**Information Gaps and Health Insurance Enrollment:**

**Evidence from the Affordable Care Act Navigator Programs**

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**Abstract**

We studied the impact of Affordable Care Act navigator programs on health insurance coverage, using the 80% cut in program funding under the Trump administration as a natural experiment. Our study design exploited county-level differences in the program prior to funding cuts. We did not find that cuts to the program significantly decreased rates of marketplace coverage or any health insurance coverage by 2019; however, our estimates could not rule out marketplace coverage declines of up to 2.7% (point estimate -1.3%, 95% CI -2.7% to 0.1%), or total coverage declines of up to 1.8 percentage points (point estimate -0.8 percentage points or -1.2%, 95% CI -1.8 to 0.2). Cuts to the navigator program significantly decreased marketplace coverage and total coverage among lower income adults, and significantly decreased total coverage among adults under age 45, Hispanic adults, and adults who speak a language other than English at home. We found no significant impact of the cuts on Medicaid enrollment (95% CI -1.9 percentage points to 0.5 percentage points); most uninsured people in the states we studied lived in locations that had not implemented Medicaid eligibility expansions. These findings suggest that before the funding cuts, navigators were helping underserved consumers obtain coverage.

## I. Introduction

Health care expenditures account for more than 18% of the United States GDP, and health insurance plays an important role in reducing the costs of care for patients and shielding patients from medical bankruptcy (Barcellos and Jacobson 2015; Finkelstein et al. 2011; Gross and Notowidigdo 2011). Yet many Americans have a limited understanding of the terms that define the financial value of insurance, such as *deductible* and *copayment,* or are unaware of the full range of insurance options available to them (Hoerl et al. 2017; Norton, Hamel, and Brodie 2014; Bhargava, Loewenstein, and Sydnor 2017). This lack of knowledge about the available health insurance options is reflected in the large number of people who enroll in dominated plans (e.g., paying more for equivalent or worse coverage than another available option) or do not enroll in freely available Medicaid coverage even though they qualify[1] (Bhargava, Loewenstein, and Sydnor 2017; Rice, McCall, and Boismier 1991; Sinaiko and Hirth 2011; Heiss et al. 2013; Sommers and Epstein 2010; Stuber and Bradley 2005).

A large government initiative implemented under the Affordable Care Act (ACA) provided free, in-person assistance with interpreting and comparing health insurance options. The ACA required comparable "assister" programs to be established in all states, although the exact funding streams and the names of the assister programs varied across states (Department of Health and Human Services 2013). In the first three years of the initiative, more than 28,000 full-time-equivalent staff working in over 4,400 assister programs helped an estimated 21.8 million consumers nationwide with their insurance decisions (Pollitz, Tolbert, and Ma 2014; Pollitz, Tolbert, and Semanskee 2016; Pollitz, Tolbert, and Ma 2015). However, little is known about the

[1] Medicaid is a public health insurance plan in the United States that provides coverage free of charge for people who meet certain qualifications set by their state of residence.

effects of this initiative on health insurance outcomes. Using data from a three-state survey, one study found higher enrollment rates in states where more people received application assistance (Sommers et al. 2015). Another study found increased marketplace enrollment in locations served by one specific assister program, Enroll America, during the first open enrollment period (Orzol and Hula 2016). However, neither study was able to distinguish the impact of state-level variation in consumer assistance programs from the effects of other policies that vary at the state level. Understanding whether and how assister programs impacted health insurance outcomes is crucial for ongoing policy discussions and for the design of similar initiatives going forward.

This paper studies the navigator program, the branch of the assister program created under the ACA for the more than 30 states that opted not to create their own health insurance marketplaces.[2] Our analysis is timely—funding for the navigator program, which is determined at the federal level, was cut by more than 80% under the Trump administration over 2017-2020 (Pollitz, Tolbert, and Diaz 2017; Keith 2018; 2019; Center for Consumer Information and Insurance Oversight 2018). In April 2021, the United States Department of Health and Human Services announced that navigator grant funding will be reinstated and increased beyond the original levels (Department of Health and Human Services Press Office 2021; Pollitz, Tolbert, and Orgera 2021). Measuring the effects of these changes in funding levels will be critical to ongoing policy discussions.

[2] Under the ACA, all states must be served by a health insurance marketplace that provides standardized coverage options available for purchase by any individual. States that implemented a state-based marketplace are responsible for performing all functions of running this marketplace. Consumers in these states apply for and enroll in coverage through marketplace websites that are established and maintained by the states.

The availability of high-quality data on program implementation and enrollment outcomes makes the navigator program an attractive topic for analysis. The available data allow the measurement of within-state variation in the implementation of the navigator program. Publicly available federal records detail which counties were served by each navigator organization in each year (Centers for Medicare and Medicaid Services 2019b). These detailed records are available because the federal government funds the navigator program via grants to specific organizations (e.g., the Southern Illinois Healthcare Foundation, or the Great Plains Tribal Chairmen's Health Board in South Dakota) rather than grants to states. In addition, there are publicly available data on enrollment in the health insurance marketplaces established under the ACA in each county served by the navigator program (Centers for Medicare and Medicaid Services 2019a). All states covered by the navigator program use the same Healthcare.gov platform for their marketplaces, and the county level enrollment data are publicly reported by CMS across all states (Department of Health and Human Services 2013; Centers for Medicare and Medicaid Services 2019a).

Our study design leveraged the 84% cut in funding for the navigator program under the Trump administration as a natural experiment. In each state, some counties were more affected by these funding cuts than others because they had been previously served by not only statewide navigator programs but also one or more navigator programs with a geographically localized service area (e.g., the Young Women's Christian Association of Greater Pittsburgh). We exploited this geographical and temporal variation to estimate event study models that measured changes in health insurance outcomes as a function of the presence of non-statewide navigator programs prior to the funding cuts. Importantly, the models adjusted for current policy at the

state and year levels (using state-by-year indicator variables) as well as national trends, time-invariant county-level characteristics, and key time-varying confounders.

We studied the impacts of these funding cuts on multiple health insurance and health care outcomes. We used three measures of health insurance coverage: enrollment in the health insurance marketplace, enrollment in Medicaid coverage, and enrollment in any health insurance coverage; we also examined enrollment in Medicare coverage as a placebo check. Additionally, following prior studies of health insurance changes or churn under the Affordable Care Act, we measured transitions across types of coverage and patterns of health care use over time (Vistnes and Cohen 2016; Sommers et al. 2016).

We did not find that cuts to the navigator program significantly decreased rates of marketplace coverage or any health insurance coverage by 2019; however, our estimates could not rule out marketplace coverage declines of up to 2.7% (point estimate -1.3%, 95% CI -2.7% to 0.1%), or total coverage declines of up to 1.8 percentage points (point estimate -0.8 or -1.2%, 95% CI -1.8 to 0.2). The cuts did significantly decrease marketplace coverage among low-income adults, and significantly decreased total coverage among low-income adults, adults under age 45, Hispanic adults, and adults who speak a language other than English at home. We found no significant impact of the cuts on Medicaid enrollment, although most uninsured people in the states we studied lived in locations that did not expand Medicaid eligibility among low-income adults. Finally, models using data from a smaller sample due to data limitations did not detect impacts of program cuts on within-person changes in health insurance coverage or health care use by 2018. Taken together, these results suggest that navigators helped underserved groups of consumers obtain coverage, consistent with the program's original intent (Congressional Research Service 2021).

This paper contributes to the literature on how information frictions shape consumers' health insurance decisions (Handel and Kolstad 2015; Handel 2013). Previous studies found that letters or automated information from decision-support algorithms can increase enrollment in insurance or improve choice quality (Domurat, Menashe, and Yin 2021; Bundorf et al. 2019; Goldin, Lurie, and McCubbin 2021; Feher and Menashe 2021). However, some researchers and practitioners have expressed a concern that reducing information frictions can exacerbate adverse selection, although the magnitude of the effect remains an empirical question (Handel 2013; Ericson and Sydnor 2017; Domurat, Menashe, and Yin 2021). We extend the literature by assessing the health insurance impacts of personalized assistance on a large scale, in the context of a large government program slated for further expansion (Department of Health and Human Services 2013; Congressional Research Service 2021; Pollitz, Tolbert, and Orgera 2021). Our finding that the navigator program influenced coverage among adults under age 45 but not older adults echoes recent findings that addressing information barriers can disproportionately increase enrollment among healthier adults (Domurat, Menashe, and Yin 2021).[3] Further, the finding that funding cuts impacted coverage among underserved groups such as those who experience a language barrier suggest that the policy may have improved equity in access to insurance.

## II. Background

The ACA was designed to reduce the uninsured rate in the United States, in part by opening new health insurance marketplaces—platforms where consumers can shop for and purchase health insurance—in each state. Despite some standardization, choice sets in the state

[3] We cannot measure the sorting of individuals who are different ages, or who differ on other risk measures, across health insurance plans.

marketplaces are complex and can be difficult for consumers to navigate without assistance (Politi et al. 2016; Barnes, Hanoch, and Rice 2015). Insurers offer standardized plans that are categorized and labeled in a tiered manner (e.g., bronze, silver, and gold) according to their actuarial value. However, plans in the same tier vary substantially in terms of carrier, physician and hospital network, and specific cost-sharing arrangements. Further, consumers' choice sets vary by county or zip code as well as household income. For example, consumers with a household income under 250% of the federal poverty level (FPL) are eligible for plans with additional cost-sharing reductions, which are categorized as silver plans. This can lead to a potentially confusing situation for some consumers because a "silver" plan may provide superior coverage – a higher actuarial value – at a lower cost than a "gold" plan (Feher and Menashe 2021; Rasmussen and Anderson 2021). Finally, premium prices and health insurance options outside the marketplaces can also vary by household income. During the time period we studied, consumers with a household income under 400% of FPL were eligible for premium subsidies based on a sliding scale, and in many states, consumers with income under 138% of FPL were eligible for publicly provided Medicaid coverage at no cost (Kaiser Family Foundation 2021).

Consumers' ability to navigate this complex set of health insurance options may be hampered by their limited knowledge of coverage details, such as the availability of subsidized or free coverage options (Barcellos et al. 2014; Hoerl et al. 2017). Low health insurance literacy may amplify their confusion. Many Americans are uncomfortable with one or more key terms used to define health insurance plan generosity, such as *provider network* and *deductible* (Barcellos et al. 2014; Long et al. 2014; Norton, Hamel, and Brodie 2014). For example, on a multiple choice test, only 16% of respondents correctly identified the cost of an out-of-network lab test with a capped allowable charge (Norton, Hamel, and Brodie 2014). Unsurprisingly,

individuals with low health insurance literacy are more likely to have difficulty comparing health insurance plans on the ACA health insurance marketplace websites (Wang et al. 2017; Hero et al. 2019; Barnes, Hanoch, and Rice 2015). Importantly, two of the key populations targeted by the ACA—low-income households and the uninsured—are most likely to have low health insurance literacy (Barcellos et al. 2014; Hoerl et al. 2017).

To address potential difficulties in navigating health insurance coverage options, the ACA established assister programs in every state. These programs were designed to "play an important role in facilitating a consumer's enrollment" in a qualified health plan[4] by providing consumers with "fair, accurate, and impartial information" about health insurance, the health insurance marketplaces, and insurance affordability programs such as subsidies in the marketplaces and the Medicaid program (Department of Health and Human Services 2013). Further, the ACA originally required that assister services be offered by at least one community-based group and one consumer-focused nonprofit group in each state. Private-sector brokers, a group of professionals who help private insurance companies sell their products, provide similar services but served a different clientele. According to a national survey of brokers and publicly funded assisters, assisters' clients were more likely than brokers' clients to be uninsured and to have limited English proficiency, a low income, and lacked Internet at home (Pollitz, Tolbert, and Semanskee 2016).

[4] A qualified health plan is an insurance plan that is certified by the health insurance marketplaces, covers a minimum list of services called essential health benefits, follows established limits on cost sharing (e.g., deductibles, copayments, and out-of-pocket maximum amounts), and meets other requirements established by the ACA.

## A. FUNDING FOR THE NAVIGATOR PROGRAM AND IDENTIFYING VARIATION

Navigator grants are federal grants that fund public-sector assisters in a subset of states, namely, states that adopted a federally facilitated[5] or partnership model[6] for their health insurance marketplaces rather than establishing their own state-based marketplace. The assisters supported by these funds are called navigators. While the total funding allocated to each state is decided federally, the distribution of navigator activities within the state is determined by the proposed service areas of grantee organizations. Programs receive funds by submitting proposals in response to annual funding opportunity announcements, and each grantee is required to disclose the counties included in their service area.

In 2015, the Centers for Medicare and Medicaid Services (CMS) changed the project period for navigator grants from 12 months to 36 months (three years). Funding was to be distributed in 12-month increments, and awards were expected to total $201 million (U.S. Department of Health and Human Services 2015). In the first two years of the three-year project period (2015 and 2016), CMS provided $60 million and $63 million, respectively, for navigator grants. In the third year of the three-year project period and the first year of the Trump administration (2017), CMS cut navigator grants substantially with very little advance notice (Pollitz, Tolbert, and Diaz 2017). In May 2017, CMS notified navigator grantees of the

[5] In a federally facilitated marketplace, the U.S. Department of Health and Human Services performs all marketplace functions. Consumers in states with a federally funded marketplace apply for and enroll in coverage through Healthcare.gov.

[6] States that run a state-based marketplace using the federal platform are responsible for performing all marketplace functions for the health insurance marketplace with one exception—the state relies on the federal Healthcare.gov website for eligibility and enrollment functions. Consumers in these states apply for and enroll in coverage through Healthcare.gov.

availability of $60 million. Grantees submitted work plans and budgets in June, with notice of awards scheduled for September 1. However, on August 31, 2017, CMS announced that the navigator grants would be cut by 41%, to just $37 million.

This funding cut substantially reduced navigators' ability to assist consumers. In a 2017 survey of representatives from 40 navigator programs, 89% expected to cut staff because of the funding reduction and 57% expected to limit the time staff could devote to helping consumers with complex cases. In addition, 54% of programs expected to scale back services for limited- or non-English speaking consumers (Pollitz, Tolbert, and Diaz 2017).

Further cuts to the navigator grants were implemented in the subsequent years of the Trump administration. In 2018, navigator program funding was reduced to $10 million, and this level was maintained for the next two years (Keith 2018; 2019). Figure 1 depicts the annual funding for navigator grants from 2014 through 2020.

The requirement that navigators provide in-person assistance was also weakened under the Trump administration. Originally, navigators were required to provide in-person assistance in all counties they served but starting in June 2018, "remote application assistance (e.g., online or by phone)" was allowed (Centers for Medicare and Medicaid Services 2018). This change in service requirements further decreased navigators' availability because many consumers who seek assistance from the program lack internet access (Pollitz et al. 2020).

One feature of these funding cuts was particularly important to our analytic strategy. The Trump administration maintained that the size of the cuts to specific navigator programs' grants was related to each program's prior success in enrolling consumers in the health insurance marketplace.[7] The data used for this calculation were not made publicly available and the claim

[7] While the text of this announcement is no longer posted online, it is quoted in Pollitz, Tolbert, and Diaz (2017).

has been disputed by navigators, who asserted that many of the enrollments they helped consumers complete were not recorded by the marketplace system (Pollitz, Tolbert, and Diaz 2017). Nonetheless, we assume that the size of the cuts experienced by specific navigator grantees may not be exogenous to the grantee's impact on health insurance outcomes. Accordingly, our analysis did not use the size of cuts for identification and instead leveraged variation in the locations served by each navigator grantee prior to cuts.

Shifts in the health insurance policy environment at both the national and state levels also shaped health insurance trends, and thus influenced our analytic strategy. First, marketplace enrollment trends were likely shaped by several national-level changes implemented by the Trump administration, such as reducing the length of the open enrollment period and expanding access to more loosely regulated plans of short duration outside the marketplace (Drake and Anderson 2020; Anderson and Shafer 2019; Kamal et al. 2018). In addition, proposed changes to the definition of a public charge (a person dependent on public aid for sustenance) implied that Medicaid enrollment became a potential roadblock to becoming a United States permanent resident (Parmet 2019; Shaw 2019), and thus Medicaid enrollment likely declined among people who were not citizens or permanent residents.

Second, certain state-level changes in health policy were relevant to insurance enrollment. During the study period, many states expanded eligibility for Medicaid among low-income adults, established state-based health insurance marketplaces, changed the process for income verification for Medicaid enrollment or renewal of Medicaid enrollment, and/or pursued demonstration waivers creating special considerations in their Medicaid programs, among other changes (Families USA 2019; Kaiser Family Foundation 2021; Georgetown University Center for Children and Families and The Henry J. Kaiser Family Foundation 2015; Guth et al. 2020;

Schwab 2019). These state-level policy shifts shaped Medicaid and marketplace enrollment outcomes (Families USA 2019; Miller and Wherry 2019; Kaestner et al. 2017; Wehby and Lyu 2018). Given these concurrent changes in health policy, accounting for background trends at the national and state levels was crucial to isolating the impacts of cuts to the navigator program.

To account for these national- and state-level trends, our analytic strategy used within-state variation to assess the impact of cuts to navigator grants. Specifically, we leveraged county-level variation in the type of navigator program available to residents just prior to the funding cuts. To clarify the identifying variation, consider a specific state in the analysis without loss of generality. This state is served by two sets of navigator programs: those in the first set ($P_S$) serve all counties in the state (e.g., the Affiliated Service Providers of Indiana), while those in the second set ($P_L$) serve some but not all counties in the state (e.g., Community Action of Southern Indiana). Each county in the state is either a control county, which was served only by the statewide programs $P_S$ in the year prior to funding cuts,[8] or a treatment county, which was served by both statewide programs $P_S$ and one or more local programs $P_L$ in the year prior to funding cuts. Now, consider the impact of funding cuts in these two types of counties—cuts to funding for $P_S$ affected both treatment and control counties, but cuts to funding for $P_L$ affected only treatment counties. Our analytic strategy used this variation.

Finally, our analytic strategy was informed by the fact that navigator grantees proposed to target their services to specific populations as part of their mission. The specific populations targeted varied across navigator programs, and most navigator programs had many target groups. For example, in 2017 Westside Family Healthcare in Delaware proposed to target chronically ill

[8] In states with no state-wide programs, $P_S$ is the empty set. In that case, counties in the control group are not served by any navigator programs.

and disabled consumers, low-income consumers, and justice involved individuals; and the Georgia Association for Primary Health Care targeted rural consumers, veterans, Latino consumers and other minoritized racial or ethnic groups, the self-employed, and women with children. Cutting funding for these navigator programs could have disproportionately affected coverage among these targeted populations. To assess whether consumers in the navigator programs' targeted populations lost coverage after funding cuts, we examined data from populations that had been targeted by many navigator programs. These populations included consumers with low income, consumers who spoke a language other than English at home, and consumers who identified as Black or as Hispanic.

## III. Data and measures

### A. EXPOSURE OF INTEREST

The main exposure of interest was whether a county was served by non-statewide (hereafter, local) navigator programs in the fall of 2016, the year before funding cuts were implemented.[9] Specifically, treatment counties were served by local navigator programs in 2016, whereas control counties were not. We used publicly available CMS records to measure the

[9] We could not analyze the impact of funding cuts in terms of dollar amount for two main reasons. First, CMS did not track the distribution of funds across counties for multi-county navigator programs, and navigator programs were not required to track the distribution. Given that no available data existed to indicate that a specific person was enrolled by a given navigator program, it was only possible to analyze at the geographic level rather than the navigator program level; accordingly, the lack of a crosswalk of funds from program level to county level was a key impediment. Second, even if we could reconstruct the allocation of funds to each county within multi-county programs, the size of funding cuts to each program could be endogenous to the program's prior performance.

service area of each navigator program (Centers for Medicare and Medicaid Services 2019b). Figure 2 shows the location of treatment and control counties within each state served by the navigator program.

## B. OUTCOMES OF INTEREST

Following the literature on insurance coverage, we used multiple measures of health insurance outcomes to study the impacts of the navigator program. We measured enrollments in the health insurance marketplaces using administrative data in Healthcare.gov, the platform used in all states served by the navigator program (Centers for Medicare and Medicaid Services 2019a; Congressional Research Service 2021). In addition to analyzing total marketplace enrollment, we examined the data by enrollment history (new enrollee vs. active re-enrollee), plan choice (enrolled in a cost-sharing reduction plan), income level (150-200% of FPL vs. 200-250% of FPL), and enrollee age (under 45, 45-54, 55-64). Importantly, data limitations influenced our selection of analytical outcomes—enrollment numbers were censored (i.e., masked in the data) if there were fewer than ten enrollees in a given enrollment category in a county. The outcomes listed above comprised all the available outcomes that were censored in fewer than 3% of counties.[10]

In addition, we measured changes in total health insurance coverage and Medicaid coverage. As noted above, two key goals of the navigator program were to inform consumers about affordability programs, including Medicaid, and to facilitate health insurance enrollment

[10] We could not analyze other outcomes, such as the number of enrollees with income over 250% or under 150% of FPL, or the number of enrollees over age 65, because these counts were low and therefore censored in many counties.

(Department of Health and Human Services 2013). Due to the lack of county-level administrative data on either Medicaid enrollment or total health insurance enrollment during the study period, we measured these outcomes using data from the American Community Survey (ACS), which is conducted by the Census Bureau and gathers information from over 3 million people annually (Ruggles et al. 2021). In a placebo check, we also examined changes in Medicare coverage among people aged 65 and older; because enrollment in Medicare at age 65 is automatic for eligible individuals, this outcome is unlikely to be affected by the navigator program.

Finally, we used panel data from a cohort of individuals to measure changes in coverage status and health care use over time (Vistnes and Cohen 2018; 2016). Shifts in health care use could occur because of changes in coverage status or changes in how consumers use their coverage after learning more about it from a navigator. Prior data suggest that in the absence of assistance, consumers often do not respond optimally to the complex structure of their insurance contract (Brot-Goldberg et al. 2017). This analysis used restricted-use data from the Medical Expenditure Panel Survey (MEPS) merged with data from the National Health Interview Survey data (NHIS), which allowed us to observe several nationally representative cohorts of individuals living in the United States. A new nationally representative cohort is recruited each year and followed for a total of three years, completing the NHIS in the first year and the MEPS in the following two years.

We analyzed multiple measures of coverage changes and patterns of health care use from these data in models with individual-level fixed effects. Coverage measures in the MEPS data included whether the participant had any coverage, Medicaid coverage, or marketplace coverage at the time of the survey; in the NHIS, we measured whether the participant had any coverage.

(Unlike NHIS and some other surveys, the MEPS includes specific variables capturing marketplace-purchased coverage, distinct from any other non-group individually purchased insurance.) The MEPS data included four health care use measures: participants' reports of any hospital outpatient visits or office-based provider visits, any overnight hospitalizations, any emergency room visits, and any dental visits for the survey year.[11] Our analysis focused on the first three measures of health care use; results were similar for dental care.

## C. STUDY SAMPLE

The analytic dataset included data from 2015 through the most recent year available.[12] Selecting 2015 as the baseline year has three practical advantages. First, as noted above, 2015 was the first year of a three-year project period for navigator grantees. If there had not been a policy change under the Trump administration, the grants distributed in 2017 would have been very similar to those distributed in 2015 and 2016 (U.S. Department of Health and Human Services 2015). Second, given that the health insurance marketplaces and the navigator program were just becoming established in 2014, this year can be considered a transition year. Finally, data on county-level enrollment in Healthcare.gov, the main outcome of interest, are not available for 2014.

The analytic dataset included the 33 states that met the eligibility criteria for the navigator program throughout the study period of 2015-2019 (i.e., did not have a state-based marketplace

[11] Comparable measures were not available in the NHIS.

[12] At the time of analysis, MEPS data were available through 2018; Small Area Health Insurance Estimates of population data were available through 2018, which precluded us from using data after 2019 in the administrative data models that adjusted for lag of county-level population; and American Community Survey data were available through 2019.

in any year between 2015 and 2019). As a result of this exclusion criterion, all states in the analytic sample were observed for the same number of periods both before and after funding cuts. The final analytic sample using the Healthcare.gov data contained 2,435 counties, including 1,333 in the treatment group and 1,102 in the control group. Due to the ACS sampling strategy, which samples different counties every year, the final analytic sample using the ACS data included only 179 counties in the treatment group and 127 counties in the control group (U.S. Census Bureau 2020).

In analyses of survey data (i.e., models of Medicaid enrollment, total health insurance enrollment, and health care use), we implemented further exclusion criteria related to the characteristics of individual survey respondents. Importantly, we included only United States citizens in the sample because the Trump administration's changes in the definition of a public charge might have changed Medicaid enrollment trends among non-citizens (Parmet 2019). To focus on people most likely to seek enrollment assistance from navigators, the main analysis excluded children, adults aged 65 and older, and people with employer-sponsored coverage. A placebo check used data from adults aged 65-80, a group unlikely to seek enrollment assistance from navigators due to nearly-universal enrollment in Medicare coverage.

## IV. Empirical strategy

Our empirical strategy compared changes in health insurance and health care outcomes across counties within states, before versus after large cuts in funding for the navigator program. Because local navigator programs served only certain counties within the state, we used county-level differences in prior exposure to the local navigator programs within each state for identification. The Trump administration implemented the funding cuts in 2017, just prior to the open enrollment period for 2018 coverage. Accordingly, in the analysis, the pre-cut period

comprised 2015-2017 and the post-cut period comprised 2018 and later years. Coefficients for the pre-cut period were used to assess the credibility that the estimates were causal.

We used event study models that compared changes in outcomes across two types of counties, those served by any of the state's local navigator programs in 2016 (treatment counties) and those not served by local navigator programs in 2016 (control counties). The models measured the adjusted difference in outcomes between treatment and control counties each year in the pre-cut and post-cut periods and tested for changes in these differences over time. These models included state-by-year fixed effects and county fixed effects in the following specification:

$$y_{cst} = \alpha_c + \varphi_{st} + Treatment_c \times \sum_{\substack{k=-3 \\ k\neq -1}}^{1} \delta_k I(t - 2018 = k) + \beta Z_{ct} + \gamma Unemployment_{ct} + \varepsilon_{cst} \quad (1)$$

where $y_{cst}$ represents an outcome (e.g., enrollment in marketplace insurance) within county *c* in state *s* in year *t*, $\alpha_c$ is a vector of county fixed effects, and $\varphi_{st}$ is a vector of state-by-year fixed effects. $Treatment_c$ is an indicator of whether the county was a treatment county. $I(t - 2018 = k)$ is an indicator variable that takes the value 1 if year *t* is *k* years away from the start of the post-cut period (2018). The omitted category was the final year of the pre-cut period. All models adjusted standard errors for clustering at the state level. The coefficients of interest were $\delta_0$ and $\delta_1$, which captured changes in outcomes associated with the treatment (i.e., larger exposure to cuts in the navigator program).

The models adjusted for a vector of time-varying covariates associated with health insurance coverage outcomes. First, because employment is a key determinant of coverage outcomes, the models adjusted for $Unemployment_{ct}$, a measure of unemployment at the county

level during the prior calendar year based on data from the Bureau of Labor Statistics. (Given the possibility of mutual causality between health policy and labor market outcomes [Aizawa and Fang 2020], we presented results with and without adjusting for this covariate.) Models also adjusted for additional time-varying covariates $Z_{ct}$, which varied depending on the data source. In the administrative data analyses, the outcome of interest was the log of enrollment at the county level; accordingly, the models adjusted for the county's population in the prior calendar year to reflect population levels during the open enrollment period (U.S. Census Bureau 2019). In the survey data, enrollment outcomes were measured at the individual level; accordingly, we controlled for individual-level characteristics which are associated with health insurance outcomes, including age, race/ethnicity (including indicators for the non-mutually exclusive categories of white, Hispanic, and Black), gender, and smoking status (only available in the MEPS and NHIS data). Models that used survey data from the same individuals over a multi-year period also included individual-level fixed effects.

The validity of the analysis relied on the assumption that trends in outcomes in the two groups of counties—treatment and control—would have remained parallel in the absence of the funding cuts initiated under the Trump administration. While this assumption cannot be tested, a lack of pre-existing differences between trends in treatment and control counties would provide evidence of its plausibility. Accordingly, we conducted an F-test of the joint significance of the coefficients identifying changes in the differences between treatment and control counties during the pre-cut period (i.e., $\delta_{-3}$ and $\delta_{-2}$, given that the year prior to cuts is the omitted category). A non-significant result would indicate parallel trends in these counties, and thus support the validity of the analysis. In a supplementary analysis, we also assessed whether a single state

might be driving the results by systematically dropping states one at a time and re-estimating the models.

To interpret the sign of the coefficients of interest, $\delta_0$ and $\delta_1$, it is helpful to know whether treatment counties were more exposed to navigator program cuts than control counties. If treatment counties were more exposed to funding cuts than control counties, a negative coefficient would suggest that cuts to the navigator program decreased coverage. CMS did not track the distribution of funds across counties for multi-county navigator programs, and navigator programs were not required to track this distribution. Therefore, to assess the plausibility of the assumption that treatment counties experienced more cuts than control counties, we invited the navigator program contacts listed in the 2016 CMS records (one contact per program) to complete an online survey. In addition, we interviewed the leaders of two multi-county navigator programs, asking them how their programs had allocated in-person staff across counties in 2016. One of these leaders also volunteered to share their formal response to the funding opportunity announcement, which explained their staff allocation strategy in detail. We then combined these data and CMS data to estimate trends over time in the navigator grant funding per baseline uninsured person, separately for treatment and control counties (Centers for Medicare and Medicaid Services 2019b). See Appendix A for details.

## V. Results

### A. DESCRIPTIVE DATA

In 2016, there were 28 statewide navigator programs that served all counties in their respective states and 75 local navigator programs that served only some of the counties in their respective states. In 2019, in the 33 states in the study sample, 66% of uninsured people and 69%

of low-income uninsured people lived in states that had not expanded Medicaid eligibility to low-income adults, according to our analysis of ACS data (Kaiser Family Foundation 2021).

Table 1 presents descriptive statistics for the treatment counties (i.e., counties served by local navigator programs in 2016) and the control counties (i.e., counties not served by a local navigator program in 2016) based on data from the first year of the study period, 2015. First, consistent with the possibility that more navigator programs will become established and funded in locations with more uninsured people, we found that treatment counties had a significantly larger population and higher uninsured rate than control counties. Furthermore, consistent with many navigator programs' stated focus on serving specific underserved populations, we found that treatment counties had a significantly larger proportion of the population who were Hispanic, who spoke a language at home other than English, or who were low-income and uninsured than control counties. However, most of these differences in population characteristics were qualitatively small. Other factors, including grant-writing skill or pure chance, likely played a role in determining the locations of funded navigator programs in 2016.

Figure 3 presents estimates of annual navigator grant funding levels in treatment and control counties. For comparability, the navigator grant amounts are divided by the number of uninsured people in the respective counties in 2013, the year before the navigator program was established (U.S. Census Bureau 2019). In 2016, treatment counties on average received $3.26 per uninsured person, whereas control counties on average received of $1.52 per uninsured person. Between 2016 and 2017, navigator funding was cut by $1.92 per uninsured person in treatment counties and by $0.70 per uninsured person in control counties. This calculation assumed that navigator grantees with multi-county service areas allocated their efforts based on the number of uninsured people in each county. As noted above, this assumption was supported

by survey and interview data from navigator grantees. When we used alternate methods to estimate the allocation of funds across counties in multi-county programs, the findings were qualitatively similar. See Figure A1 in Appendix A.

## B. IMPACTS OF CUTS TO THE NAVIGATOR PROGRAM

Tables 2 through 4 present the main results. These tables compare the additional changes in health insurance enrollment in treatment counties in 2018 (after a 41% cut to the navigator grants) and 2019 (after an 84% cut to the navigator grants as well as the elimination of the requirement to provide in-person services), compared to control counties. The results are presented with and without adjustment for local unemployment trends, which in nearly all cases does not substantively affect the findings; for brevity, the numbers listed in this sub-section describe impacts on coverage through 2019 using the model with adjustment for local unemployment trends. Figures B1 through B3 in Appendix B depict the event study coefficients graphically.

We began by estimating the effects of cuts to the navigator grants on enrollment in the health insurance marketplace, measured using county-level administrative data. Table 2 presents changes in the log counts of marketplace enrollment from models that adjusted for county population, among other characteristics. Column 1 in Table 2 shows the effects of the cuts on total marketplace enrollment. We found no significant impact of navigator program cuts on marketplace enrollment, although 95% confidence intervals include coverage declines of up to 2.7% (point estimate -1.3%, 95% CI -2.7% to 0.1%).

The subsequent columns in Table 2 present impacts of navigator program cuts on enrollment, by enrollment history (new enrollee vs. active re-enrollee), plan choice (enrolled in cost-sharing reduction plan), income level (150-200% of FPL vs. 200-250% of FPL), and

enrollee age (under 45, 45-54, 55-64). We found no significant impact of navigator program cuts on enrollment in plans with cost-sharing reductions, although 95% confidence intervals include declines of up to 6.6% (point estimate -3.3%, 95% CI -6.6% to 0.03%); however, the *F*-test assessing differential pre-trends for this outcome had a *p*-value below 0.2, suggesting these findings should be interpreted with caution. Cuts to the navigator program significantly decreased marketplace enrollment among people with incomes between 150 to 200% of FPL by 2.4% (95% CI -4.4% to -0.4%). While point estimates for declines in marketplace coverage by 2019 were larger for people under 45 than for older age groups, we failed to reject the null hypothesis of no differences across age groups in the effect of cuts.

Next, we examined the effects of navigator funding cuts on total health insurance coverage and Medicaid coverage rates, measured using the ACS data. Column 1 in Table 3 reports estimates of the effects of funding cuts on coverage in the full sample; Panels A and B present results for any insurance coverage, and Panels C and D present results for Medicaid coverage. We found no significant impact of navigator program cuts on total health insurance coverage, although our confidence intervals include declines of up to 1.8 percentage points (point estimate -0.8 percentage points, or a decline of 1.2% compared to the baseline mean, 95% CI -1.8 to 0.2 percentage points). Likewise, we failed to reject the null hypotheses that the cuts did not affect Medicaid coverage (point estimate -0.7 percentage points or -2.4%, 95% CI -1.9 to 0.5 percentage points); the *p*-value of an *F*-test assessing differential pre-trends was below 0.1, suggesting these findings should be interpreted with caution.

Motivated by CMS records demonstrating that navigator programs targeted specific underserved populations, we stratified the data in additional analyses. First, we examined data from consumers in the same income and age categories examined in the administrative data

(income 150-200% of FPL vs. 200-250% of FPL; aged under 45, 45-54, or 55-64). We also examined data from consumers in specific racial or ethnic groups (white, Hispanic, or Black, not modeled as mutually exclusive categories) and consumers who spoke a language other than English at home. The subgroup findings are shown in Columns 2-10 in Table 3. Declines in insurance coverage by 2019 were statistically significant among consumers with incomes between 200 and 250% of FPL (-3.7 percentage points or -5.8%, 95% CI -7.0 to -0.4 percentage points), consumers under age 45 (-1.6 percentage points or -2.5%, 95% CI -3.0 to -0.2 percentage points), consumers who identified as Hispanic (-3.5 percentage points or -6.3%, 95% CI -6.2 to -0.8 percentage points), and consumers who spoke a language other than English at home (-3.0 percentage points or -5.0%, 95% CI -5.4 to -0.6 percentage points). The decline in coverage among Black consumers was statistically significant at the 10% level but not the 5% level (-2.8 percentage points or -4.2%, 95% CI -6.1 to 0.5 percentage points). We also observed a significant decline in Medicaid coverage among consumers who spoke a language other than English at home, but the findings from a test of pre-existing differential trends raised doubts about the validity of this finding (-2.6 percentage points or -9.4%, 95% CI -4.8 to -0.4 percentage points, pre-trend *F*-test *p*-value 0.001).

Finally, we examined the impacts of navigator funding cuts on changes in health insurance coverage and health care consumption using the MEPS and merged NHIS data, which allow us to follow individuals over time. While a key advantage of these data is that we can add individual fixed effects to the models, there are important disadvantages as well: the 2019 MEPS data were not available at the time of analysis and the MEPS sample size was smaller than the ACS sample size by a factor of 100. Table 4 presents estimates of the effects of cuts to the navigator program on changes in health insurance coverage, marketplace coverage, and

Medicaid coverage using these data. Table B1 in Appendix B presents estimates of the effects of navigator funding cuts on changes in use of any outpatient care, inpatient care, and emergency care. The signs of the estimated changes in coverage are mostly consistent with the findings from the ACS and administrative data. However, the confidence intervals are large, and the estimated changes in health insurance coverage and health care use are not statistically significant.

Supplemental analyses supported the validity of these findings and robustness to alternate specifications. First, we conducted a placebo check that used data from individuals aged 65 to 80 in the ACS and examined Medicare coverage as the outcome of interest. The findings, shown in Table B2 in Appendix B, show no significant impacts of cuts to the navigator program on Medicare coverage, as expected given that enrollment in Medicare at age 65 or older is automatic for people who are eligible. Second, to assess whether our findings were driven by specific states, we conducted a cross validation exercise in which we systematically dropped each state one at a time and re-estimated the model. When states were systematically dropped in this manner, all findings that were statistically significant at the 5% level in the main analysis remained statistically significant 100% of the time, whereas findings that were statistically significant only at the 10% level in the main specification were intermittently significant. See Table B3 in Appendix B. These supplemental analyses suggest the robustness of the patterns that were statistically significant at the 5% level in our main analysis, including declines in marketplace coverage among lower-income adults, and declines in any coverage among lower-income adults, adults with age under 45, Hispanic adults, and adults who spoke a language other than English at home.

## VI. Discussion

This paper provides the first independent estimates of the navigator program's impacts on health insurance outcomes. In addition to contributing to the health economics literature on health insurance choices and information gaps, the findings can inform ongoing policy decisions regarding funding for the navigator program (Congressional Budget Office 2019; Department of Health and Human Services Press Office 2021).

The results indicated that the navigator program improved access to insurance among several underserved or hard-to-reach groups of consumers. Cuts to program funding significantly decreased coverage among people with lower incomes, adults under age 45, Hispanic adults, and people who spoke a language other than English at home. Importantly, the analysis of coverage rates included only United States citizens. Thus, the coverage impacts among consumers who spoke a language other than English at home cannot be accounted for by concurrent changes to the definition of a public charge, a change that only affected coverage rates among non-citizens (Parmet 2019).

Evidence from federal records, consumer surveys, surveys of the navigators, and recent research support the plausibility of these findings. Many groups of consumers we found to be impacted by cuts to the navigator program – including Hispanic consumers, low-income consumers, and consumers who prefer a language other than English – were intentionally targeted by navigator programs, according to CMS records and surveys of the navigators (Pollitz, Tolbert, and Semanskee 2016; Centers for Medicare and Medicaid Services 2019b). Furthermore, data from a survey of navigator programs conducted in 2017 after the announcement of funding cuts suggested that the cuts reduced the availability of language translation services (Pollitz, Tolbert, and Diaz 2017). Evidence from consumer surveys also supports the plausibility of

coverage impacts differing by ethnicity. In a survey of people who had recently sought coverage, Hispanic adults were more likely than non-Hispanic white adults to have asked for assistance with health insurance enrollment from someone other than a family member (Pollitz et al. 2020). Finally, the finding that enrollment impacts occurred only among adults under 45 years of age aligns with recent research showing that addressing information frictions attracted lower-cost enrollees to the marketplace (Domurat, Menashe, and Yin 2021).

We did not detect an effect of navigator program cuts on overall health insurance coverage, Medicaid coverage, or marketplace coverage across the full population, although our confidence intervals cannot rule out some meaningful declines in coverage. Our estimates of the changes in total health insurance coverage, marketplace enrollment, and Medicaid coverage were -0.8 percentage points or -1.2% (95% CI -1.8 to 0.2 percentage points), -1.3% (95% CI -2.7% to 0.1%), and -0.7 percentage points or -2.4% (95% CI -1.9 to 0.5 percentage points), respectively. It is likely that Medicaid eligibility rates were low among low-income adults in the states we studied, however. Our analysis of 2019 ACS data suggested that two-thirds of the uninsured people in the states we studied lived in locations that had not expanded eligibility for Medicaid to low-income adults (Kaiser Family Foundation 2021). Additional models with individual fixed effects did not detect an impact of navigator funding cuts on within-person changes in health insurance coverage or health care use. Data limitations prevented us from measuring changes in coverage or health care use in 2019 in the analysis with individual fixed effects, which was potentially important given the larger cuts to the navigator program in 2019 compared to prior years.

The analysis had several advantages. First, the models used data from the 33 states that met the eligibility criteria for the navigator program throughout the study period of 2015-2019,

and cuts to the navigator program were implemented concurrently nationwide. These features obviate the bias that can arise in event study models due to unbalanced panels or staggered adoption of the focal policy (Athey and Imbens 2021; Lechner, Rodriguez-Planas, and Kranz 2016). Second, the analysis adjusted for the impact of concurrent state-level and national-level policy changes, as well as time-invariant characteristics at the county level. These adjustments were important because of the notable shifts in national- and state-level policies that occurred during the study period, and the lack of balance of baseline characteristics across treatment and control counties. Furthermore, an advantage of the difference-in-differences design we used is that a lack of balance on baseline characteristics does not necessarily invalidate the analysis. Third, the models used detailed data on the implementation of the navigator program and marketplace enrollment at the county level. Comparable marketplace data were available across states because all states covered by the navigator program use the same Healthcare.gov platform for their marketplaces (Centers for Medicare and Medicaid Services 2019a; Congressional Research Service 2021).

The analysis also had limitations. First, we could only measure navigator funding distributed by the federal government. As federal grant funding declined, some navigator programs raised funds from other philanthropic sources and these funds are not measured in the study data. However, by focusing only on federal funding, we generated evidence that can inform a key policy decision: how much federal funding to devote to the navigator program. Second, we did not observe the intensity of navigator activity in each county, such as how funds or staff were distributed across counties in multi-county navigator programs. Rather, we only observed the grants at the program level and the counties in each program's service area. Nonetheless, the interpretation of the signs of the coefficients relied only on the assumption that

the cuts affected treatment counties more than control counties, which we verified for a range of plausible assumptions about the distribution of funds across counties. Finally, we did not observe whether navigator programs connected their clients to SNAP or other local services. Potential spillover effects of navigator funding cuts on receipt of other social programs could be examined in future research.

In conclusion, this study shows that funding the navigator program – a program which provides consumers with free one-on-one assistance with health insurance enrollment decisions – increases health insurance coverage for underserved populations. This finding contributes to ongoing discussions on how health policy can enhance equity in access to insurance.

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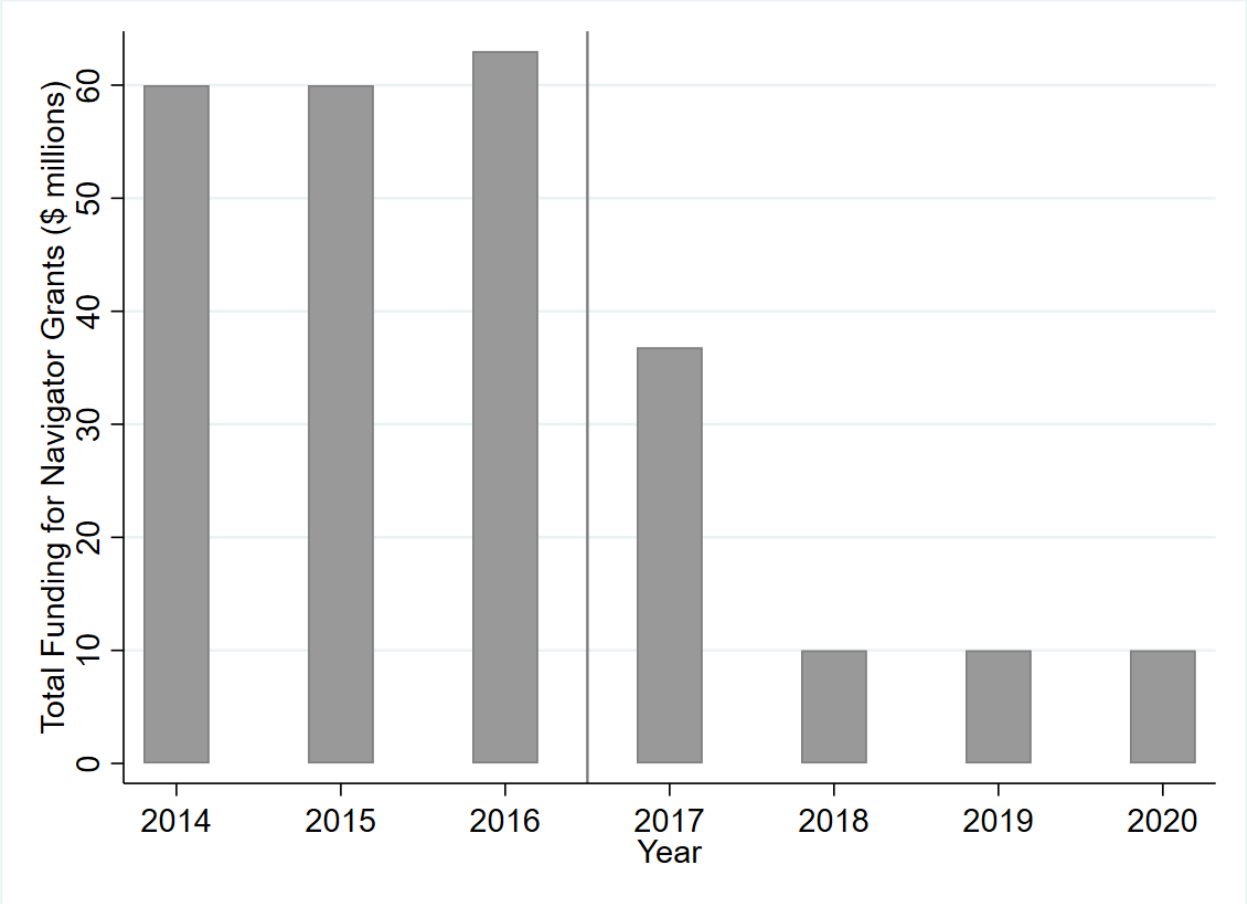
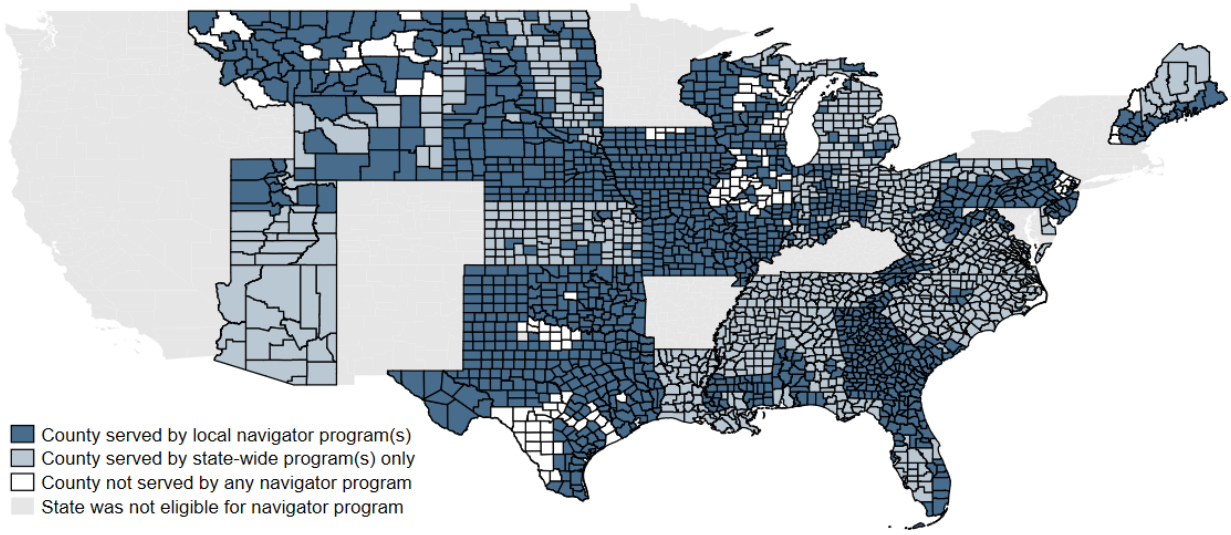
## Tables and Figures

**Figure 1. Annual funding for the navigator program**




Source: Authors' calculations using annual data on navigator grants from the Centers for Medicare and Medicaid Services.

**Figure 2. Location of treatment and control counties (i.e., counties with vs. without local navigator programs in 2016)**




Source: Authors' calculations using data from the Centers for Medicare and Medicaid Services.

The treatment counties in the analysis are the counties in dark blue, which were served by one or more non-statewide ("local") navigator programs in 2016. The control counties include the counties in light blue, which were served by statewide navigator programs in 2016, and counties in white, which were not served by any navigator programs in 2016. As required by the ACA, all states have assister programs; the states shown in gray were ineligible for the navigator grants but were given federal funding via other mechanisms to establish other assister programs.

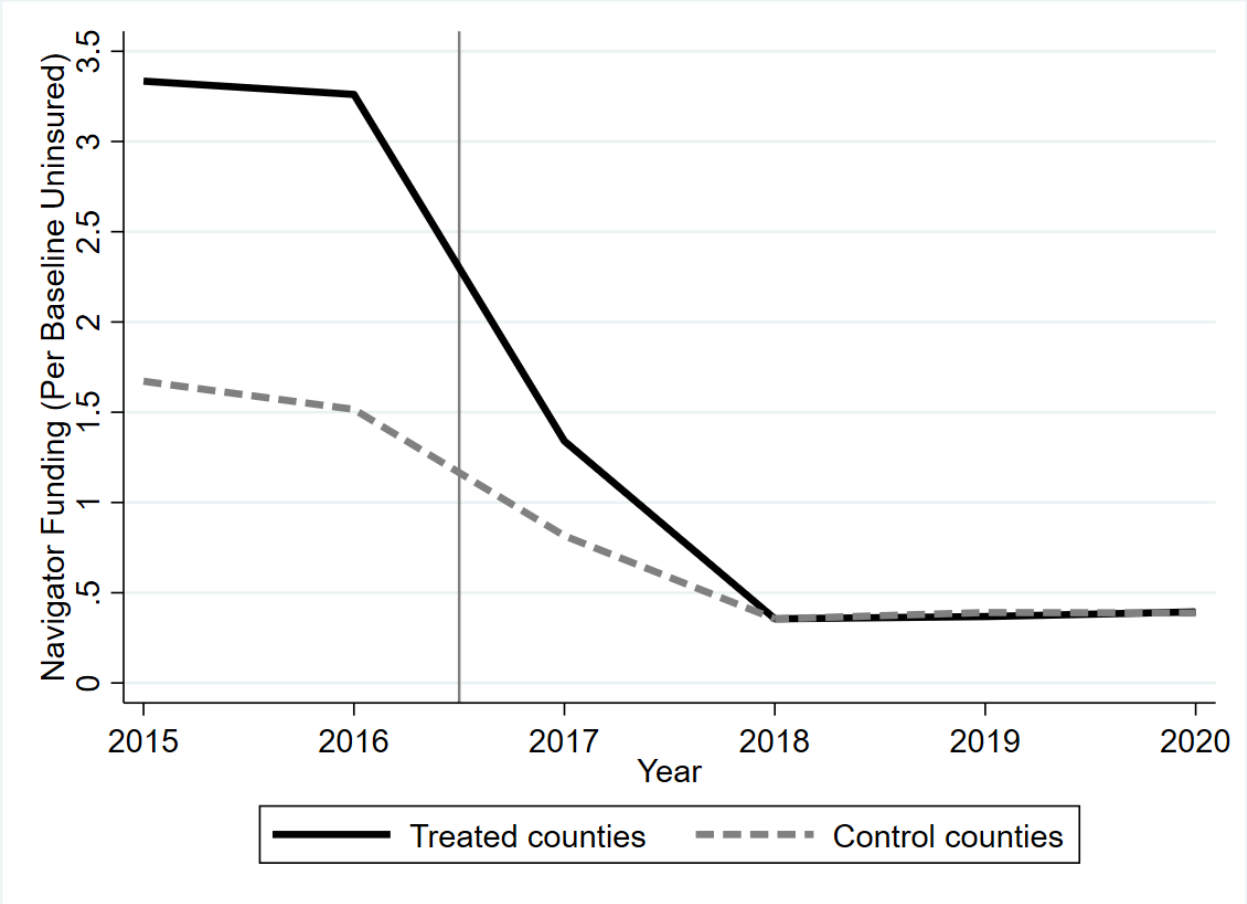
**Table 1. Summary statistics at baseline**

| | Treatment counties | Control counties | *P*-value |
|---|---|---|---|
| | (1) | (2) | (3) |
| ***Panel A: American Community Survey (ACS) Data*** | | | |
| Any insurance coverage | 0.661 | 0.686 | <0.001 |
| Medicaid coverage | 0.300 | 0.323 | <0.001 |
| Directly purchased coverage (including marketplace) | 0.281 | 0.269 | <0.001 |
| Age | 39.7 | 40.0 | <0.001 |
| Female | 0.507 | 0.506 | 0.691 |
| Hispanic | 0.190 | 0.128 | <0.001 |
| White | 0.666 | 0.679 | <0.001 |
| Black | 0.232 | 0.231 | 0.871 |
| Speak a language other than English at home | 0.216 | 0.144 | <0.001 |
| Income as % of FPL | 218.7 | 211.2 | <0.001 |
| No insurance coverage & income below 400% of FPL | 0.308 | 0.288 | <0.001 |
| ***Number of Counties*** | 179 | 127 | |
| ***Sample Size*** | 137,808 | 79,481 | |
| ***Weighted Sample Size*** | 16,642,640 | 8,797,781 | |
| ***Panel B: Small Area Health Insurance Estimates (SAHIE) Data*** | | | |
| Population | 79,930 | 58,093 | 0.010 |
| ***Number of counties*** | 1,333 | 1,102 | |

Source: Authors' analysis of 2015 ACS data and 2015 SAHIE data.

Note: Panel A reports health insurance status, income, and demographic characteristics measured for the study sample (non-elderly adults who were United States citizens and lacked employer-sponsored coverage) in the baseline year of 2015. The estimates used sample weights. Panel B reports the average population in the counties in 2015. Column 3 reports the *p*-value on a test of the null hypothesis that the means of the two groups are equal.

**Figure 3. Estimated funding for navigator programs in treatment and control counties, prior to and after funding cuts**




Source: Authors' calculation using data from the Centers for Medicare and Medicaid Services and Small Area Health Insurance Estimates project. In this calculation, multi-county navigator programs were assumed to allocate funds to each county based on the size of the uninsured population; alternate assumptions are considered in Appendix A.

**Table 2. Impact of cuts to the navigator program on marketplace enrollment**

| Sample | Total | Enrollment History: New Enrollee | Enrollment History: Active Re-enrollee | Plan Choice: Enrolled in Cost-Sharing Reduction Plan | Income as % of FPL: 150-200% | Income as % of FPL: 200-250% | Enrollee Age: Under 45 | Enrollee Age: 45-54 | Enrollee Age: 55-64 |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Panel A: Adjust for State-by-Year and County Fixed Effects | | | | | | | | | |
| Treated * 2018 | -0.004 | 0.020 | -0.008 | -0.016* | -0.007 | -0.011 | -0.0003 | -0.0005 | -0.003 |
| | (0.005) | (0.018) | (0.010) | (0.010) | (0.006) | (0.008) | (0.008) | (0.006) | (0.005) |
| Treated * 2019 | -0.014* | 0.005 | -0.019 | -0.033** | -0.024** | -0.013 | -0.016 | -0.003 | -0.002 |
| | (0.008) | (0.012) | (0.012) | (0.016) | (0.010) | (0.014) | (0.010) | (0.010) | (0.009) |
| *Pre-trend check p-value* | [0.748] | [0.331] | [0.620] | [0.141] | [0.925] | [0.934] | [0.617] | [0.837] | [0.984] |
| Panel B: Adjust for State-by-Year and County Fixed Effects and Local Unemployment Trends | | | | | | | | | |
| Treated * 2018 | -0.004 | 0.020 | -0.008 | -0.016 | -0.006 | -0.011 | -0.00006 | -0.0003 | -0.002 |
| | (0.005) | (0.018) | (0.010) | (0.010) | (0.006) | (0.008) | (0.007) | (0.006) | (0.005) |
| Treated * 2019 | -0.013* | 0.006 | -0.018 | -0.033* | -0.024** | -0.012 | -0.015 | -0.002 | -0.001 |
| | (0.007) | (0.012) | (0.012) | (0.017) | (0.010) | (0.014) | (0.010) | (0.010) | (0.008) |
| *Pre-trend check p-value* | [0.734] | [0.324] | [0.627] | [0.119] | [0.930] | [0.918] | [0.591] | [0.821] | [0.989] |
| Baseline mean | 6.749 | 6.120 | 5.418 | 6.221 | 5.400 | 4.921 | 5.903 | 5.292 | 5.555 |
| Observations | 12,164 | 11,955 | 11,893 | 12,076 | 11,957 | 11,807 | 10,428 | 11,899 | 12,062 |

Source: Authors' analysis of administrative data on enrollment in Healthcare.gov paired with county-level population data from the Small Area Health Insurance Estimates project and county-level unemployment data from the Bureau of Labor Statistics.

Note: The dependent variable was the log of marketplace enrollment. All regressions included state-by-year fixed effects and county-level fixed effects and adjusted for population size in the county during the open enrollment period. Regressions in the second panel also adjusted for the unemployment rate in the county during the open enrollment period. Column 1 examines the full sample. Columns 2 and 3 stratify the sample by enrollment history. Column 4 examines enrollment in cost-sharing reduction plans. Columns 5 and 6 stratify the sample by income level. Columns 7, 8, and 9 stratify the sample by enrollee's age. Other income and age categories were omitted due to higher levels of censoring in the data. The *p*-value for a test for parallel pre-trends across groups corresponding to each model is in brackets. Robust standard errors, shown in parentheses, allowed for clustering at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Table 3. Impact of cuts to the Navigator program on total health insurance coverage and Medicaid coverage**

| Panels A and B: Dependent Variable=Any Health Insurance Coverage | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Income as % of FPL | | | Age | | Race/Ethnicity | | | Language at Home |
| Sample | Total | 150-200% | 200-250% | Under 45 | 45-54 | 55-64 | White | Hispanic | Black | Non-English |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Panel A: Adjust for State-by-Year and County Fixed Effects | | | | | | | | | | |
| Treated * 2018 | -0.001 | 0.029 | -0.039** | -0.003 | 0.009 | -0.001 | -0.005 | 0.009 | -0.002 | 0.008 |
| | (0.006) | (0.02) | (0.019) | (0.007) | (0.01) | (0.008) | (0.005) | (0.01) | (0.015) | (0.011) |
| Treated * 2019 | -0.008* | 0.022 | -0.037** | -0.015** | 0.001 | 0.004 | -0.002 | -0.035*** | -0.029* | -0.03** |
| | (0.005) | (0.02) | (0.017) | (0.007) | (0.012) | (0.01) | (0.006) | (0.014) | (0.017) | (0.013) |
| *Pre-trend check p-value* | [0.617] | [0.507] | [0.387] | [0.709] | [0.102] | [0.124] | [0.291] | [0.47] | [0.993] | [0.703] |
| Panel B: Adjust for State-by-Year and County Fixed Effects and Local Unemployment Trends | | | | | | | | | | |
| Treated * 2018 | -0.001 | 0.029 | -0.039** | -0.003 | 0.009 | -0.001 | -0.005 | 0.009 | -0.001 | 0.008 |
| | (0.006) | (0.021) | (0.019) | (0.007) | (0.01) | (0.008) | (0.005) | (0.01) | (0.015) | (0.011) |
| Treated * 2019 | -0.008* | 0.022 | -0.037** | -0.016** | 0.001 | 0.004 | -0.002 | -0.035*** | -0.028* | -0.03** |
| | (0.005) | (0.02) | (0.017) | (0.007) | (0.012) | (0.01) | (0.006) | (0.014) | (0.017) | (0.012) |
| *Pre-trend check p-value* | [0.634] | [0.463] | [0.345] | [0.674] | [0.162] | [0.156] | [0.314] | [0.461] | [0.983] | [0.71] |
| Baseline Mean | 0.6901 | 0.652 | 0.6426 | 0.634 | 0.7084 | 0.8051 | 0.6998 | 0.5592 | 0.6734 | 0.6032 |

| Panels C and D: Dependent Variable=Medicaid Coverage | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Income as % of FPL | | Age | | | Race/Ethnicity | | | Language at Home |
| Sample | Total | 150-200% | 200-250% | Under 45 | 45-54 | 55-64 | White | Hispanic | Black | Non-English |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Panel C: Adjust for State-by-Year and County Fixed Effects | | | | | | | | | | |
| Treated * 2018 | 0.0002 | 0.016 | -0.005 | 0.001 | -0.009 | 0.006 | -0.004 | -0.011 | 0.016 | -0.019 |
| | (0.005) | (0.02) | (0.022) | (0.009) | (0.011) | (0.008) | (0.005) | (0.017) | (0.014) | (0.014) |
| Treated * 2019 | -0.007 | -0.0001 | -0.02 | -0.01 | -0.013 | 0.003 | -0.001 | -0.003 | -0.012 | -0.026** |
| | (0.006) | (0.022) | (0.023) | (0.011) | (0.012) | (0.01) | (0.006) | (0.009) | (0.011) | (0.011) |
| *Pre-trend check p-value* | [0.123] | [0.532] | [0.611] | [0.598] | [0.081] | [0.984] | [0.023] | [0.327] | [0.273] | [0.001] |
| Panel D: Adjust for State-by-Year and County Fixed Effects and Local Unemployment Trends | | | | | | | | | | |
| Treated * 2018 | 0.0003 | 0.016 | -0.005 | 0.001 | -0.008 | 0.006 | -0.004 | -0.01 | 0.016 | -0.019 |
| | (0.005) | (0.019) | (0.022) | (0.009) | (0.011) | (0.008) | (0.005) | (0.017) | (0.014) | (0.014) |
| Treated * 2019 | -0.007 | 0.0002 | -0.02 | -0.01 | -0.013 | 0.003 | -0.001 | -0.003 | -0.012 | -0.026** |
| | (0.006) | (0.022) | (0.023) | (0.011) | (0.012) | (0.01) | (0.006) | (0.009) | (0.012) | (0.011) |
| *Pre-trend check p-value* | [0.059] | [0.562] | [0.6] | [0.534] | [0.041] | [0.994] | [0.023] | [0.34] | [0.154] | [0.001] |
| Baseline Mean | 0.2943 | 0.2484 | 0.1731 | 0.3007 | 0.2935 | 0.2802 | 0.2526 | 0.2857 | 0.4409 | 0.2755 |
| Observations | 1,067,154 | 102,266 | 81335 | 589,366 | 205,685 | 272,103 | 753,372 | 169,299 | 206,065 | 194,550 |

Source: Authors' analysis of ACS data paired with county-level unemployment data from the Bureau of Labor Statistics. The sample included non-elderly adults who were United States citizens and lacked employer-sponsored coverage.

Note: The dependent variable was an indicator of whether the participant had any insurance in Panels A and B and was an indicator for whether the participant had Medicaid insurance in Panels C and D. All regressions included state-by-year fixed effects and county-level fixed effects, and adjusted for the respondent's race/ethnicity (Black, white, Hispanic), age in years, and gender (male, female). Regressions in Panels B and D also adjusted for the unemployment rate in the county during the open enrollment period. Column 1 includes the full sample. Columns 2 and 3 stratify the sample by the respondent's income level. Columns 4, 5, and 6 stratify the sample by the respondent's age, and Columns 7, 8, and 9 stratify the sample by the respondent's race/ethnicity. Column 10 includes only sample members who spoke a language other than English at home. The *p*-value for a test of parallel pre-trends across groups corresponding to each model is in brackets. The estimates used ACS sample weights. Robust standard errors, shown in parentheses, allowed for clustering at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table 4. Impact of cuts to the Navigator program on changes in health insurance coverage**

| Dataset | MEPS (Data Over 2-Year Period) | | | MEPS merged with NHIS (Data Over 3-Year Period) |
|---|---|---|---|---|
| Outcome | All Coverage | Marketplace Coverage | Medicaid Coverage | All Coverage |
| | (1) | (2) | (3) | (4) |
| Panel A: Adjust for State-by-Year, County, and Individual Fixed Effects | | | | |
| Treated * 2018 | -0.021 | -0.027 | 0.001 | -0.035 |
| | (0.041) | (0.049) | (0.031) | (0.027) |
| *Pre-trend check p-value* | [0.802] | [0.763] | [0.558] | [0.695] |
| Panel B: Adjust for State-by-Year, County, and Individual Fixed Effects as well as Local Unemployment Trends | | | | |
| Treated * 2018 | -0.026 | -0.057 | -0.001 | -0.038 |
| | (0.044) | (0.056) | (0.030) | (0.035) |
| *Pre-trend check p-value* | [0.902] | [0.756] | [0.521] | [0.525] |
| Baseline mean | 0.732 | 0.133 | 0.293 | 0.739 |
| Observations | 7592 | 7592 | 7592 | 10020 |

Source: Authors' analysis of restricted-use MEPS and merged NHIS data paired with county-level unemployment data from the Bureau of Labor Statistics. The sample included non-elderly adults who were United States citizens and lacked employer-sponsored coverage.

Note: The dependent variable in Columns 1 and 4 was an indicator of whether the participant currently had health insurance coverage. The dependent variable in Column 2 was an indicator of whether the participant was covered by marketplace health insurance. The dependent variable in Column 3 was an indicator of whether the participant was covered by Medicaid health insurance. All regressions included state-by-year fixed effects, county-level fixed effects, and individual-level fixed effects. Regressions in the second panel also controlled for the unemployment rate in the county during the open enrollment period. The *p*-value for a test for parallel pre-trends across groups corresponding to each model is in brackets. The estimates used MEPS sample weights.

Robust standard errors, shown in parentheses, allowed for clustering at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

## Appendix A: Estimating the allocation of funds across counties in multi-county navigator programs

### 1. DATA COLLECTION

We conducted brief interviews with the leaders of two navigator programs that were funded in 2016. We asked the leaders how the program had allocated efforts across counties in their multi-county services area prior to the 2017 funding cuts. Both respondents noted that staff resources were allocated based on the size of the uninsured population in each county.

To examine whether other navigator programs used similar allocation strategies, we conducted a survey of other grantees. We emailed an invitation to participate in a Qualtrics survey to representatives from all remaining 100 recipients of 2016 navigator grants (i.e., all 2016 navigator grantees except the two already interviewed). The list of email addresses for the 2016 grantees was obtained from the CMS website.[13] The Qualtrics survey included the following question, with text bolded as shown below:

How did your program assign staff across counties (before 2017)?

- Based on **total population** in the county
- All counties staffed **equally**, regardless of population
- Based on size of **eligible/uninsured population**
- Other (please specify)

[13] https://www.cms.gov/CCIIO/Programs-and-Initiatives/Health-Insurance-Marketplaces/Downloads/2016-Navigator-Summaries_12-16-2016-Updated.pdf

We received responses from seven 2016 navigator grantees (7% response rate). Four grantees reported that their program allocated efforts based on the number of uninsured people in each county while two indicated that all counties were staffed equally, and one wrote their own answer ("All staff cover a seven-county region. There are no staff assigned to individual counties").[14]

Based on these data, the main estimates of funding allocation across counties assume that navigators allocated resources based on the size of the uninsured population, which was the most common response in the survey and interview data. As shown below, models using alternate assumptions produced qualitatively similar results.

**2. Estimation of the distribution of resources across counties in multi-county navigator programs**

We extracted navigator grantee data from the CMS website, including the amount of funding given to each grantee and the counties included in their service area each year (Centers for Medicare and Medicaid Services 2019b). We combined these data with information on the size of the uninsured population and the total population in each county in 2013, drawn from the Small Area Health Insurance Estimates program (U.S. Census Bureau 2019).

We used a three-step process to estimate annual navigator funding per baseline uninsured person in treatment and control counties. First, we allocated the funds received by each navigator grantee across the counties in their service area. Because the exact allocation across counties was

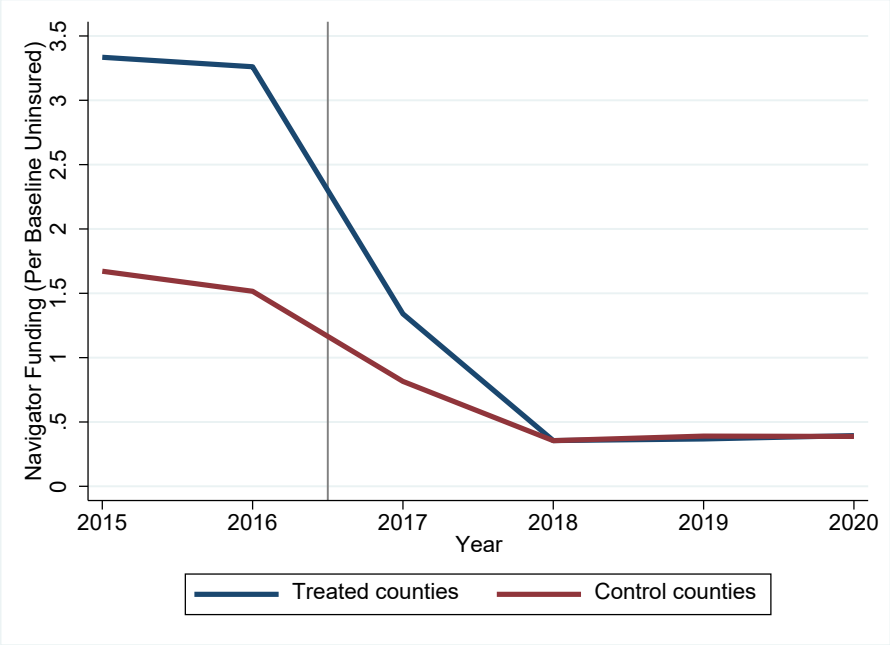
[14] The use of present tense in the answer suggests the respondent may have misread the question, which inquired about staffing patterns prior to 2017. Given that in-person activities were required in all counties prior to 2018, it might have been difficult for all staff to cover a seven-county region.

not tracked, we calculated the allocation using three different methods to assess the robustness of the findings. The main specification assumed that (a) funds were allocated to each county based on the share of the total uninsured population in the program's service area that resided in the county. Two alternate specifications assumed that (b) funds were allocated based on the size of the total population rather than the size of the uninsured population, or (c) each county received an equal share of funds. In the second step, we estimated total navigator funding at the county level by aggregating the funds calculated in the first step for all programs serving each county. This step was necessary because most counties in the sample were served by multiple navigator programs, including state-wide programs. In the third step, we divided the total navigator funding in treatment counties by the total uninsured population in these counties in 2013 to obtain annual funding per baseline uninsured person; we then repeated this exercise for control counties.

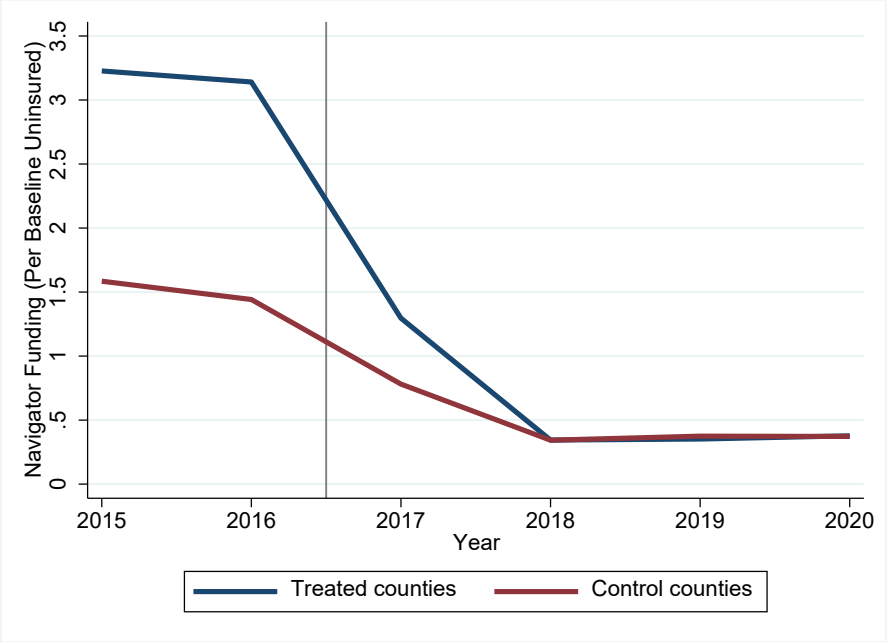
The resulting patterns of funding over time in treatment and control counties are shown in Figure A1 below. Panel A represents the main specification, and Panels B and C represent the two alternate specifications. These three specifications show qualitatively similar patterns over time, namely, that treatment counties received more funds from navigator grants than control counties, but that these differences decreased or disappeared by 2018 (the open enrollment period for 2019 coverage).

**Figure A1. Estimated funding for navigator programs in treatment counties and control counties, prior to and after funding cuts based on three different specifications**

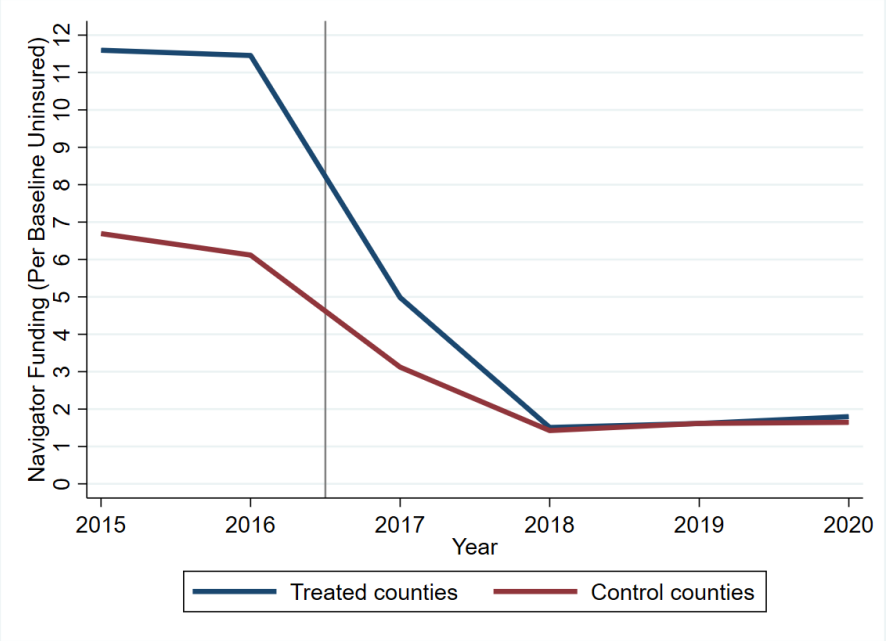
Panel A. Multi-county navigator programs were assumed to allocate funds to each county based on the size of the uninsured population (main specification)



Panel B. Multi-county navigator programs were assumed to allocate funds based on the size of the total population in each county



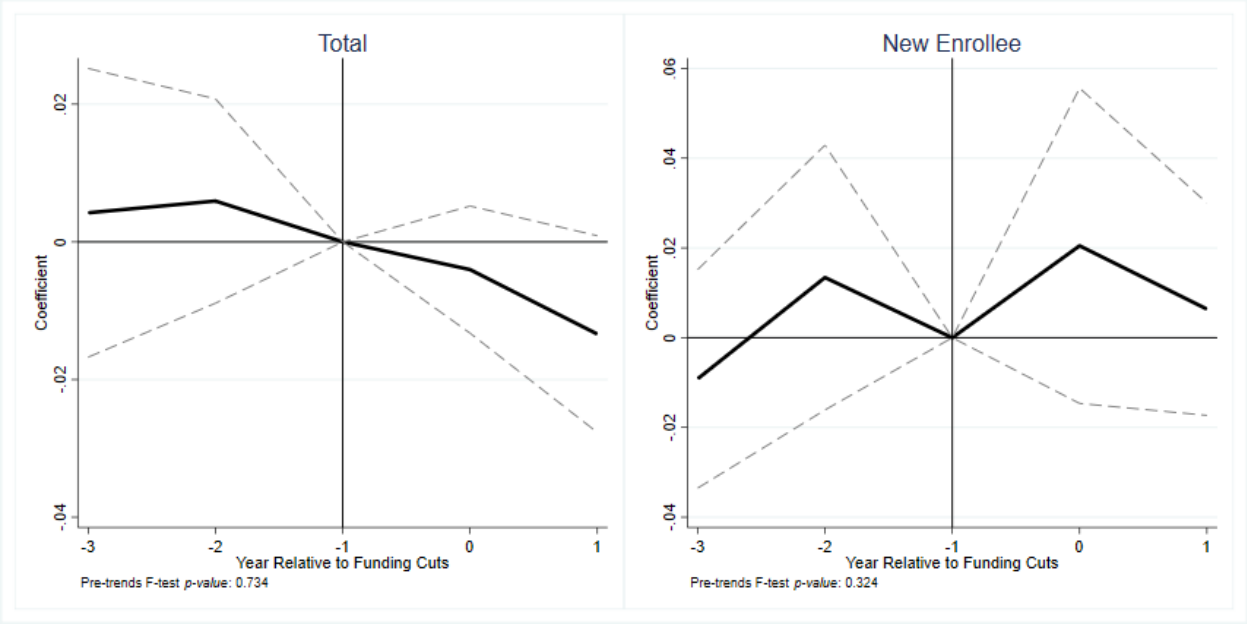

Panel C. Multi-county navigator programs were assumed to allocate funds equally across all counties served



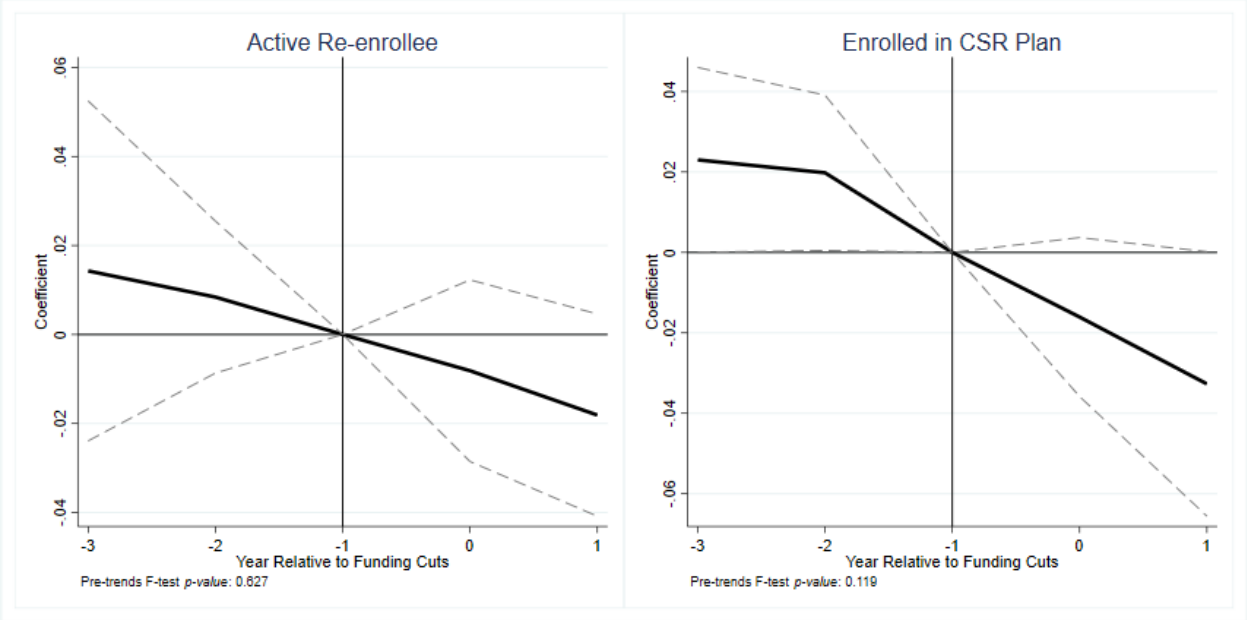
## Appendix B. Additional tables and figures

### Figure B1. Impact of cuts to the navigator program on marketplace enrollment: graphs of event study coefficients

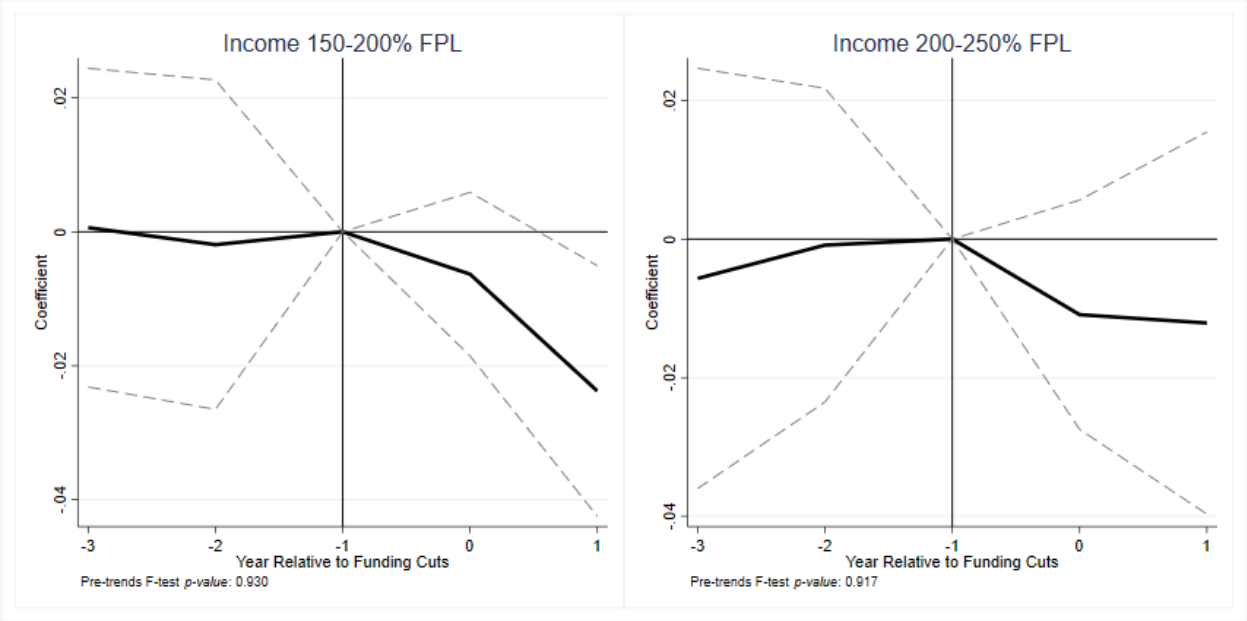
Panel A. Total and new enrollees



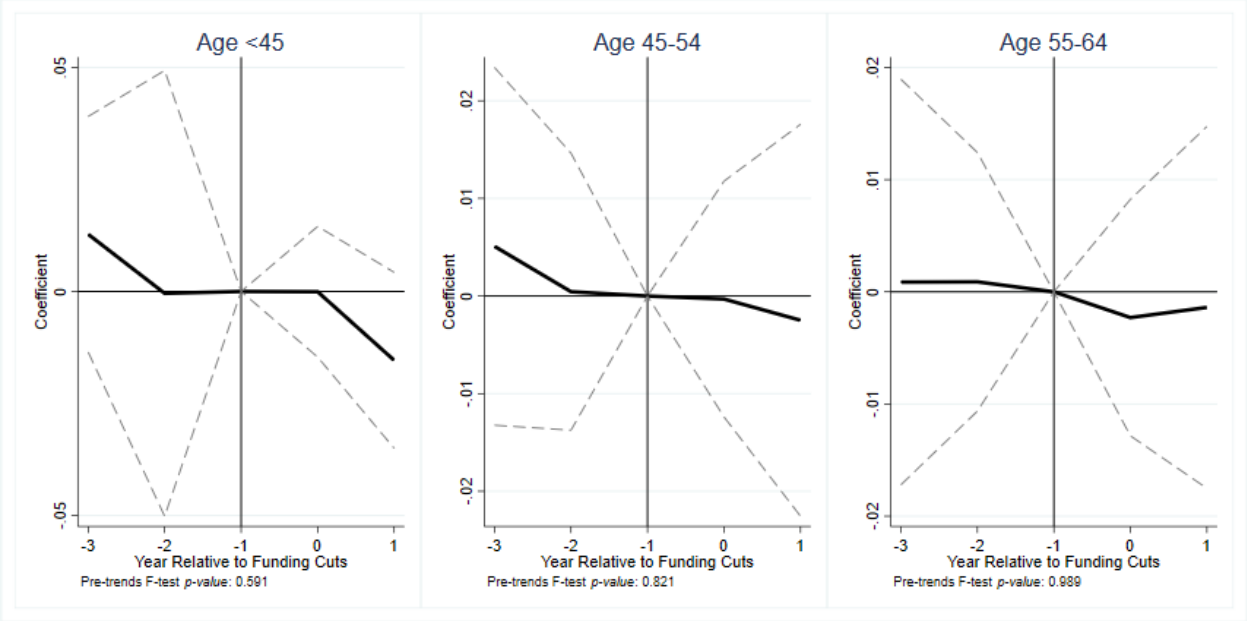

Panel B. Active re-enrollees and enrollment in cost-sharing reduction plans



Panel C. By enrollee income




Panel D. By enrollee age

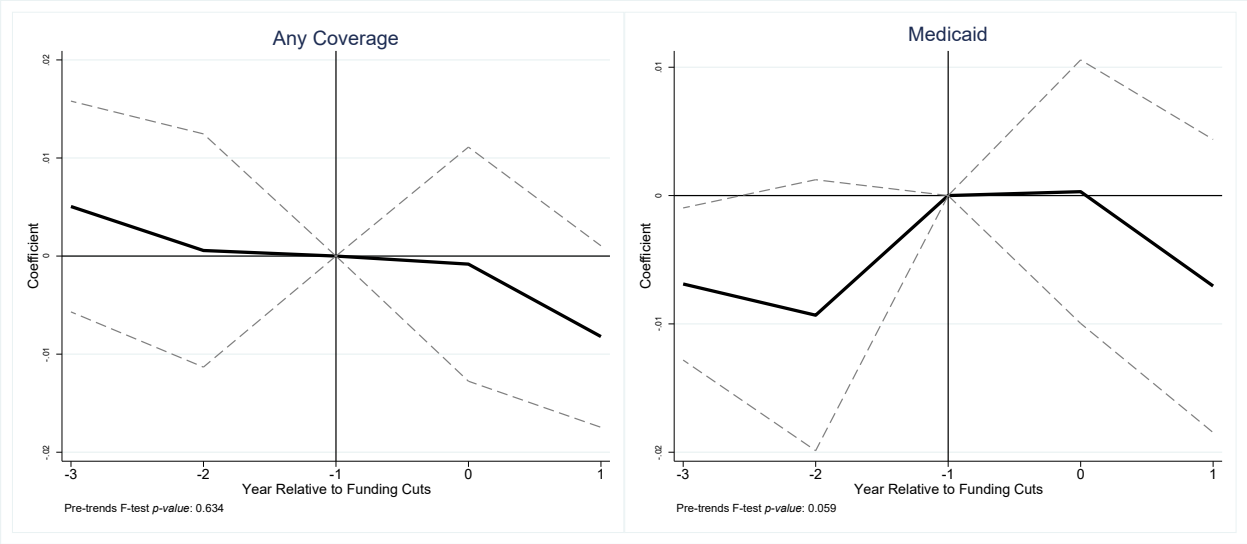



Source: Authors' analysis of administrative data on enrollment in Healthcare.gov paired with county-level population data from the Small Area Health Insurance Estimates project and county-level unemployment data from the Bureau of Labor Statistics.

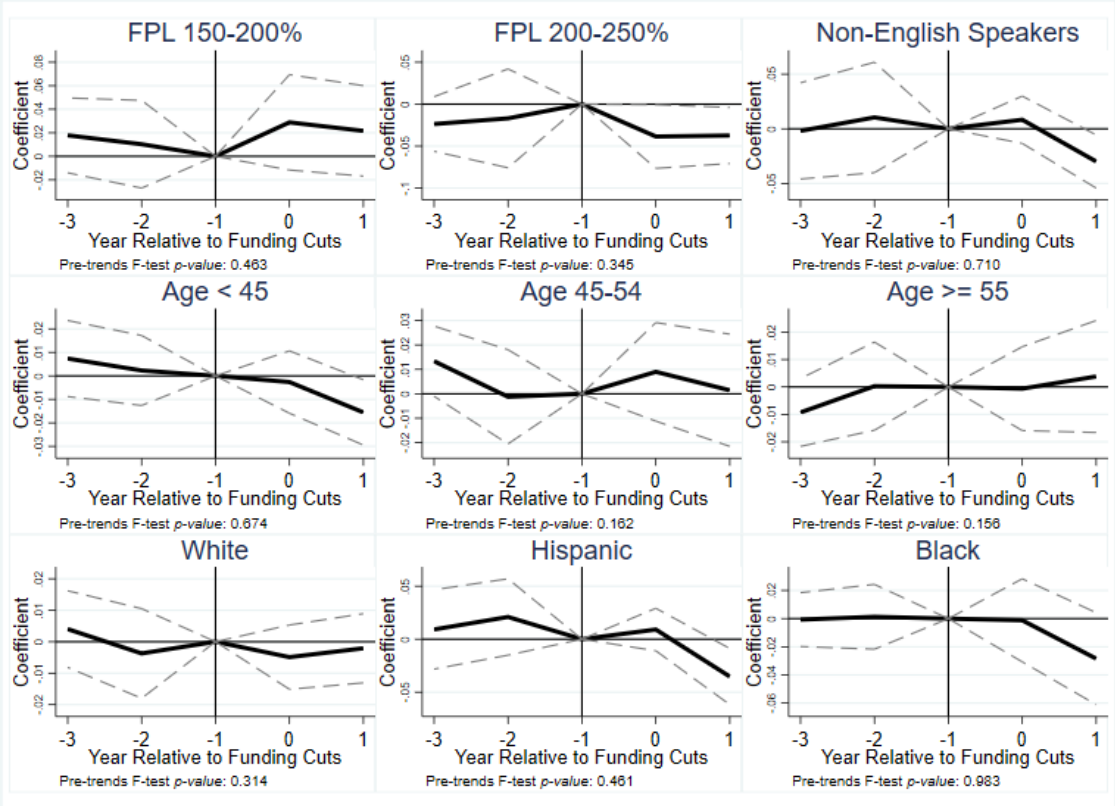
Note: Dashed lines represent 95% confidence intervals.

**Figure B2. Impact of cuts to the navigator program on total health insurance coverage and Medicaid coverage: graphs of event study coefficients**

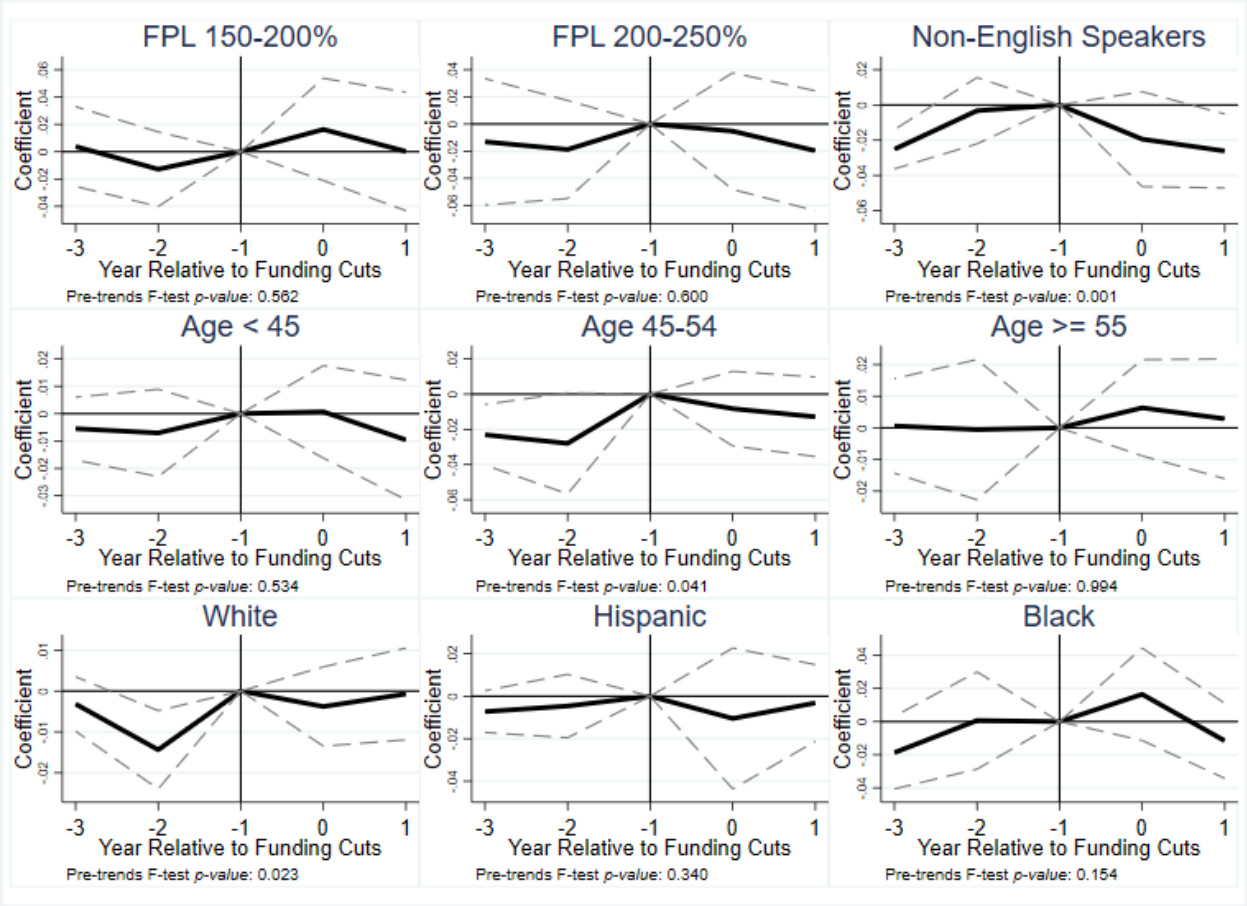
Panel A. Full sample




Panel B. Health insurance coverage event studies by consumer characteristics



C. Medicaid coverage event studies by consumer characteristics

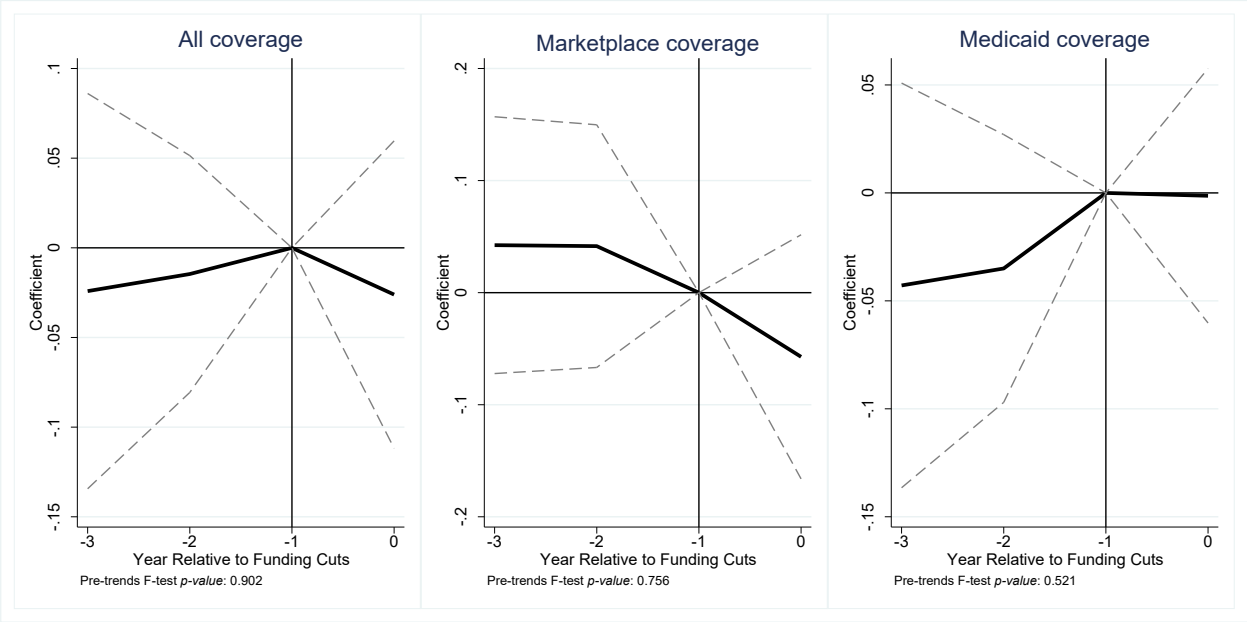



Source: Authors' analysis of ACS data paired with county-level unemployment data from the Bureau of Labor Statistics. The sample included non-elderly adults who were United States citizens and lacked employer-sponsored coverage.

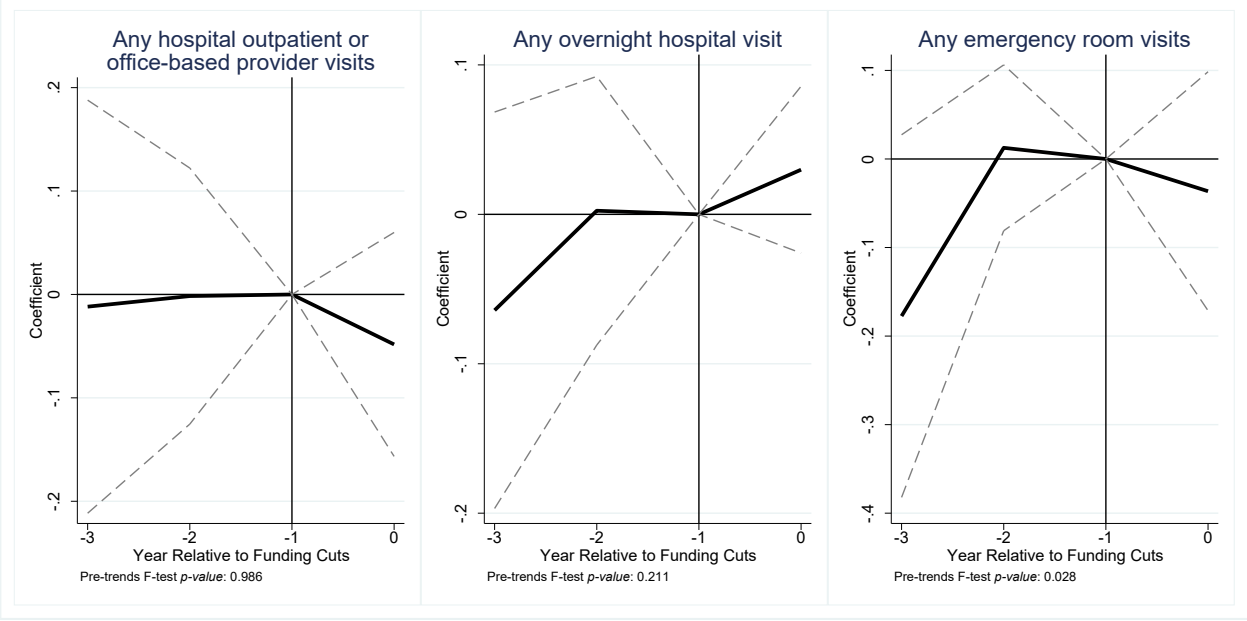
Note: Dashed lines represent 95% confidence intervals.

**Figure B3. Impact of cuts to the navigator program on changes in health insurance coverage and health care use: graphs of event study coefficients**

Panel A. Health insurance coverage




Panel B. Health care use



Source: Authors' analysis of restricted-use MEPS and merged NHIS data paired with county-level unemployment data from the Bureau of Labor Statistics. The sample included non-elderly adults who were United States citizens and lacked employer-sponsored coverage.

Note: Dashed lines represent 95% confidence intervals.

**Table B1. Impact of cuts to the navigator program on changes in health care use**

| Outcome | Outpatient Care | Inpatient Care | Emergency Room Visit |
|---|---|---|---|
| | (1) | (2) | (3) |
| Panel A: Adjusted for State-by-Year, County, and Individual Fixed Effects | | | |
| Treated * 2018 | -0.054 | 0.017 | -0.070 |
| | (0.039) | (0.030) | (0.049) |
| *Pre-trend check p-value* | [0.936] | [0.405] | [0.043] |
| Panel B: Adjusted for State-by-Year, County, and Individual Fixed Effects as well as Local Unemployment Trends | | | |
| Treated * 2018 | -0.048 | 0.030 | -0.036 |
| | (0.055) | (0.028) | (0.069) |
| *Pre-trend check p-value* | [0.986] | [0.211] | [0.028] |
| Baseline mean | 0.662 | 0.080 | 0.205 |
| Observations | 7592 | 7592 | 7592 |

Source: Authors' analysis of MEPS data paired with county-level unemployment data from the Bureau of Labor Statistics. The sample included non-elderly adults who were United States citizens and lacked employer-sponsored coverage.

Note: The dependent variable in Column 1 was an indicator of whether the participant reported any hospital outpatient or office-based provider visits during the survey year. The dependent variable in Column 2 was an indicator of whether the participant reported spending any nights in the hospital during the survey year. The dependent variable in Column 3 was an indicator of whether the participant reported any emergency room visits during the survey year. All regressions included state-by-year fixed effects, county-level fixed effects, and individual-level fixed effects. Regressions in the second panel also controlled for the unemployment rate in the county during the open enrollment period. The *p*-value for a test of parallel pre-trends across groups corresponding to each model is in brackets. The estimates used MEPS sample weights. Robust standard errors, shown in parentheses, allowed for clustering at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Table B2. Impact of cuts to the navigator program on Medicare coverage among people aged 65-80 years: a placebo test**

| Panels A and B: Dependent Variable=Medicare Coverage Among Aged 65 to 80 | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Income as % of FPL | | Race/Ethnicity | | | Language at Home |
| Sample | Total | 150-200% | 200-250% | White | Hispanic | Black | Non-English |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Panel A: Adjust for State-by-Year and County Fixed Effects | | | | | | | |
| Treated * 2018 | 0.001 | 0.003 | 0.007 | -0.001 | -0.017 | 0.016* | 0.036 |
| | (0.002) | (0.004) | (0.005) | (0.002) | (0.011) | (0.009) | (0.031) |
| Treated * 2019 | 0.000 | -0.004 | 0.005* | 0.000 | -0.009 | -0.004 | 0.013 |
| | (0.002) | (0.007) | (0.003) | (0.002) | (0.008) | (0.013) | (0.022) |
| *Pre-trend check p-value* | [0.869] | [0.664] | [0.435] | [0.439] | [0.653] | [0.988] | [0.980] |
| Panel B: Adjust for State-by-Year and County Fixed Effects and Local Unemployment Trends | | | | | | | |
| Treated * 2018 | 0.001 | 0.003 | 0.006 | -0.001 | -0.018 | 0.016* | 0.036 |
| | (0.002) | (0.004) | (0.005) | (0.002) | (0.011) | (0.009) | (0.031) |
| Treated * 2019 | 0.000 | -0.004 | 0.005* | 0.000 | -0.009 | -0.004 | 0.013 |
| | (0.002) | (0.007) | (0.003) | (0.002) | (0.008) | (0.013) | (0.022) |
| *Pre-trend check p-value* | [0.872] | [0.658] | [0.374] | [0.542] | [0.670] | [1.000] | [0.979] |
| Baseline Mean | 0.987 | 0.994 | 0.993 | 0.989 | 0.980 | 0.980 | 0.974 |
| Observations | 530,335 | 58,283 | 52,945 | 44,3954 | 38,592 | 60,063 | 13,668 |

Source: Authors' analysis of ACS data paired with county-level unemployment data from the Bureau of Labor Statistics. The sample included adults aged 65 to 80 who were United States citizens and lacked employer-sponsored coverage.

Note: The dependent variable was an indicator for whether the respondent was currently insured through Medicare. All regressions included state-by-year fixed effects and county-level fixed effects and adjusted for the respondent's race/ethnicity (Black, white, Hispanic), age in years, and gender (male, female). Regressions in Panel B also adjusted for the unemployment rate in the county during the open enrollment period. Column 1 includes the full sample. Columns 2 and 3 stratify the sample by the respondent's income level. Columns 4, 5, and 6 stratify the sample by the respondent's race/ethnicity. Column 7 includes only sample members who spoke a language other than English at home. The *p*-value for a test of parallel pre-trends across groups corresponding to each model is in brackets. The estimates used ACS sample weights. Robust standard errors, shown in parentheses, allowed for clustering at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table B3. Cross-validation test: Impact of cuts to the navigator program on health insurance coverage**

| Outcome | Subgroups | Adjust for State-by-Year and County Fixed Effects | | | | | Adjust for State-by-Year and County Fixed Effects and Local Unemployment Trends | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Main Result: Coefficient | Main Result: Standard error | Proportion coefficients negative | Proportion coefficients significant at 5% level | Proportion significant at 10% level | Main Result: Coefficient | Main Result: Standard error | Proportion coefficients negative | Proportion coefficients significant at 5% level | Proportion significant at 10% level |
| Marketplace enrollment | Total | -0.014* | (0.01) | 100% | 15.15% | 81.82% | -0.013* | (0.01) | 100% | 15.15% | 78.79% |
| | Enrolled in Cost-Sharing Reduction Plan | -0.033** | (0.02) | 100% | 66.67% | 96.97% | -0.033* | (0.02) | 100% | 24.24% | 90.91% |
| | 150-200% of FPL | -0.024** | (0.01) | 100% | 100% | 100% | -0.024** | (0.01) | 100% | 100% | 100% |
| Any coverage | Total | -0.008* | (0.01) | 100% | 0% | 100% | -0.008* | (0.01) | 100% | 0% | 100% |
| | 200-250% of FPL | -0.037** | (0.02) | 100% | 100% | 100% | -0.037** | (0.02) | 100% | 100% | 100% |
| | Under Age 45 | -0.015** | (0.01) | 100% | 100% | 100% | -0.016** | (0.01) | 100% | 100% | 100% |
| | Hispanic | -0.035*** | (0.01) | 100% | 100% | 100% | -0.035*** | (0.01) | 100% | 100% | 100% |
| | Black | -0.029* | (0.02) | 100% | 0% | 100% | -0.028* | (0.02) | 100% | 0% | 100% |
| | Speak language other than English at home | -0.03** | (0.01) | 100% | 100% | 100% | -0.03** | (0.01) | 100% | 100% | 100% |
| Medicaid coverage | Speak language other than English at home | -0.026** | (0.01) | 100% | 100% | 100% | -0.026** | (0.01) | 100% | 100% | 100% |

Source: Authors' analysis of ACS and marketplace enrollment data paired with county-level unemployment data from the Bureau of Labor Statistics. The ACS sample included non-elderly adults who were United States citizens and lacked employer-sponsored coverage.

Note: This table presents a cross validation exercise for the findings from Tables 2 and 3 that were statistically significant at the 5% or 10% level in the main analysis. In this exercise, we systematically dropped states one at a time and re-estimated the model after dropping each state. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.