distance to 3DM on the average characteristics of patients who select into 3D-screening. The model is estimated using the sample of rural patients who screen with 3DM (N=72,595). Each column shows the average change in patient characteristics for a one-mile increase in distance to the nearest 3DM provider. All regressions include zip code and period fixed effects. Standard errors are clustered at the zip code level.

The descriptive patterns in this section suggest that patients' choice of breast cancer screening technology is strongly influenced by distance. When rural patients have 3DM available at their nearest hospital, there are no substantial differences in the probability of 3D-screening between rural and urban patients. These average effects are informative but are not sufficient to determine optimal policy. On one hand, the sensitivity of patients to distance when making screening choices suggests that targeting investments in screening infrastructure may be most effective when funds are prioritized to the most isolated rural areas. This approach addresses geographical barriers that might prevent access to 3DM for the most under-served populations. However, if a patient's decision to screen with 3DM is primarily a function of its availability at their nearest hospital, rather than the absolute distance, it may be efficient to target investments to rural providers in more populated areas. A targeting rule based on potential market size could have a stronger effect on overall screening utilization by maximizing the number of patients who substitute toward quality for a given public investment in rural diagnostic technology. To address this ambiguity I estimate a structural model of demand for breast cancer screening. This model recovers patients' underlying preferences for screening technologies relative to travel costs. Allowing distaste for travel to vary across patients based on race, insurance status, observable risk, and previous care history, the model disentangles the relevant factors that determine patients' screening choices. This structural approach is useful as it allows for detailed predictions of patients' response to changes in the supply of 3DM.

4 Demand Model

4.1 Demand Specification

I model a woman's choice of breast cancer screening provider and modality as a differentiated product discrete choice problem. In period t, individual i in market m chooses among a set of hospital, modality options j, s that maximizes utility:

$$U_{ijsmt} = \underbrace{\delta_{jsmt} + \mu_{ijsmt}}_{V_{ijsmt}} + \epsilon_{ijsmt} \tag{5}$$

where δ_{jsmt} is the mean utility of screening service s at hospital j in market m at time period t, which reflects vertical differentiation in individuals' preferences over hospitals and screening technologies. The idiosyncratic terms, $\mu_{ijsmt} + \epsilon_{ijsmt}$, capture individual-specific variation from mean utility. Hospitals are horizontally differentiated in distance, so that patients have preferences over travel time to hospital j which may vary with observable patient characteristics. I also allow utility to vary based on a patient's previous screening choices to capture preferences for familiar providers or inertia in choices over time.

I specify μ_{ijsmt} as:

$$\mu_{ijsmt} = \gamma d_{ij} + \sum_{c=1}^{C} \kappa_c (d_{ij} * \underbrace{Z_{ic}}_{Demographics}) + \alpha_1 \mathbb{1}(Prev_{ijt} = 1) + \alpha_2 \mathbb{1}(Prev_{ijt} = 1) * d_{ij} + \rho\, CZ_{ij} * d_{ij} \tag{6}$$

where d_{ij} is round trip distance between i's zip code and provider j in ten mile increments. To capture heterogeneity in travel cost, I interact distance with Z_{ic}, a vector of observable patient characteristics, including race, an indicator for Medicaid or self-pay insurance status, and an indicator for family history of breast cancer. I include an indicator denoting whether i's last scan was with hospital j which is also interacted with distance. Finally, I interact distance with CZ_{ij}, an indicator for whether hospital j is in i's commuting zone, which allows travel cost to vary based on final location. This allows for the possibility that patients are more likely to visit providers in areas where they frequently travel or work (Fowler, 2024).

Mean service utility is specified as:

$$\delta_{jsmt} = \beta_{3D}\, 3DM_{jmt} + \beta_x X_{jmt} \cdot 3DM_{jmt} + \underbrace{h_j}_{Hospital\,FE} + \underbrace{\tau_t}_{Period\,FE} + \underbrace{\xi_{jsmt}}_{\text{Unobserved Taste Shock}} \tag{7}$$

Where $3DM_{jmt}$ is an indicator for 3D-technology, and X_{jmt} is a vector of hospital characteristics. Parameter β_{3D} reflects additive effect of 3DM on the mean utility of receiving a screening at provider j, and β_x captures heterogeneity in patients' taste for 3DM across providers.

I do not model the choice to delay or forgo screening and thus assume the market size is equal to the total number of patients receiving scans. I choose to model this limited form of substitution because my model relies on variation from changes in access to higher quality services. While some patients do in fact choose to delay recommended screenings, I do not find evidence that this behavior is impacted by changes in local access to 3DM.[3] In each market, I define a particular hospital screening service combination as the outside good. Assuming ϵ_{ijsmt} follows a type one extreme value distribution, the individual probability of patient i in market m and period t choosing service s at hospital j can be written:

$$s_{ijsmt} = \frac{exp(\delta_{jsmt} + \mu_{ijsmt})}{\sum_{j,s} exp(\delta_{jsmt} + \mu_{ijsmt})} \tag{8}$$

4.2 Estimation and Identification

Sample and Market Selection: I estimate the model for Georgia hospitals that offer either 2DM or 3DM from 2016–2019 outside of Atlanta. This includes 42 rural hospitals and 37 non-rural hospitals. When conducting analyses related to the effect of rural 3DM adoption, I restrict attention to the set of rural hospitals that adopted 3DM by the last month of 2018 to ensure adequate coverage before and after adoption. To highlight the impact of changes in access to higher quality diagnostic care, I also limit this adoption sample to hospitals that had prior 2DM services.[4] Finally, I require that hospitals consistently report discharge data across each quarter year from 2016–2019. The final sample includes 16 rural adopters or 72% of all subsidized Georgia hospitals who adopt 3DM from 2017-2019.

Markets are constructed based on the Georgia Department of Community Health's defined state health planning regions. Each of these designated regions typically encompasses approximately 10 counties, with an average of seven mammography providers operating within each county. The providers located within these defined markets collectively capture an average of 92% of observed screenings for patients residing in these regions. I normalize the utility of screening with an out-of-market provider to zero. The health planning region corresponding to the Atlanta metro area is excluded from this analysis since it does not contain any subsidized rural hospitals.[5] The final sample includes a total of 79 hospitals with each operating in one of twelve unique markets.

[3] Appendix C, shows a null relationship between local screening compliance and 3DM adoption.

[4] This only excludes two adopting hospitals.

[5] Additionally, travel cost in this market may not be reflective of the broader state due to traffic patterns and the availability of public transit.

Estimation: I estimate the parameters of this model using a two stage maximum likelihood procedure. Following Goolsbee and Petrin (2004), I estimate the idiosyncratic taste parameters θ=(γ,κ_c,α,ρ) in the first stage by maximizing the log-likelihood function (9). Where $I_{i,j,s,m,t}$ is an indicator for patient i in market m at time t choosing to screen at hospital j with technology s. Conditional on any candidate value of θ, I solve for the vector of option specific mean utilities, δ_{jsmt}, such that the observed market shares match those predicted by the model (Berry, 1994). After recovering mean utilities, at the optimal values of θ, I estimate the technology preference parameter β_{3D} in a second stage linear regression, corresponding to equation 7, where service mean utilities are regressed on an indicator for screening modality. This regression includes hospital and period fixed effects in addition to interactions between hospital characteristics and technology type which account for heterogeneity in patients' taste for 3DM across providers. To address the endogeneity concern that a hospital's decision to adopt 3DM is influenced by local demand shocks, my preferred specification is estimated via a 2SLS procedure where the subsidy is used to instrument for technology availability.

$$LL(\theta) = \sum_{i,j,s,m,t} I_{i,j,s,m,t} \cdot log\left(\frac{s_{ijsmt}(\theta)}{\sum_{j,s} s_{ijsmt}(\theta)}\right) \tag{9}$$

Identification: Generally, travel cost sensitivity is identified by patients' substitution between local and more distant providers, but I also leverage variation in the timing of 3DM adoption at the local rural hospital which changes the minimum distance to 3DM over time. This provides an additional source of identification and helps to separate preferences for screening modalities and hospitals from travel sensitivity. Similar variation is used to identify α, which captures inertia.

Using patient identifiers to link patients' choices over time, α is identified by the tendency for patients to re-visit the provider where they received their last scan. Identification is strengthened by variation in these patterns when new screening modalities are added to the choice set. Accounting for inertia is crucial in identifying patient's preferences for screening technologies. By accounting for switching cost, I am able to distinguish patients' preferences for local 3DM from preferences for familiar providers.

The identifying assumption in the second stage of estimation is that the instrument generates variation in the 3DM supply that is orthogonal to latent demand shocks that would otherwise influence a hospital's decision to adopt 3DM. I argue that by providing capital-constrained rural hospitals with the liquidity needed to invest in 3DM, this policy effectively moved hospitals across the adoption threshold. Exploiting this variation helps to separate taste for technology from confounding trends in local demand.

5 Results

5.1 Preference Estimates

Results from the maximum likelihood stage of estimation, are reported in Table 5, part one. Patients exhibit a distaste for distance, with a γ coefficient of -0.743. This aversion to distance is stronger among Medicaid/Self-Pay patients and non-white patients. The positive estimate for ρ suggests that patients place less weight on distance if a hospital is within their commuting zone where they are more likely to travel for work. Patients demonstrate a strong preference for familiar providers, as reflected by a large positive value for α_1. Furthermore, the interaction between inertia and distance, represented by α_2 is equal to 0.308, suggests that patients are willing to travel further to providers they are familiar with. Next I quantify the elasticity of screening choice with respect to distance. Column 2A reports the average own-distance elasticities across sub-groups. Consistent with the results from Table 5, non-white patients insured by Medicaid are more sensitive to distance exhibiting a distance elasticity that is 25% above the baseline estimate.

Part two of Table 5 presents the results from the second-stage estimation procedure, where preferences for technology are recovered. The estimates from the naive Ordinary Least Squares (OLS) regression are reported alongside the results from the two-stage least squares (2SLS) procedure. The instrument for 3D availability demonstrates a strong first stage, satisfying the relevance criteria with an F-statistic of 35, indicating that the policy created meaningful variation in the availability of 3DM. A comparison of the point estimates for beta 3D reveals that the naive OLS estimate likely overstates patients' preferences for 3DM, as it is equal to 1.97, whereas the 2SLS estimate, which accounts for endogeneity, is 1.75. This adjusted result reflects a strong patient preference for 3D-screening, implying that patients would be willing to travel an additional 25 miles round trip to access 3D technology when compared to the estimated travel costs. Interactions between hospital characteristics and 3D-technology are less precisely estimated, but suggest that the effect of 3DM is stronger when hospitals are larger and not affiliated with a system.

Table 5: Demand Parameter Estimates

Parameter	Estimate	$\mathcal{E}_d$
Panel A:	(1A)	(2A)
Maximum Likelihood Estimation		
α_1 (Inertia)	3.508	
	(0.006)	
γ Round Trip Distance (10 mi)	-0.743	-1.6
	(0.007)	
Distance Interactions		
κ_{race} (White)	0.0372	-1.5
	(0.001)	
κ_{ins} (Medicaid/ Self-Pay)	-0.029	-1.75
	(0.004)	
κ_h (Family-History)	0.072	-1.4
	(0.001)	
α_2 Inertia	0.308	-0.91
	(0.007)	
ρ Commuting-Zone	0.179	-1.3
	(0.009)	
Panel B: Taste for 3DM	(1B)	(2B)
	OLS	2SLS
β_{3D}	1.97***	1.75**
	(0.079)	(0.915)
Characteristic Interactions		
Above Median Beds	0.295*	0.32
	(0.177)	(0.220)
Critical Access	-0.099	-0.081
	(0.122)	(0.147)
System		-0.48^{*}
	(0.291)	(0.31)
Hospital Year Observations	1041	1041
First Stage F-stat		35.14

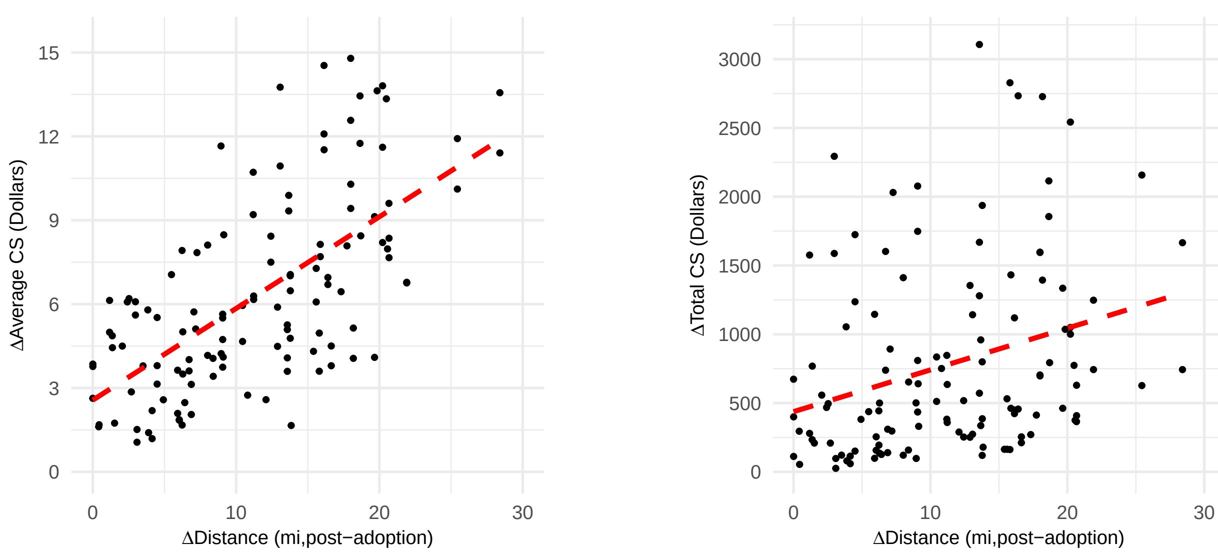
Notes: Panel A shows results of the logit choice model. Point estimates for utility parameters are shown in column 1A. Standard errors shown in parentheses. Column 2A reports the average marginal effects of a 10 mile increase in relative distance to 3DM on the probability of 3D-screening. The model is estimated using 4,751,681 unique screening observations from 2016–2019. Panel B reports the results from the regression decomposing the effect of 3D-technology on mean utility. 1B reports the OLS estimates where the independent variable is a binary indicator for 3D.

5.2 Patient Level Effects of Adoption

To measure the value patients in rural Georgia place on local access to 3DM, I use revealed preference estimates to calculate patients' willingness to pay for local access to 3DM. Denoting the option to screen with 3DM at a given rural adopter as k_{3D} and omitting market, time notation for brevity, equation 10 gives the change in travel miles needed to compensate patient i for the expected utility loss between choice set J and J', which excludes 3DM at the adopting rural hospital. I then average across patients and monetize $CV_i(J, J')$ to construct a measure of the average value patients place on 3DM at rural hospital k. I monetize this measure at a rate of \$0.77 per-mile to determine each patient's willingness to pay for local access to 3DM.[6] Figure 4 plots the average willingness to pay measure at the zip code level across changes in distance to 3DM post-adoption. I find a strong linear relationship between remoteness and average willingness to pay for local 3DM. In Panel B, I plot the total consumer surplus gain at the zip code level. Total consumer surplus is generally increasing in distance, but the relationship is weaker as the zip-codes initially furthest from 3DM tend to have lower populations.

$$CV_i(J, J') = \frac{1}{\tau_i} \left\{ \ln \left(\sum_{j,s \in J} \exp(V_{ijs}) \right) - \ln \left(\sum_{j,s \in J'} \exp(V_{ijs}) \right) \right\} \tag{10}$$

Figure 4: Consumer Surplus Gains Across Distance



Notes: This figure plots average compensating variation (right) and total consumer surplus (left) from local 3DM adoption against reductions in travel distance. Points reflects zip code averages of estimated willingness-to-pay. Dollar values are calculated by monetizing travel miles at \$0.77 per mile.

[6] This value is based on the IRS's reimbursement rate for a mile of travel in 2017 \$0.53 times 1.417 driving miles per straight-line mile (Boscoe et al., 2012).

Next, I quantify the effect of adoption on rural 3DM take-up. I use my model to construct choice removal diversion ratios. I use these diversion estimates to simulate patient demand in a counterfactual where 3DM is not available at rural adopters.

$$D_i(k_{3D} \rightarrow j_s) = \frac{(\hat{s}_{ijs})}{1 - \hat{s}_{ik\,3D})} \tag{11}$$

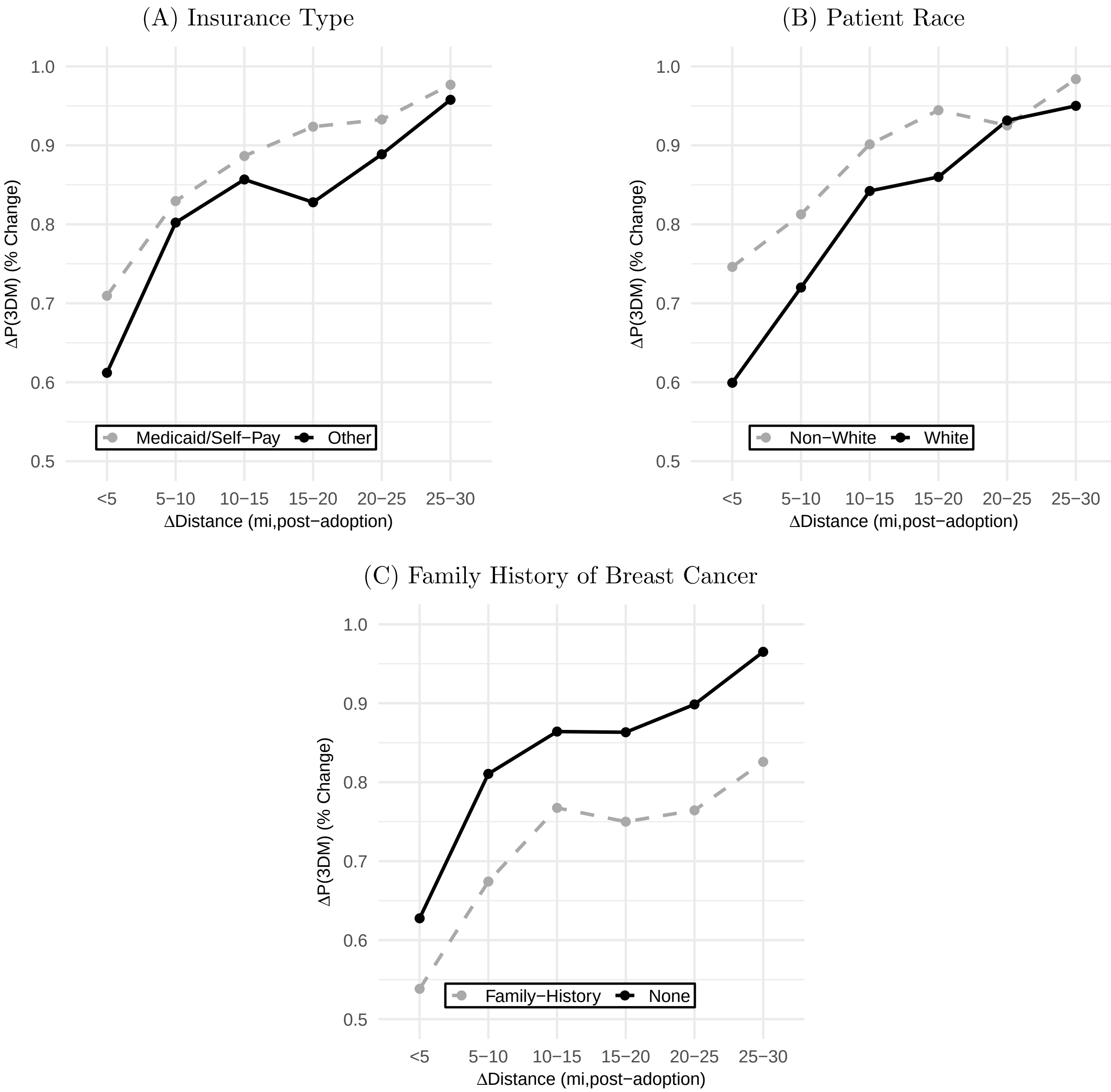
$$\Delta P_i(3D) = 1 - \sum_{j_{3D} \in J} D_i(k_{3D} \rightarrow j_{3D}) \tag{12}$$

Equation 11 gives the probability that patient i would be diverted to a given hospital screening alternative, j_s, if k_{3D} were removed from the choice set. Aggregating the set of alternative 3DM providers in a patient's choice set, I use equation 12 to measure how technology diffusion at subsidized rural hospitals impacted the likelihood of 3DM utilization. Figure 5 plots the average percentage change in the predicted probability of 3DM use across distance bins.

Panel A shows this relationship for patients based on insurance status. Across each distance bin, the model predicts that adoption will increase the probability of screening more for self-pay and Medicaid patients. A similar pattern is present in Panel B where non-white patients see a larger increase in the probability of 3DM usage. Notably, the gaps between subgroups are largest for the first distance bin, suggesting that smaller absolute travel burdens have a more salient impact on non-white patients of lower socioeconomic status. Finally, Panel C plots the same relationship based on whether patients have a family history of breast cancer. Consistent with the reduced form estimate, the model predicts that women with a family history of breast cancer are less responsive to distance when making screening decisions.

Table 6 reports the effect of rural 3DM diffusion across the distribution of observed rural adopters. Each estimate is calculated using the subgroup of patients for whom hospital k is the closest 3DM provider. Column 1 shows that rural 3DM adoption increases the mean probability of 3DM screening by 59 percentage points. I use technology substitution probabilities to predict the total reduction in false-positive screenings attributable to substitution to 3DM at hospital k. Assuming a false-positive reduction probability of 0.016 per scan, column 2 reports an average annual drop in the frequency of false-positive screenings equal to 24 (Friedewald et al., 2014). Columns 3-4 show that on average, rural patients value local 3DM at 24.74 travel miles, or \$19.03 based on a travel monetization rates of \$0.77 per-mile.

Figure 5: Technology Substitution Across Distance Bins.



Notes: Panels show the predicted change in 3DM utilization after local adoption by patient subgroup. Each panel plots average percentage changes in the probability of 3DM screening across differential-distance bins. Estimates come from the structural demand model, which incorporates travel costs and heterogeneous preferences by insurance status (Panel A), race (Panel B), and family history of breast cancer (Panel C).

Table 6: Impact of Rural 3DM Adoption on Consumer Welfare

	ΔP(3D)	ΔT1 Error	$\overline{\text{CV}}$ (miles)	$\overline{\text{WTP}}$ ($)
Mean	0.59	24	24.74	19.03
25th pct	0.48	10	17.86	13.75
75th pct	0.65	29	31.20	24.02

Notes: This table compares the impact of observed 3DM adoptions on share of patients screened with 3DM, expected false positive scans, consumer surplus and expected travel miles.

6 Welfare Effects and Counterfactual Simulations

6.1 Social Welfare

$$\Delta TS_k = \sum_i \sum_t \beta^t (\Delta CS_{it} - \Delta c_{it} - F_{it} + \underbrace{\Delta T1_{it} \cdot \text{R(Diagnostic)}}_{\text{Downstream savings}} + \underbrace{\eta^{SV} \cdot \Delta\pi_{it}^k}_{\text{Profit transfers}}) \tag{13}$$

I perform a simple back-of-the-envelope calculation to measure the welfare effects of 3DM diffusion in rural markets. Equation 13 quantifies the change in social welfare per-screening due to the availability of 3DM at a given rural hospital k. I define adoption's impact on social welfare as the change in consumer surplus net of the change in marginal resource cost of screening and the fixed cost of 3DM adoption. I take estimates of the purchase price and annual service cost of 3DM equipment from CMS's Practice Expense File. Assuming a discount rate of 3 percent over a useful equipment life of 8 years, gives a per period fixed cost F_{kt} =$23,800. I assume the marginal cost of screenings are constant across hospitals, but set the relative incremental cost of providing screening 3D-screening for hospital j at $13.7. Since 3D-screenings are less likely to return false-positive results, technology substitution likely reduces the incidence of unnecessary follow-up screenings. To reflect the positive spillovers from technology substitution, I calculate the expected reduction in health care spending by monetizing the change in the probability of a false positive recall for patient i at the Medicare reimbursement rate for a follow-up diagnostic scan. Finally, η^{SV} reflects the social value of screening profits at adopting rural hospitals, where $\eta^{SV} > 0$ relaxes the assumption that profit transfers between firms are welfare neutral. I calibrate this parameter using data on supplemental payments received by Georgia hospitals made under the Medicaid Disproportionate Share Hospital program (DSH) which reimburses hospitals for a portion of financial losses from providing care to indigent patients (Dranove et al., 2022). States have broad discretion in how they distribute these supplemental payments often distributing funds based on hospitals underlying financial health to mitigate the risk of closure. In 2016, rural hospitals meeting the criteria for the RHTC program received an additional \$0.19 in DSH payments for every dollar of uncompensated care implying that the state of Georgia places higher weight on their financial health. To reflect this preference, I set $\eta^{SV} = 0.19$.

Table 7: Impact of Rural 3DM Adoption on Social Welfare

	Total	Average
ΔCosts		
Fixed	-2,200	-137.50
Marginal	-990	-61.88
ΔVariety Gains		
CS	4,300	268.75
ΔSpillovers		
Error-Costs	440	27.50
$\eta^{SV} \cdot \pi_k$	660	41.25
Δ Welfare	2,100	131.25

Notes: This table reports welfare effect of 3DM adoptions for my primary sample of RHTC hospitals. Dollar values are reported in thousands.

Table 7 shows the components of total surplus, for the observed set of rural adopters. Column 1 shows the total effect across the entire sample while Column 2 reports hospital level averages. All dollar values are reported in thousand. I calculate an increase in total consumer surplus of \$4.3 million. Accrued fixed-cost spending totals to \$2 million while marginal screening costs increased by \$990 thousand. In my preferred specification, reductions in errors saves \$440 thousand while adopter profits result in a welfare increase of \$1 million. After accounting for these spillovers, I calculate a net welfare increase of \$2.1 million. However, even without accounting for the positive spillovers adoptions are on net welfare improving.

6.2 Counterfactual Simulations

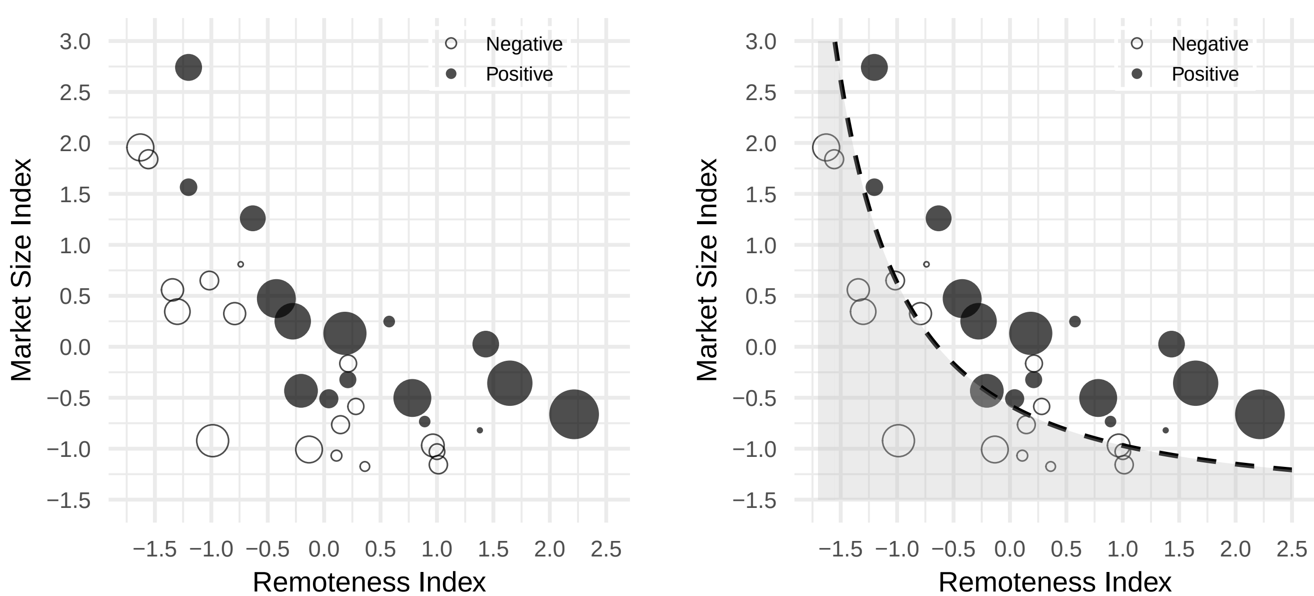
Finally, I perform counterfactual exercises, using my model to simulate the effect of alternative distributions of rural 3DM supply from 2017-2019.

Implementation: I consider the set of 33 rural Georgia hospitals who offered 2DM but not 3DM in 2016. This sample of potential rural adopters includes the 16 hospitals who actually adopt 3DM after receiving subsidies as well as the 17 never-adopters who only offer 2DM from 2016–2019. This analysis, requires out-of-sample predictions for demand at hospitals not observed to adopt 3DM.

I simulate counterfactual demand for 3DM at these hospitals using my technology preference estimates to predict service mean utilities via equation 7. To address concern that non-adopters may have lower latent demand, I draw values of ξ_{jsmt} from the bottom 10th percentile of the empirical distribution. For each counterfactual period, I draw 200 ξ_{jsmt}s for each non-adopter to compute the corresponding logit choice probabilities and report final counterfactual demand and welfare estimates as averages across the 200 simulation draws.

Figure 6 plots the welfare effects of rural 3DM adoptions at each rural hospital in characteristic space. The y-axis shows screening eligible Hospital Service Area population as a proxy for potential market size while the x-axis shows distance between the adopting hospitals and the nearest incumbent 3DM provider, a proxy for horizontal differentiation. Both axes are normalized by z-scores. I plot the welfare effect of each adoption, with the color of each bubble reflecting whether the change in total surplus was positive (dark bubbles) or negative (clear bubbles). The size of each bubble corresponds to the absolute value of the adoption's impact on total surplus. There is a clear concentration of welfare negative adoptions in the left region of the graph where rural adopters are located relatively close to incumbent 3DM providers. Conversely, hospitals with low potential market sizes are also more likely to have a negative impact on social welfare since screening volumes are insufficient to justify the large fixed cost of 3DM upgrades.

Figure 6: Welfare Effects Across Market Characteristics.



Notes: Each bubble represents a rural Georgia hospital in counterfactual adoption simulations. Bubble size is proportional to the absolute welfare effect, with color indicating sign (dark = positive, light = negative).

These patterns are reflective of the underlying trade-off between access and cost efficiency in rural health care markets. The right panel of figure 6 illustrates this trade-off by tracing a iso-welfare frontier across distance–population space. This boundary approximates the combinations of distance and market size for which the incremental welfare effect of adoption is constant. Thus, its convex slope represents the marginal rate of substitution between remoteness and market size. The shape of this curve reflects the fact that the social value of adoption is increasing in both market size and differentiation, but at a diminishing rate. As a result, gains from adoption are concentrated among hospitals that are simultaneously far enough from incumbents and large enough in potential patient volume. This relationship between welfare and market characteristics suggests that allocation mechanisms that account for remoteness and potential market size can more efficiently direct funds to hospitals where welfare gains from adoption are largest.

Finally, I explore counterfactuals, using my model to simulate demand for breast cancer screenings in rural Georgia under alternative distributions of rural 3DM supply. First, I use the model to solve for the optimal allocation of 3DM by simulating all possible combinations to find the set of providers that maximize social welfare. Second, I show the effect of a blanket investment approach, where all rural Georgia hospitals offer 3DM. Finally, I test selective allocation rules that limit 3DM adoption to hospitals above the 25th percentile of the distance or population distributions, and a two-part criterion combining a 25th percentile distance cutoff with a 25th percentile market size cutoff.

Table 8: Welfare Effects Under Counterfactual 3DM Allocations

	Optimal	Universal	Dist $> q_1$ (12-miles)	M $> q_1$ (2.5k)	Dist $\cap$ M $> q_1$
N	14	33	24	25	16
ΔTS	4,500	453	3,338	3,110	3,927
Share ΔTS_k >0	100%	36%	63%	68%	88%
Social Return on Investment	2.30	0.10	0.99	0.90	1.80

Notes: This table reports welfare effect of simulated technology upgrades across alternative supply distributions. Dollar values are reported in thousands.

Table 8 summarizes the effects of each counterfactual allocation on total surplus. Column 1 illustrates the welfare gains at the optimal set of rural 3DM suppliers. I solve for this set by iterating over all possible combinations of rural 3DM adoptions within each market selecting the group of potential 3DM adopters that maximize total surplus. This first-best allocation includes 14 hospitals which all have a positive effect on welfare increasing total surplus by \$4.5 million which corresponds to a \$2.3 social return on every dollar of investment in the rural 3DM supply. Column 2 reports the effect of universal 3DM adoption. While this allocation would have a positive net effect on social welfare, it is poorly targeted. Only 36% of hospitals offering 3DM under this blanket approach have a positive effect on net welfare.

Column 3 shows that the selective allocation rule based purely on distance, increase social welfare relative to universal adoption. These gains come from improved targeting of funds toward hospitals that are horizontally differentiated from incumbents in terms of distance, highlighting the importance of product variety in this setting. However, 10 of the 24 adopters in this set have a negative effect on welfare suggesting that allocating investments based on distance alone is insufficient since this approach tend to select adopters with insufficient scale compared to the optimal set. Similarly, the population based allocation performs better than the blanket approach. This targeting mechanism eliminates investment at the subgroup of providers who operate in sparsely populated markets, where screening volumes are insufficient to justify the large fixed cost of 3DM upgrades. However it still does not preclude socially redundant investments in markets where pre-existing access to 3DM was high.

Finally, I consider a two-part allocation criterion that targets funds based on distance and potential market size. This counterfactual combines the previous two conditions targeting investments at hospitals above the 25th percentile of the distance and market size cutoff. Preventing 3DM investment at hospitals at the tails of the characteristic distribution substantially increases the welfare effect of adoption achieving 86% of the welfare gains relative to the optimal allocation.

7 Conclusion

This paper studies the welfare consequences of 3DM adoption at rural hospitals in Georgia. Using quasi-exogenous variation from the state's Rural Hospital Tax Credit, I estimate both reduced-form effects of distance on screening choice and a structural model of patient demand. The results show that local access to 3DM substantially increases utilization of the technology, driven primarily by substitution away from lower-quality 2D-screenings. Patients exhibit strong disutility of travel, and the value they place on local adoption is highest in markets that were previously most remote from 3DM. Welfare analyses indicate that, on average, adoption improved total surplus. However, I find that the benefits of adoption vary widely across rural markets. While some adoptions generated large welfare gains, others produced net losses when placed in sparsely populated or already well-served markets. An allocation rule that conditions adoption on both remoteness and market size substantially improves targeting, delivering larger net welfare gains without unnecessary public spending.

These results highlight a fundamental tension in rural health policy: expanding geographic access to advanced medical technologies generates meaningful welfare gains, but those gains are highly heterogeneous and sometimes offset by cost inefficiencies. My analysis shows that adoption of 3DM at rural Georgia hospitals improved patient welfare on average, with every public dollar invested yielding \$0.95 in total surplus. Yet, adoptions produced net welfare losses when new scanners were placed in markets with either limited patient volume or close proximity to existing 3DM providers. These findings underscore that technology subsidies, while effective in relaxing financial constraints and facilitating adoption, can lead to over-investment if not carefully targeted. This suggests that blanket subsidies may not be the most effective way to close technology gaps. Instead, allocation mechanisms that account for observable market characteristics can more efficiently direct funds to hospitals where the welfare benefits of adoption are largest. The targeting rule I propose balances the trade-off between serving isolated patients and ensuring sufficient scale, offering a transparent framework that could be applied to other rural service lines.

These findings contribute to broader debates in health economics and industrial organization. This study provides empirical evidence on how fixed costs, geographic frictions, and patient heterogeneity interact to shape welfare outcomes from technology diffusion. In particular, I complement prior work showing that provider entry often entails both beneficial increases in product variety and socially redundant business stealing. My results show that in rural markets, these forces can be balanced by targeting funds based on observable market characteristics.

My results have a number of caveats. First, the welfare calculations rely on back-of-the-envelope monetization of travel costs and fixed cost bounds which can be biased by measurement error. Second, while I document meaningful heterogeneity across patient subgroups, data limitations prevent a full accounting of unobservable health risks that may shape willingness to travel. Finally, my setting focuses on breast cancer screening and it is unclear whether the results would fully generalize to other diagnostic technologies where cost and quality differ.

Nevertheless, these findings illustrate that rural technology upgrades can yield important improvements in access to high-quality diagnostic care, but efficiency depends on where funds are targeted. This analysis provides a framework for designing allocation policies that better balance access and cost-efficiency. Overall, this analysis illustrates that investments in rural health care quality can yield meaningful welfare gains by bringing services closer to those in need, but maximizing those gains requires careful attention to where and how those investments are made.

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Appendix Tables

Table A1: Program Information and Funding Allotments from 2017-2019

	2017	**2018**	**2019**
Eligibility			
County Population	35,000	50,000	50,000
Qualifying Hospitals	50	58	58
Participating Hospitals	49	58	58
Donations ($1,000s)			
Statewide Cap	10,000	60,000	60,000
Total	9,227	59,505	46,516
Mean	188.3	1,025.9	802.0
25th Percentile	59.0	634.2	340.5
50th Percentile	128.0	865.0	579.5
75th Percentile	243.0	1,268.5	918.2

Notes: This table shows eligibility for the program and the evolution of donations received from 2017-2019. In 2017, RHTC funds were only available to non-private hospitals in counties with populations below 35,000. In 2018, the population limit was raised to 50,000 and the number of participating hospitals increased to 58. Over this time frame, nearly every qualifying hospital received RHTC funds. The statewide cap on donations was raised by $50 million in 2018, which led to a sharp increase in total and average funds received. Source: Georgia Department of Community Health.

Table A2: Reported Use of Funds and Spending Across Categories in 2018

	Funds Available	**Funds Spent**	**Funds Reserved**
Mean	$1,080,189	$871,584	$208,604
25th Percentile	$684,623	$415,541	$0
50th Percentile	$904,350	$802,032	$0
75th Percentile	$1,292,252	$1,234,524	$386,388

Category	**Mean Spending**	**Median Spending**	**Frequency of Spending**
Operations	$383,898	$93,570	32
Personnel	$32,329	$13,125	16
Med-Equipment	$249,948	$82,409	36
Facilities	$219,484	$24,180	26
Other	$147,725	$35,741	53

Notes: This table shows summary statistics from hospital level reports on utilization of RHTC funds in 2018. Columns 2, 3, and 4 shows summary statistics for the amount of RHTC funds available to hospitals in 2018, funds spent in 2018, and unspent funds that hospitals kept as financial reserves. On average, hospitals spent 80% of funds available, and held the remaining 20% as cash reserves. The reported distribution shows that more than half of all hospital spent all available funds in 2018. The bottom half of panel B shows a breakdown of hospital spending across categories. The largest share of RHTC funds were spent on regular operating expenses. The second largest reported expenditure category in 2018 is purchases of medical equipment. Source: Georgia Department of Community Health.

Table A3: Summary Statistics

	Treated	Control	*p-value*
Panel A: Hospital			
Net Worth	14,417.7	16,359.51	(0.428)
	[21,544.1]	[29,247.45]	
Fixed Assets	14,537.8	13,876.4	(0.595)
	12,426.8	14,227.5	
Hospital Equipment	11,760.7	11,342.4	(0.59)
	[7,438.6]	[8,906.7]	
FTE	0.25	0.29	(0.37)
	[0.16]	[0.32]	
Inpatient Days	6.65	7.18	(0.475)
	[6.42]	[8.54]	
Beds	51.4	49.5	(0.80)
	[41.00]	[56.49]	
Government Owned	0.63	0.64	
Hospital Count	58	95	
Panel B: County			
County Population	23,808.9	27,623.9	(0.01)
	[13,700.7]	[17,244.8]	
Percent Uninsured	18.7	16.7	(0.01)
	[3.2]	[3.6]	
Percent Above 65	15.9	16.5	(0.05)
	[4.1]	[2.7]	
Percent Employed	89.6	87.5	(0.01)
	[2.9]	[3.9]	

Notes: This table displays mean 2016 characteristics for subsidized rural Georgia hospitals and rural control hospitals from other southern states. Standard deviations are shown in brackets and p-values are shown in parentheses. County demographic variables are taken from the American Community Survey. Source: HCRIS.

Table A4: Identifying Screening Mammograms from CPT Codes

Modality	Screening	Diagnostic
3DM	77063	G0279, G0204, G0206
2DM	77067, G0202, 77057, 77052	77065, 77066,77051, 77055, 77056, G0204, G0206

Notes: This table displays the procedure codes used to identify screening and diagnostic mammography encounters across imaging modalities.

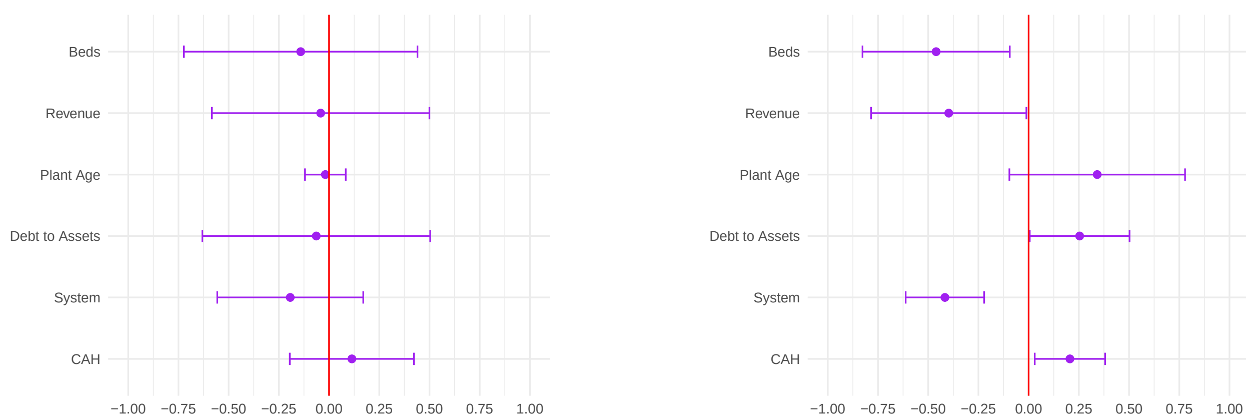
Table A5: Comparing HCUP Screening Counts to Medicare Claims

Service	Medicare	HCUP	Percent
Screening 3DM	85,515	74,859	87
Screening 2DM	173,719	132,223	76

Notes: This table displays a comparison of screening mammography procedure counts between my primary data source and public-use Medicare aggregate files across Georgia in 2018. To match the Medicare population, I subset the HCUP data to individuals insured by Medicare FFS. At the state level, I capture 87% of 3DM screenings and 76% of 2DM screenings.

Appendix Figures

Figure A1: Characteristics of Rural 3DM Suppliers Change in the Post-Subsidy Period



(a) GA vs Control 2016 **(b) GA vs Control 2019**

Notes: These coefficient plots show estimated differences in mean characteristics between rural hospitals offering 3DM in GA vs control states. In 2016, these hospitals are very similar, but by 2019, the group of rural hospitals offering 3DM in GA are smaller and have lower historic resources. This suggests that the subsidy changed the composition of GA 3DM suppliers. All variable normalized by Z score transformation. Source: HCRIS

Appendix C

This section tests for evidence of the effect of rural 3DM adoption on county level mammography screening compliance. I use two measures of screening compliance in this analysis, the first is constructed using Georgia HCUP data from 2016-2019. Over this sample period, the United States Preventative Service Taskforce recommended women ages 50 and up receive a screening mammogram every two years. I calculate two-year screening compliance at the county level using patient identifies in the discharge data to construct a measure of the number of unique screenings given to women in each Georgia county over a two year interval. I then scale this count by the ACS estimate of female county population for women 50 and up. I supplement this analysis with an additional county level compliance measure from the Dartmouth Atlas Dataverse's Selected Primary Care Access and Quality Measures Data set. This data contains county level two year mammography screening compliance rates for women ages 67-69 in the fee-for service medicare population. For each data set, estimate the following two-way fixed effects model:

$$Y_{ct} = \beta_0 + \beta_1 * Rural * Post_{ct} + C + \tau + e_{ht}$$

Where Rural is an indicator for whether county c is defined as rural by the RHTC eligibility criteria, and $Post_{ct}$ is an indicator that equals 1 if any hospital in county c provides 3DM at time t. I estimate this model using county and year fixed effects. β_1 captures the average effect of rural 3DM adoption on county screening compliance rates, and is identified by differences in compliance trends between rural adoption counties all other counties in the state before and after adoption. Column 1 of Table A6 reports estimate of β_1 using the HCUP compliance measures while column 2 shows the estimate from the Medicare FFS sample. Both estimates are small and statistically indistinguishable from zero, suggesting that rural 3DM adoption leads to substitution across screening types rather than an increase in screening compliance.

Table A6: County Screening Compliance and Rural 3DM adoption

	(1)	(2)
$Rural * Post_{ct}$	0.0103	0.002
	(0.809)	(0.953)
Data Set	HCUP	Dartmouth Atlas
Sample Mean	0.68	0.71
County FE	Y	Y
Year FE	Y	Y
County Year Observations	415	415

Notes: This table shows estimates from a model regressing county level screening compliance rates on an indicator for rural 3DM adoption. Source: HCUP/Dartmouth Atlas.