Can Adding a Checkbox to Tax Forms Increase Take-up of Medicaid?

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Recent version can be found at

https://nbviewer.org/github/sjtkim/TaxFormCheckbox/blob/main/TFCB_SejungTKim.pdf

Abstract

This paper investigates the impact of statewide interventions aimed at boosting Medicaid take-up in Maryland, utilizing a checkbox incorporated into state tax forms. I first demonstrate that the checkbox encourages potential beneficiaries to self-identify to receive the interventions. Using novel administrative data from the Maryland Health Benefit Exchange, I find that more than 100,000 individuals with a family income under \$70,000 checked this box. Through difference-in-difference specifications, I provide suggestive evidence that the checkbox and subsequent interventions led to approximately 30,000 additional individuals enrolling in Medicaid. I also find evidence of potential crowd-out of employer insurance enrollment, with the size of the estimates being roughly half the size of increases in Medicaid take-up. Further, I discover that the increases in Medicaid take-up and crowd-out of employer insurance are driven by demographic groups that had larger proportions of individuals who checked the box.

Keywords: take-up; self-identification; Medicaid enrollment; crowd-out; statewide intervention

JEL Codes: H31; H53; H75; I13; I18; J18

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1 Introduction

The United States has implemented a multitude of safety net programs aimed at assisting low-income families. However, take-up of each of the programs has been far from perfect. For instance, more than 20 percent of eligible tax filers do not claim Earned Income Tax Credit (EITC) benefits each year (U.S. Internal Revenue Service, 2022). More concerning is that as the COVID-19 pandemic era extensions of safety net programs expire, there will be a significant increase in the number of individuals who are no longer protected by programs such as Medicaid. Re-establishing, increasing participation in, and targeting the appropriate populations in these programs will pose challenges. As a part of ongoing efforts to overcome incomplete take-up of public assistance programs, interventions have been proposed and tested in field experiments (Finkelstein and Notowidigdo, 2019; Armour, 2018; Bhargava and Manoli, 2015; Chetty et al., 2013; Currie, 2006; Goldin et al., 2021).

However, a major issue with scaling these interventions statewide is the associated administrative burden. One facet of this burden involves the direct costs of sending the interventions. As outlined by Finkelstein and Notowidigdo (2019), Benefits Data Trust estimated that sending relevant material for information interventions incurs about \$1 per individual the information is sent to and \$7 per individual if call assistance is added. While the magnitude of such direct costs scaled to state-level may vary depending on the chosen interventions, there exists a second type of administrative burden that could prove more demanding. This is the cost of identifying and determining whom to give the interventions to. Similar to researchers conducting field experiments, states must initially identify potential beneficiaries likely eligible for benefits and then invest further resources to locate individuals more inclined to enroll in programs following the interventions. This decision-making process of identifying specific groups of potential enrollees poses a substantial administrative burden for state governments, requiring significant intellectual and financial resources.

This paper studies the effects of statewide interventions designed to enhance Medicaid enrollment by employing a checkbox integrated into state tax forms as a mechanism for individuals to self-identify as potential beneficiaries. Starting in 2020, Maryland included an extra line with a checkbox in state individual tax forms. By checking the box, taxpayers grant permission for the state of Maryland to share their information with the Maryland Health Benefit Exchange (MHBE). Subsequently, MHBE processes taxpayers' information to determine pre-eligibility for Medicaid and low-cost insurance. Then, MHBE reaches out to taxpayers who marked the checkbox with information treatments and reminders. The treatments include providing information on pre-eligibility of Medicaid or other low-cost insurance, instructions on the enrollment process, and a phone number in case additional help is needed. Then, reminders are also sent to taxpayers' addresses to further enhance enrollment. In 2021, MHBE actively called each and every individual who checked the box to provide assistance in enrolling.

The introduction of the checkbox on state tax forms could operate as a low-cost means of reaching target populations. By allowing individuals to self-identify as potential beneficiaries, states incur nearly zero marginal cost in the process of identifying whom to give the interventions to. Furthermore, in contrast to when states or researchers identify potential targets, the treatments are exclusively sent to taxpayers who voluntarily check the box and express a willingness to receive the interventions. Consequently, this suggests resources for interventions are spent on individuals who are more likely to end up taking up benefits when exposed to the interventions. If the self-screening strategy of the checkbox proves to be successful in motivating Medicaid-relevant populations to check the box and receive interventions, it could potentially serve as an extremely low-cost method of targeting those with a higher probability of ultimately taking up a variety of safety net benefits.

Although the significant potential of this policy has led other states to follow Maryland's lead, no active research has been done thus far on this unique policy.[1] In response, I conduct the first analysis of whether the self-identification strategy reached Medicaid-relevant populations, whether it led to behavioral changes in Medicaid take-up, and on the existence of potential crowd-out effects.

I find three main empirical results. First, using novel administrative data from MHBE, I find that the checkbox successfully identified Medicaid-relevant groups for intervention outreach. A substantive 117,000 individuals checked the box on their Maryland state tax forms between 2020 and 2022.[2] Further, the checkbox disproportionately reached lower-income families. Over 90 percent of or more than 100,000 tax filers who marked the box had a family income below $70,000. The shares of individuals who checked the box in each income bin (relative to the total population of each income bin) were also largest in the lowest income bins and then decreased as income increased. These findings imply that the incidence of the checkbox is primarily concentrated on individuals who have a greater need for public assistance programs.

Second, I uncover that these patterns translate into increased Medicaid enrollment. Using data from the American Community Survey (ACS), I find noticeable increases in the share enrolled in Medicaid in Maryland compared to neighboring states after the checkbox was implemented. Difference-in-difference models indicate an increase of approximately 30,000 Medicaid enrollees after the interventions (95 percent confidence interval of 14,000 and 46,000 individuals). Even in the most conservative specification, up to 65 percent of these numbers can be explained by the checkbox and subsequent interventions. Additionally, event study figures show that the increase in Medicaid enrollment started in 2020 when the checkbox was implemented, and synthetic control methods demonstrate similar results.

Moreover, I demonstrate that the impacts of the checkbox and following interventions on Medicaid enrollment are concentrated within demographic groups that had a higher proportion of taxpayers who checked the box. Combining individual-level administrative data I received from MHBE (on income and age of taxpayers who checked the box) and public use data from ACS, I divide the population into demographic groups by income and age. By plotting the share of individuals who marked the checkbox within each demographic group against

[1] Colorado, Illinois, Massachusetts, New Mexico, Pennsylvania, and Virginia have recently implemented this checkbox. California, New Jersey, and Maine will implement starting next year.

[2] Individuals with insurance can also check the box. However, if we compare the number of individuals who checked the box to the number of uninsured individuals to gauge how large 117,000 is, it amounts to 32 percent of the uninsured population in Maryland.

the difference-in-difference estimates of each corresponding group, I find that the overall increase in Medicaid enrollment rates is driven by groups with larger shares of taxpayers who marked the box. That is, groups with larger shares of individuals who checked the box also exhibit larger increases in Medicaid enrollment.

The third main empirical finding is that there is a potential crowd-out effect resulting from the statewide interventions.[3] Specifically, increases in Medicaid take-up due to the interventions subsequently led to reductions in employer insurance enrollment. The magnitude of the reductions in employer-based insurance implies that the crowd-out effects were roughly half the size of increases in Medicaid take-up. This aligns with estimates from Garthwaite et al. (2014) and Cutler and Gruber (1996), which find crowd-out of private or employer-based insurance to be around half the size of the increase in Medicaid enrollment. In addition, I find that the sizes of decreases in employer insurance for different demographic groups are larger for groups with a higher share of taxpayers who checked the box. In other words, groups with a higher proportion of individuals who checked the box show more significant decreases in employer-based insurance enrollment (and larger increases for Medicaid enrollment), suggesting more substantial crowd-out for such groups.

These empirical findings hold policy relevant implications for individual behavioral responses to statewide interventions. When scaling interventions seen in field experiments to a statewide level, there is uncertainty on whether the interventions will be effective, while it is certain that administrative costs will be significantly more demanding. Consequently, it is imperative to assess effectiveness of strategies that could alleviate the administrative burden and also evaluate whether the interventions lead to an increase in take-up. The empirical findings imply that even without the state actively investing massive amounts of resources to identify prospective beneficiaries, the checkbox can prompt such individuals to receive treatment. In particular, checkbox on state tax forms induced over 100,000 individuals with a family income under $70,000 to self-identify as potential targets of the interventions. Another notable implication is that the interventions successfully increased Medicaid enrollment in a statewide policy setting. This also implies the likelihood of considerable health benefits throughout the state, as previous research has indicated that interventions reaching out to taxpayers may reduce mortality through increased insurance enrollment (Goldin et al., 2021). Although outside the scope of this paper, the findings also imply that there is a need to consider crowd-out effects when assessing comprehensive welfare effects of low-income employees taking up Medicaid.

This paper first contributes to a line of literature on incomplete take-up of safety net programs and interventions to increase take-up. Existing literature proposes ignorance, transactions costs, incomplete understanding, and stigma as possible explanations for why individuals do not enroll in benefits (Finkelstein and Notowidigdo, 2019; Armour, 2018; Bhargava and Manoli, 2015; Chetty et al., 2013; Currie, 2006; Goldin et al., 2021; Smeeding et al., 2000; Currie, 2006; Moffitt, 1983). To find whether addressing some of these frictions can increase take-up, Finkelstein and Notowidigdo (2019) conducts an RCT using information and assistance interventions and finds

[3] While the checkbox is aimed at increasing insurance enrollment of the uninsured, insured taxpayers can also check the box, and they still receive information on pre-eligibility.

that providing knowledge of potential eligibility leads to sizable increases in Supplemental Nutrition Assistance Program (SNAP) take-up. Studies also find significant effects of information provisions and reminders on take-up of Disability Insurance benefits (Armour, 2018), postsecondary education (Barr and Turner, 2018), and EITC filing (Guyton et al., 2017). On the other hand, there are also papers that find a null effect of such interventions. Linos et al. (2022) employ a field experiment with several information and assistance interventions but do not detect any significant effects on take-up of EITC. Studies that find similar null effects suggest that the high initial cost is a too significant hurdle to overcome for the population they study (Linos et al., 2022; Castleman et al., 2020). In common, these studies carefully design field experiments to investigate the outcomes to be expected if we were to implement these interventions as a statewide policy. I extend this literature by studying the effects of an actual statewide implementation of such behavioral interventions aimed at improving take-up of safety net programs.

Next, this paper contributes to the literature investigating the impacts of increased enrollment in safety net programs on enrollment in other programs. Of particular importance within this context is Cutler and Gruber (1996), which reveals that Medicaid expansions in the late 1980s and early 1990s resulted in a reduction of employer insurance. Alternatively, Garthwaite et al. (2014) examines a large disenrollment in Medicaid, which happened in Tennessee in 2014, and finds that employer insurance along with labor supply on the extensive margin increased immediately. These papers are corroborated by others which find similar results (Gruber and Simon, 2008; LoSasso and Buchmueller, 2004). Other papers examine spillover effects of Medicaid expansions on other safety net programs such as SNAP or EITC and find mixed results (Baicker et al., 2014; Burney et al., 2021; Schmidt et al., 2021). I contribute to this body of literature by adding that behavioral interventions to increase take-up of safety net programs can also result in corresponding declines in employer insurance.

Finally, this paper is relevant to the literature studying the incidence of interventions aimed at increasing take-up of public assistance programs. Finkelstein and Notowidigdo (2019) finds that a combination of information and assistance interventions results in less needier individuals applying for and enrolling in SNAP. Some other papers find that individuals with lower education and worse health are more responsive to information interventions compared to their less needier counterparts (Armour, 2018; Bhargava and Manoli, 2015; Guyton et al., 2017). This paper contributes to the literature by investigating the incidence of a unique intervention where the state sends out a checkbox to all taxpayers and individuals self-identify themselves as potential targets. One difference is that the incidence studied in existing literature is about which groups respond to interventions conditional on having been treated with the interventions. On the other hand, the incidence in this study is related to which groups choose to receive the interventions. I find that a vast majority of taxpayers who marked the checkbox are from households with a lower family income. This suggests that the checkbox is an extremely cost-effective outreach method, as it induces those in higher need to receive the interventions without requiring significant upfront resources to determine the target population ex-ante.

While the results and implications hold significant importance, there are potential threats to identification. First, the COVID-19 outbreak during the same period could have introduced differential effects on trends in insurance enrollment behavior in Maryland and neighboring states. Second, the study is limited to two years of post-treatment data. With additional post-treatment data, it may be possible to assess the longer term effects of the checkbox, including whether individuals continue to stay on Medicaid or whether the effects are short-lived. Extended data would also open up opportunities to investigate long-term effects on health outcomes.

These potential limitations can be addressed with time. As more states adopt the checkbox, the number of states available for study that are not confounded by concurrent shocks (such as the COVID-19 pandemic) will increase. This would also allow for employing additional methods to investigate the impacts of the checkbox more thoroughly, such as a staggered difference-in-difference design. The number of post-treatment years will also naturally increase with time, enabling analyses of longer-term effects.

Another note is that the checkbox can only reach individuals who file taxes. While the results demonstrate that in our sample of taxpayers, more financially vulnerable individuals mark the checkbox and receive the interventions, some needier individuals do not file taxes. This implies that although the checkbox is potentially a powerful tool in having target populations self-identify themselves, it should be accompanied with outreach efforts to the lowest income non-taxpayers.

The rest of the paper proceeds as follows. Section 2 describes background information on the checkbox and the data used in following analyses. Section 3 analyzes the first stage of checking the box. Section 4 includes the main results and accompanying analyses on Medicaid enrollment and crowd-out, and Section 5 concludes.

2 Background and Data

I first provide background information on the Maryland checkbox. I also explain the Maryland Health Benefit Exchange (MHBE) administrative data and American Community Survey (ACS) data, which are used for analyses in the subsequent sections.

2.1 State Tax Form Checkbox

In the past few years, several states introduced either an additional line in state tax forms or an additional form asking if taxpayers are willing to share their information with state health agencies. Seven states have implemented this measure (Colorado, Illinois, Pennsylvania, New Mexico, Maryland, Massachusetts, and Virginia), and three are planning to do so in the following tax year (California, New Jersey, and Maine). Among these states, Maryland was the pioneer in adopting this policy. In this study, I concentrate on Maryland because it is the sole state where sufficient time has passed since implementation, allowing for an investigation of its impact on Medicaid enrollment.

Maryland included an extra line with a checkbox in state individual tax forms starting in 2020. By checking the box, taxpayers grant permission for the state of Maryland to share relevant information with the Maryland Health Benefit Exchange (MHBE), a state health agency responsible for administrating Maryland's insurance marketplace. The exact wording of the question is "I authorize the Comptroller of Maryland to share information from this tax return with the Maryland Health Benefit Exchange for the purpose of determining pre-eligibility for no-cost or low-cost health care coverage". It is positioned in section "Maryland Health Care Coverage" of Maryland Form 502,page 2.

For taxpayers who mark the checkbox, MHBE uses the information to determine eligibility for Medicaid or low-cost insurance, whether the taxpayer has a Maryland address, and whether they are already enrolled in relevant insurance plans. Next, MHBE notifies each individual about their potential eligibility. Taxpayers receive information on their pre-eligibility for Medicaid and low-cost insurance even if they are not eligible. As the income threshold for Medicaid depends on the federal poverty line, which changes every year, individuals close to the threshold may not be sure whether they qualify for Medicaid. Informing those who check the box about the potential eligibility will lower information costs and may induce taxpayers to take up Medicaid. In addition, the initial notice also includes instructions on how to apply for insurance through Maryland Health Connection (MHC, health insurance marketplace of Maryland). Subsequently, a postcard is sent to taxpayers who checked the box as a reminder to apply. For those who provided their email address on the tax form, emails are sent every three days, offering assistance in completing the enrollment process if they started but did not finish their applications using Maryland Health Connection. In 2021, MHBE also called every person who marked the checkbox and offered assistance enrolling. Starting in 2022, they have transitioned to calling only those who initiated the application process through Maryland Health Connection but did not finish due to the high costs of calling everyone who checked the box.

2.2 Maryland Health Benefit Exchange Data

The first main data source I use is administrative data from Maryland Health Benefit Exchange.

State-Level Data The state-level data shows number of taxpayers who checked the box in Maryland from 2020 to 2022. It provides the numbers by total eligible, total enrolled through Maryland Health Connection, by age, and by race. These statistics are all given for Medicaid plus Maryland Children's Health Program (MCHP), insurance with Advance Premium Tax Credit (APTC), and unassisted insurance plans. In our main analyses, we focus on Medicaid enrollment.

Note that these numbers do not account for everyone who enroll in the aforementioned insurance plans. For example, individuals may register for Medicaid at local health departments instead of using the MHC online application. In addition, there are individuals who must apply to Medicaid without using Maryland Health Connection. These include individuals who are older, disabled, with chronic illness, or need home and community-based services who must instead apply through a separate program called “myMDTHINK”, which is run by Maryland Department of Human Services.

Individual-Level Data I also use individual-level data on those who checked the box received from the Maryland Health Benefit Exchange (MHBE). In particular, I have data on income relative to the federal poverty line of tax unit, number of individuals in the tax unit, and age of taxpayer. From the information on percentage of poverty line, and number of individuals in tax unit, I calculate the family income of these tax units. This income data and age data will be used in heterogeneity analyses in later chapters. The MHBE did not provide data on which of these individuals ended up enrolling in Medicaid.

2.3 American Community Survey Data

The second primary data source is the American Community Survey. The ACS is publicly available repeated cross-sectional data collected by the Census. From the ACS, we use the 1-year estimates, which utilize 12 months of collected data for areas with populations over 65,000 individuals. In the analyses using ACS, I restrict to individuals aged 18 to 64 with family income below $70,000 as they are the population most likely relevant to Medicaid enrollment.

The main variables of interest in this dataset are the insurance variables. Specifically, I use variables asking whether individuals are enrolled in Medicaid, public insurance, employer insurance, private insurance, or any insurance at the time of interview. Respondents are categorized as having public insurance if enrolled in Medicaid, Medicare, or Department of Veterans Affairs insurance. Respondents are considered as enrolled in private insurance if they have employer-based insurance, insurance purchased from private companies, and Tricare or other military health care. Respondents with either public or private insurance are classified as having any insurance. In other words, those enrolled in Medicaid would be a subset of those enrolled in public insurance, and they would again be a subset of those enrolled in any insurance.

Table 1 presents summary statistics on insurance variables and demographic characteristics for Maryland and neighboring states. The sample is individuals 18-64 with a family income of less than $70,000 from 2016 to 2021. Virginia is not included in the control group of neighboring states because of Medicaid expansions in 2019. The overall proportion of individuals enrolled in different types of insurance is similar across Maryland and neighboring states. Other demographic variables are also balanced across Maryland and neighboring states, with the exception of race. The proportion of Black individuals is much lower in neighboring states compared to Maryland, mainly driven by West Virginia. To account for this, we also use a different set of states as the control group for robustness checks in later chapters.

3 Taxpayer Response to Checkbox

In this section, I provide analysis on the extent to which taxpayers in Maryland checked the box. I also assess whether the taxpayers checking the box are of low-income backgrounds possibly eligible for Medicaid.

3.1 Evidence of Taxpayers Checking the Box

I document evidence of taxpayers marking the checkbox on state tax forms. Data used in this section is at the state-year level and is provided by the Maryland Health Benefit Exchange. Figure 1 shows the number of people who checked the box on individual state tax forms in Maryland. Around 58,000 taxpayers checked the box in 2020. The numbers decreased to approximately 33,000 and 26,000 in 2021 and 2022. This decrease may reflect the fact that a considerable amount of taxpayers already checked the box earlier in 2020. Altogether, the number of taxpayers who checked the box totals 117,000 individuals in Maryland.

Figure 2 shows the number of eligible taxpayers by type of insurance conditional on having checked the box. Eligibility is categorized into eligible for Medicaid, eligible for Advance Premium Tax Credit (APTC), eligible for insurance but without assistance, and ineligible. Medicaid constitutes around 1/3 of the total numbers. Figure 3 represents the number of people who ended up enrolling in different types of insurance after checking the box on state tax forms through Maryland Health Connection (MHC). Note that this number only includes taxpayers who enrolled through MHC. Those who checked the box, received information, and then enrolled in insurance through another channel are not counted, implying that the actual number of taxpayers who sought insurance due to the checkbox is larger. Especially if the proportion of individuals who enrolled in person at local departments or were required to enroll through "myMDTHINK" is high, the number of individuals who enrolled in Medicaid after the checkbox and following interventions will have been underestimated. Figure 4 decomposes taxpayers enrolled in Medicaid through Maryland Health Connection by age group, and taxpayers under the age of 35 make up over half of the enrollment.

3.2 Self-Identification of Prospective Beneficiaries

I now utilize individual-level data from MHBE to uncover whether those marking the box are prospective target populations relevant to Medicaid. The MHBE provided individual-level data on income and age regarding those who checked the box for years 2021 and 2022, but not 2020. I exploit this data to document income characteristics for those who checked the box. If taxpayers who are in higher need of and are more likely to receive Medicaid are checking the box relative to those who are not, it would imply that the checkbox is working as a means of having potential beneficiaries opt-in to receiving interventions. Incidence in this sense differs from incidence studied in existing literature such as Finkelstein and Notowidigdo (2019) or Bhargava and Manoli (2015). The incidence in such literature relates to whether conditional on receiving treatment, are those responding to the treatment more or less needier individuals. In the context of this paper, I am studying whether more needier (and more likely to be eligible) individuals are deciding to receive the interventions.

Figure 5 documents the shares of taxpayers who checked the box relative to the estimated populations of each income bin. I measure the total population for each income bin using data from ACS and combine this with MHBE administrative data. The figure shows that the proportion of individuals who checked the box is largest for the two lowest income bins, and then decreases as income increases. This provides evidence that the lower income individuals are those self-identifying into checking the box to receive interventions.

Further, in Figure 6, I find that more than 90 percent of positive-income taxpayers who checked the box are categorized as having a family income under $70,000, and more than 75 percent have a family income under $40,000. Considering that approximately $40,000 is the annual family income Medicaid eligibility threshold for a family of 4, the figures demonstrate that most individuals checking the box are likely eligible for Medicaid.

4 Effect on Medicaid and Crowd-Out of Employer Insurance

The main analyses in this section show evidence of an increase in Medicaid enrollment rates in Maryland starting 2020 accompanied with crowd-out of employer-based insurance. Heterogeneity analysis by demographic groups provides that the increase in Medicaid and decrease in employer insurance are driven by demographic groups with a high proportion of individuals who checked the box.

4.1 Raw Trends in Medicaid and Employer Insurance Enrollment Rates

Next, I use public use data to investigate the effects of the checkbox on take-up of Medicaid. I utilize publicly available data from the American Community Survey (ACS). I restrict the sample to individuals in the age range of 18-64 and family income less than $70,000 as they are the most relevant population to Medicaid. While I focus on analyses comparing 2020 to earlier years, I also show how raw trends shifted in 2021. The changes in enrollment in 2021 might capture a lag in treatment effect due to the time required in going from checking the box to being enrolled in Medicaid - taxpayers check the box in state forms around March or April, then MHBE has to process and reach back to the individuals, and then the taxpayers need to go through their applications.

Figure 7 shows raw trends in the share enrolled in Medicaid among the selected population. The control group includes neighboring states of Delaware, West Virginia, Pennsylvania, and District of Columbia. I exclude Virginia because of its ACA Medicaid expansions in 2019. In Panel A, we see a clear trend break in Maryland Medicaid enrollment going from 2019 to 2020. Share enrolled in Medicaid trends almost identically in Maryland and neighboring states until 2019, and then shows a clear divergence in 2020. There was also a considerable increase in Medicaid take-up in 2021 for both Maryland and neighboring states, but of a similar magnitude. The difference in levels of Medicaid enrollment in 2021 seems to be driven by the trend break in 2020.

Panel B shows raw trends in share enrolled in employer insurance for Maryland and neighboring states. Maryland and neighboring states trended relatively similarly up to 2020. In 2021, there is a more apparent trend break. While I cannot make definitive conclusions at this point, this is suggestive of crowd-out from gaining Medicaid in Maryland. It is possible to keep Medicaid and employer insurance at the same time. However, considering that our sample consists of lower-income households, individuals who gain Medicaid will likely drop employer insurance to reduce premiums. A potential reason we see a substantial decrease in 2021 instead of 2020 is because individuals need time for adjustment. A large fraction of employer insurance has designated open enrollment periods for disenrolling from coverage unless one has a special qualifying event such as marriage or divorce. Such periods usually last around 1-2 months towards the end of the year.

A competing explanation for the sharp drop in employer insurance enrollment for Maryland in 2021 could be that employment dropped sharply in Maryland compared to other states, which could lead to a dramatic loss in employer insurance. Figure 8 shows that in 2020, there was a reduction in employment in Maryland compared to control states of around 1 percent point. This shows suggestive evidence that part of the decline in employer insurance could be because of reductions in employment. I look further into this possibility in later chapters.

4.2 Effect of Checkbox and Following Interventions on Insurance Enrollment Rates

Now I employ difference-in-difference methods to empirically investigate the effects of the checkbox policy. The data from ACS used in this analysis is repeated cross-sectional data. The benchmark regression specification is as follows:

$$y_{ist} = \beta \cdot Treated_s \times Post_t + X_i'\delta + \eta \cdot U_{st} + \alpha_s + \alpha_t + \varepsilon_{ist} \tag{1}$$

where y_{ist} is the outcome of interest (Medicaid enrollment, public insurance enrollment, any insurance enrollment, private insurance enrollment, employer insurance enrollment) for taxpayer i living in state s in year t. $Treated_s$ represents state treated by the checkbox implementation, namely Maryland. $Post_t$ indicates years after checkbox implementation. β are our difference-in-difference coefficients of interest. X_i are individual demographic characteristics, including dummies for age group, sex, education level, race, and marital status. U_{st} represents demeaned unemployment rates in state s at time t. [4] α_s is state fixed effects, and α_t is year fixed effects.

Table 2 shows results of the difference-in-difference regressions. Panel A represents the benchmark case where our whole sample of interest (individuals aged 18-64 with family income under $70,000) is included, and neighboring states are used as the control group. Panel B uses a different set of control states, where New Jersey replaces West Virginia from the set of neighboring states. I showed earlier in Table 1 that insurance variables and demographic controls are well-balanced between Maryland and neighboring states, with the exception of race. Thus, I check for robustness using a control group that replaces West Virginia with an almost-neighboring

[4] This is calculated as the difference between unemployment in year t and the average unemployment (of years used in the analyses) for each state s.

state that has a closer racial composition to Maryland. Panel C is restricted to individuals aged younger than 35. This is because MBHE asserts that the tax form checkbox had larger effects on younger populations. Panel D uses the new control group and restricts to individuals aged younger than 35.

Difference-in-difference estimates in Column 1 show increased Medicaid enrollment rates after the checkbox implementation of 1 to 2 percentage points. This is a substantial increase, considering the baseline was around 20 percentage points. Column 2 demonstrates a significant increase in public insurance enrollment, and the sizes of point estimates imply that the increase in Medicaid drives this.

The magnitude of the point estimates in Columns 1 and 2 imply an increase of approximately 30,000 more individuals enrolling in Medicaid compared to neighboring states or a 95 percent confidence interval of approximately 14,000 to 46,000 individuals. In the Appendix, Figure 4 shows that around 3,300 taxpayers aged 18-64 checked the box and then enrolled in Medicaid through Maryland Health Connection during 2020-2021. This amounts to roughly 11 percent of the increase we estimate from the regressions (7 percent to 24 percent of the 95 percent confidence interval). These are lower bounds for the effect of the checkbox.

Considering taxpayers who check the box but enroll outside of Maryland Health Connection, the proportion of the estimates that the checkbox implementation can explain is higher. Indeed, individuals may choose to enroll in person at local health departments, and in addition, individuals who are disabled or have chronic disease are required to apply through a separate process using "myMDTHINK". If we make the strong assumption that all taxpayers aged 18-64 who checked the box and are eligible for Medicaid end up enrolling (through Maryland Health Connection + other channels), then the total count is around 30,000 individuals. Under this assumption, 100 percent of the diff-in-diff estimates can be explained by the checkbox implementation (65 percent to 214 percent of the 95 percent confidence interval).

It is also conceivable that the checkbox itself might induce individuals to take up Medicaid, albeit their not checking it. This is because even for taxpayers who were reluctant to check the box and give information to MHBE or taxpayers who did not check the box because they already knew of their eligibility, the checkbox itself may act as a reminder to apply for Medicaid. Unfortunately, it is not possible to separate out and check the existence of this effect with the currently available data.

Taking the maximum percentage of the lower 95 percent confidence interval and the minimum percentage of the upper 95 percent confidence interval, which can be explained by the checkbox and following interventions, we can bound the actual share of the diff-in-diff estimates explained by the policy at 24 to 65 percent. While this is a wide range, we can at the least affirm that the introduction of the checkbox contributes to explaining the increase of Medicaid take-up in Maryland.

Columns 4 and 5 show suggestive evidence of crowd-out. In Column 4, we see a substantial decrease in employer insurance, where the sizes of estimates are close to the sizes of increases in Medicaid enrollment. While the sizes are similar, there may also be other reasons that can be attributed to a decrease in employer insurance. Especially conceivable is that employment in Maryland may have seen larger decreases compared to neighboring states in 2020. The results of exploring this possibility are shown in Column 5. The sizes of decreases in employment in our populations of interest are roughly half the sizes of the decreases in employer insurance. If I assume that all individuals who lost employment were those who had employer insurance while working, I can attribute half of the decrease in employer insurance in Maryland compared to control states to a differential drop in employment. I can then attribute the other half of the decrease in estimates to crowd-out from an increase in Medicaid enrollment. This is plausible because, as I have explained, our sample consists of lower-income households who are likely to drop employer insurance if they realize they are eligible for Medicaid after the checkbox and following interventions.

4.3 Dynamic Responses to the Checkbox and Following Interventions

Next, I turn to event study versions of the analyses above to investigate how the effects of the checkbox policy evolved over time. The event study specification is as follows:

$$y_{ist} = \sum_{\tau=\tau_A}^{\tau_B} \beta_\tau Treated_s \mathbb{1}\{t=\tau\} + X_t'\delta + \eta \cdot U_{st} + \alpha_s + \alpha_t + \varepsilon_{ist} \tag{2}$$

where y_{ist} is the outcome of interest (for example, Medicaid enrollment) for taxpayer i living in state s in year t. $Treat_s$ represents state treated by the checkbox implementation, namely Maryland. β_τ are our coefficients of interest showing how the outcome variables evolve in Maryland versus control states throughout time after treatment. As in our original difference-in-difference equation, X_i is individual demographic characteristics, including dummies for age group, sex, education level, race, and marital status. U_{st} denotes demeaned unemployment rates in state s at time t. α_s is state fixed effects, and α_t is year fixed effects.

Figure 9 shows that the implementation of the checkbox is associated with approximately a 1 to 2 percent point increase in Medicaid enrollment (from a baseline of around 20 percent point). Panel A is the benchmark case where all age groups are included, and the control group states are neighboring states. Panels B-D show different variations of the benchmark results. Panel B restricts to individuals aged younger than 35, which follows from MBHE's assessment that the tax form checkbox had larger effects on younger populations. Panel C changes the control group by excluding West Virginia and including New Jersey to better balance race, as explained earlier. Panel D uses the new control group and is restricted to individuals aged younger than 35. We see that in all panels, there seems to be some evidence of an increase in Medicaid take-up after the checkbox was implemented. The increase is more pronounced for individuals under age 35.

In some instances, we see that Medicaid enrollment increases in 2020 compared to control states, but in other cases, the increase happens in 2021. This may be for two reasons. First, as discussed earlier, most tax units file taxes in March-April, and then it takes time for the MHBE to communicate and provide taxpayers with the information interventions. Consequently, there may be a substantial number of individuals who were asked about insurance enrollment before receiving the relevant information treatments and reminders (ACS surveys people year-round).

Another reason could be that in 2021, MHBE called every taxpayer who checked the box to offer assistance. In other words, taxpayers who checked the box in 2020 only received call assistance if they contacted the provided phone number, whereas taxpayers who checked the box in 2021 received a proactive call to aid in the application process. Unfortunately, the MHBE does not currently have data that would enable me to separate out how effective the call assistance was in inducing individuals to take up Medicaid.

Figure 10 plots results using Medicaid and other types of insurance as outcome variables. Panel A is the same plot from Figure 9, while Panels B-D plot results where the outcome variable is public insurance (Medicaid, Medicare, Department of Veterans Affairs insurance), private insurance (employer provided, purchased from private companies, Tricare or other military health care) and employer insurance. The plots show there was an increase in all public insurance. The sizes of the coefficients imply that this increase is mainly due to increases in Medicaid enrollment.

The decreases in employer insurance and private insurance enrollment in Panels C and D are suggestive evidence that new enrollment in Medicaid through the checkbox may be leading to crowd-out. As discussed earlier, the null effect for 2020 may be because of the time required for adjustment - most employer-based insurance and other private insurance have specific enrollment/disenrollment periods, usually towards the end of the year. This also rules out a reverse-causality story where individuals in Maryland lost employer-based insurance first and then sought out Medicaid as a result.

I also show event study results using all other states besides Maryland as controls in Appendix Figure A1. This allows us to cluster at the state-level and increase power. We see that Medicaid take-up increases after the checkbox implementation, but we see possible pre-trends for Medicaid and public insurance. In Figure A2, I use all states excluding 11 states that had Affordable Care Act (ACA) expansions in our event time window as control states. We check that Medicaid take-up in Maryland increased after 2020, but again, we cannot rule out the possibility of existing pre-trends. This gives us good reason to use the neighboring states, which apparently do not have pre-trends, as controls for the main specification.

4.4 Heterogeneity Analysis

Now, I combine MHBE administrative data on taxpayers who checked the box with ACS data to investigate which groups are driving the enrollment effects in our earlier analyses. Specifically, I run the difference-in-difference regressions on different age groups (18 to 29, 30 to 41, 42 to 53, and 54 to 64) and also on discrete family income groups ($1 to $20k, $20k to $40k, $40k to $60k, $60k+). I compare the estimates with the numbers and shares of taxpayers who checked the box for each group to verify that the estimates are driven by groups that were checking the box. The population is restricted to individuals aged 18-64 with positive family income. Note that while the difference-in-difference estimates use 2020 and 2021 as post years, the number of taxpayers who checked the box is calculated with values from 2021 and 2022 because of data constraints.

Figure 11 plots difference-in-difference coefficients against the shares of taxpayers who checked the box for each age and family income group. The total population for each bin is calculated using person weights from ACS. Panel A indicates results for the outcome variable Medicaid. I find that the sizes of increases in Medicaid are positively correlated with shares of taxpayers who checked the box. Panel B indicates results for when the outcome variable is employer insurance enrollment. Here, we find evidence that the shares of checkbox participants for each group are negatively correlated with the point estimates. In particular, I discover that the 18-29 age group and family income $1-$20k group are driving a large portion of the increases in Medicaid and decreases in employer-provided insurance. For these two groups, the negative employer insurance enrollment estimates are roughly half the size of the positive Medicaid enrollment estimates. This is in line with the magnitude of crowd-out effects in papers such as Garthwaite et al. (2014) and Cutler and Gruber (1996).

Appendix Figure A3 shows difference-in-difference estimates plotted against the numbers of taxpayers who checked the box by age group and by family income group. That is, instead of plotting the difference-in-difference estimates against shares of taxpayers who checked the box by group as in Figure 11, I plot against the absolute numbers of taxpayers who checked the box by group. Panel A demonstrates that the sizes of increases in Medicaid enrollment are positively correlated with the numbers of taxpayers who checked the box. Panel B indicates that point estimates are negatively correlated with the numbers of checkbox participants who checked the box. This strengthens conclusions drawn from Figure 11 and provides further suggestive evidence that the policy interventions increased Medicaid enrollment but also resulted in crowding out of employer insurance.

4.5 Evidence from Synthetic Control Method

In this section, I use synthetic control method to check robustness of earlier analyses on Medicaid enrollment. I use a five year pre-period from 2015 to 2019 after the ACA Medicaid expansion in 2014. In the appendix, I also include results using a longer pre-period from 2011 to 2019, restricting to years after the Health Care and Education Reconciliation Act of 2010. I match on the share enrolled in Medicaid for years 2015, 2017, 2019 and averages of demographic controls throughout 2015 to 2019, including age, race, college education, family income, marital status, and income restriction of Medicaid to construct the hypothetical control state. I do not use Medicaid enrollment for all years from 2015 to 2019 in order to avoid overfitting. I also drop certain states from the donor pool that enacted the ACA Medicaid expansion after 2014. This excludes 11 states of Virginia, Indiana, Alaska, Pennsylvania, Montana, Louisiana, Maine, Idaho, Utah, Nebraska, and Oklahoma from the donor pool. Table 3 shows the resulting matched states used in constructing the hypothetical control state and the weights for each state.

In Figure 12, Panel A illustrates the raw trends in Maryland compared to the hypothetical synthetic Maryland. It shows a trend break in Medicaid take-up in Maryland in 2020 when contrasted with the synthetic Maryland. The differential increase going from 2020 to 2021 is even more pronounced. Panel B plots the difference in actual and hypothetical (from synthetic control state) Medicaid enrollment for Maryland (black line) alongside that of all other states in the donor pool (gray lines). The figure demonstrates an increase in Medicaid enrollment in 2020, with an even more significant increase observed in 2021. This could be attributed to a lagged treatment effect due to the time required in adjusting or because of the proactive call assistance intervention in 2021. Results using a nine year pre-period of 2011 to 2019 are included in Figure A4. The resulting plots closely resemble those in Figure 12.

5 Conclusion

This paper investigates the implementation of a checkbox on state tax forms that induced taxpayers to self-identify as potential targets and explores the effects of this checkbox and subsequent interventions on take-up of Medicaid. Combining administrative data from MHBE and public use data from ACS, I find three main empirical results. First, I find that the checkbox successfully prompts prospective beneficiaries to self-identify themselves for intervention outreach. More than a hundred thousand taxpayers in Maryland checked the box on their Maryland state tax forms, predominantly with low income. Second, I uncover that these patterns translate into increased Medicaid enrollment of approximately 30,000 additional individuals. Indeed, among different demographic groups, I find a positive correlation between the sizes of the increases in enrollment rates and shares of individuals who checked the box. Further, the benchmark case event study figure shows that the increase in Medicaid enrollment starts in the year of checkbox implementation. Finally, there is potential crowd-out of employer insurance at roughly half the size of increases in Medicaid take-up. Demographic groups with a higher proportion of individuals who checked the box show larger decreases in employer-based insurance enrollment, suggesting stronger crowd-out effects for such groups.

The paper demonstrates that self-identification strategies can be effective in reaching out to potential beneficiaries when implementing interventions at a state-level. While it is low-cost compared to states actively finding prospective targets, the crucial factor is whether the relevant population comply with the self-identification strategy. This paper shows that in the context of Maryland state tax forms, financially vulnerable individuals likely eligible for Medicaid do indeed self-identify for interventions. Over 90 percent of the 117,000 individuals who checked the box had a family income below $70,000 and over 75 percent had a family income under $40,000. This has notable implications for researchers and policymakers, suggesting that such self-identification strategies are not only low-cost but also successful in identifying target populations of public assistance programs. Additionally, the paper provides analyses on statewide implementations of interventions aimed at improving safety net program take-up. I assess how effective interventions used in field experiment settings are at a state-level. While I refrain from making definitive conclusions due to potential threats to identification, further research on how effective such interventions are in increasing take-up of programs on a statewide level may yield more conclusive results.

Further research can advance this paper in several ways. First, it would be beneficial for future studies to revisit the checkbox implementation in the coming years, especially as more adopt similar strategies. With seven states already implementing the checkbox and three to follow next year, there is a broad scope for further research using newly produced administrative data or through collaboration with state health agencies from the implementation stage.

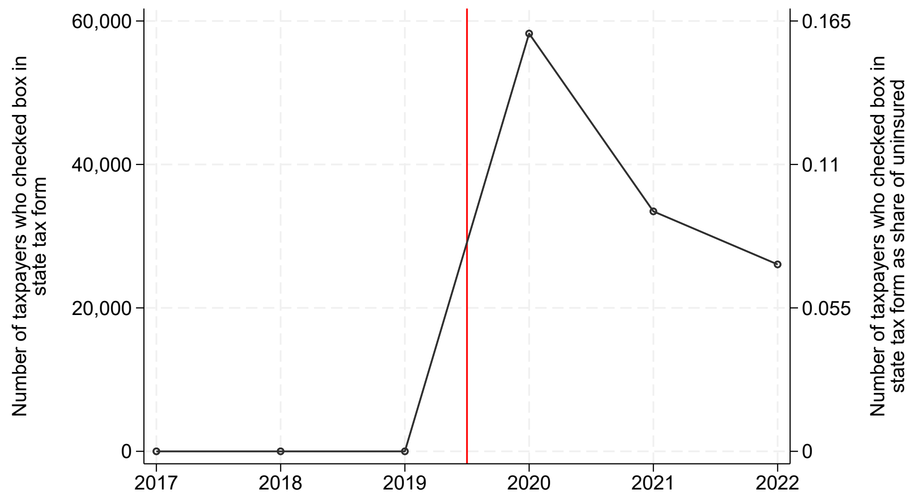
Second, future research can explore the extended effects of increased Medicaid enrollment from this policy. For example, estimating total welfare effects from this checkbox and following interventions could be interesting as states could assess and compare costs associated with this approach against alternative state outreach initiatives. Another noteworthy aspect to study could involve employment lock during the COVID-19 pandemic. Investigating whether increases in Medicaid enrollment could have decreased individuals' incentives to maintain employment status in order to have employer-based insurance during the pandemic would provide valuable insights.

Third, researchers could study the extent to which the checkbox itself served as a reminder for taxpayers to apply for Medicaid. It is plausible that, even without the interventions from MHBE, taxpayers may have been reminded about Medicaid after seeing it on the tax form. Understanding the degree to which this is true holds policy-relevant implications for evaluating the effectiveness of different interventions.

Fourth, future research could examine how self-identification could be applied in contexts beyond filing tax forms. Investigating the effectiveness of reaching non-taxpayers through a similar checkbox on other forms such as Supplemental Nutrition Assistance Program (SNAP) or Unemployment Insurance applications would have noteworthy implications.

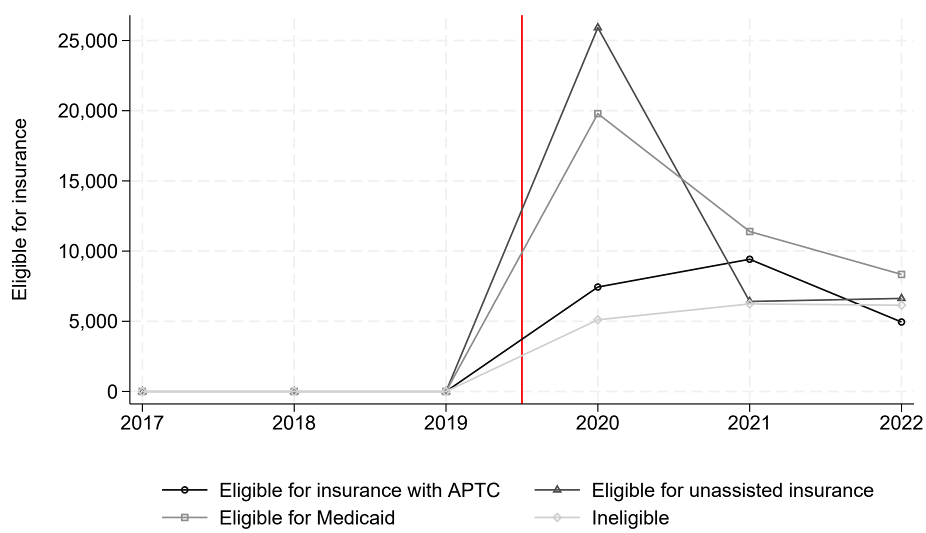
Figures

Figure 1: Number of Taxpayers who Checked the Box on State Tax Form



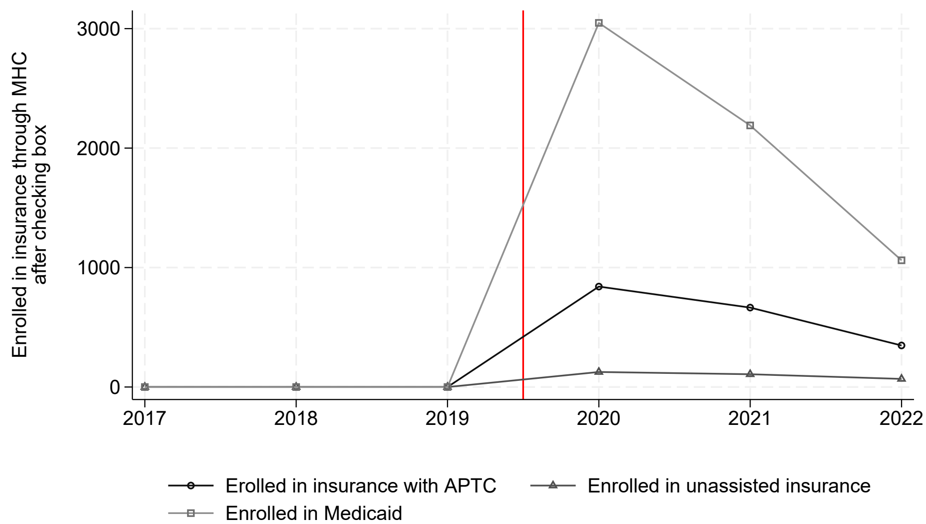
This figure shows the numbers of taxpayers who checked the box on individual state tax forms in Maryland by year. The second y axis shows the numbers as shares of uninsured individuals in Maryland. Although individuals with insurance can also check the box, the second y axis is provided as a comparison to gauge how large the numbers are. The checkbox in Maryland state tax forms was implemented starting in 2020.

Figure 2: Number of Eligible Taxpayers who Checked the Box by Program



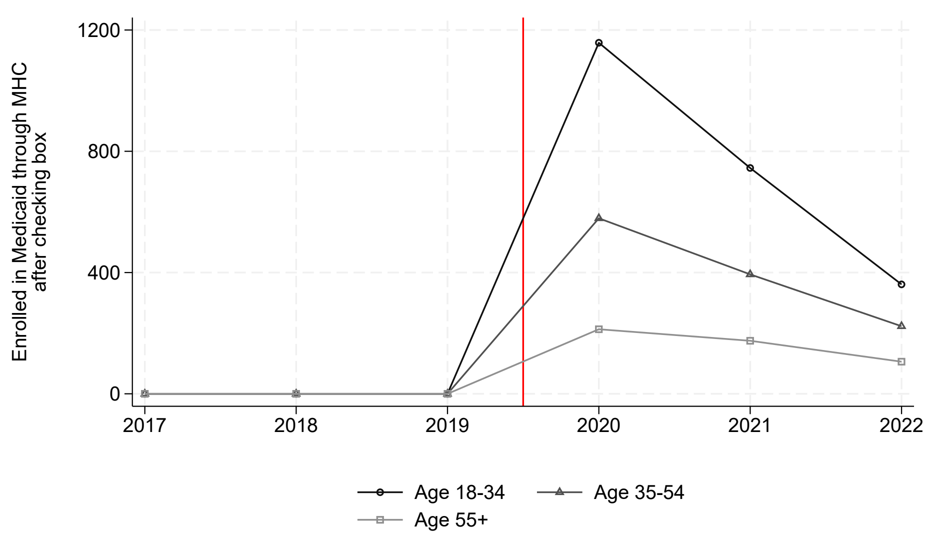
This figure shows the numbers of taxpayers who checked the box and were eligible for Medicaid/MCHP, insurance with APTC, and unassisted insurance by year. Ineligible consists of taxpayers who were already enrolled in Medicaid, or did not have a valid Maryland address. The checkbox in Maryland state tax forms was implemented starting in 2020.

Figure 3: Number of Eligible Taxpayers who Checked the Box and Enrolled through MHC by Program



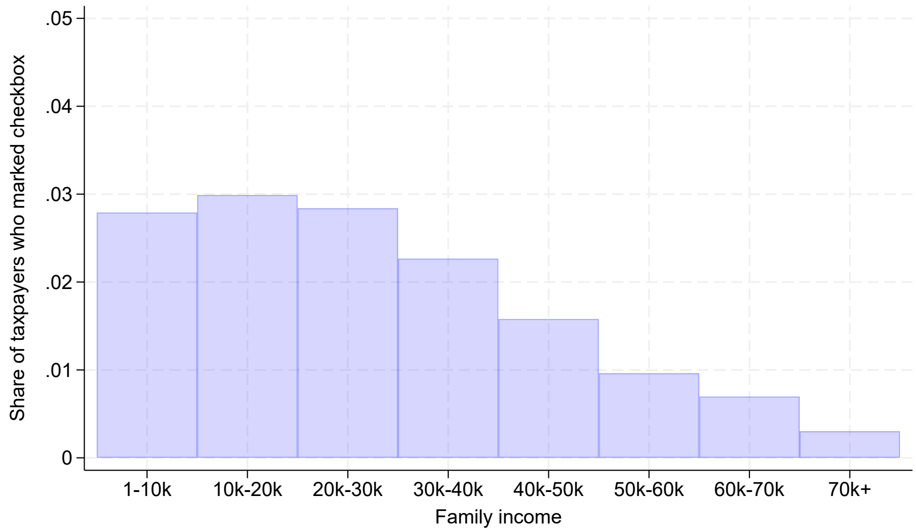
This figure shows the numbers of people who checked the box and then enrolled through Maryland Health Connection (MHC) for different types of insurance including Medicaid/MCHP, insurance with APTC, and unassisted insurance. The checkbox in Maryland state tax forms was implemented starting in 2020.

Figure 4: Number of Taxpayers who Checked the Box and Enrolled in Medicaid through MHC by Age Group



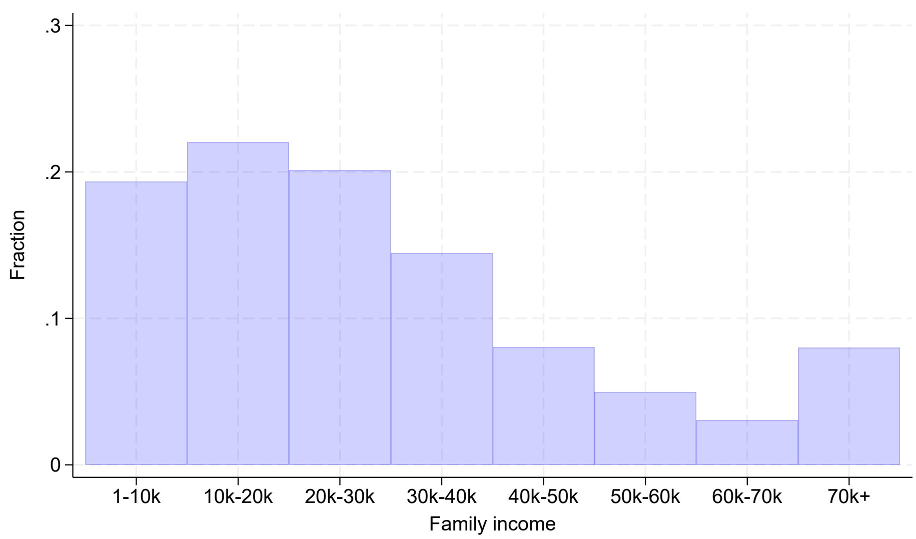
This figure shows the number of taxpayers who checked the box and then enrolled in Medicaid or MCHP through Maryland Health Connection (MHC) by age group. The age groups are 18 to 34, 35 to 54, and 55 or over. The checkbox in Maryland state tax forms was implemented starting in 2020.

Figure 5: Share of Taxpayers who Checked the Box by Family Income Bin



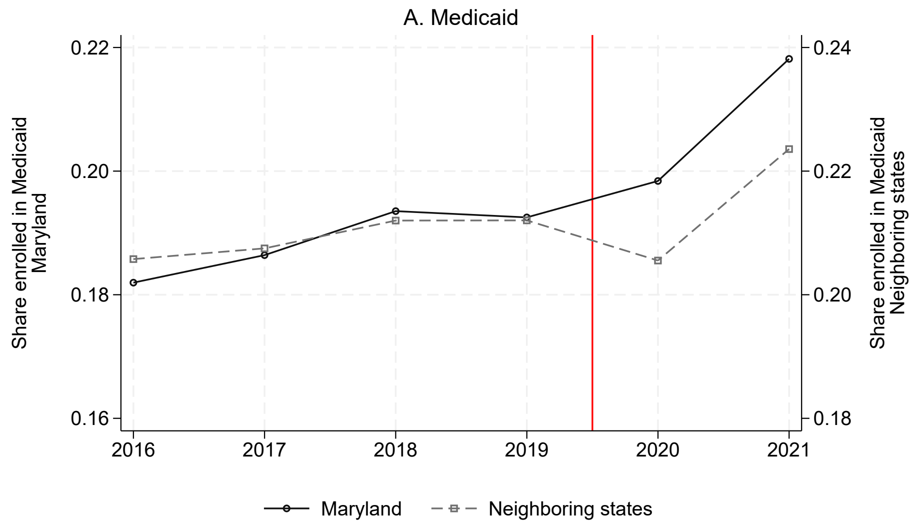
This figure shows the share of taxpayers who checked the box by family income. The total population for each income bin is calculated as the sum of person weights of individuals aged 18-64 using 2021 data from ACS. The number of individuals who checked the box for each income bin is for the years 2021 and 2022 and is restricted to individuals with positive income.

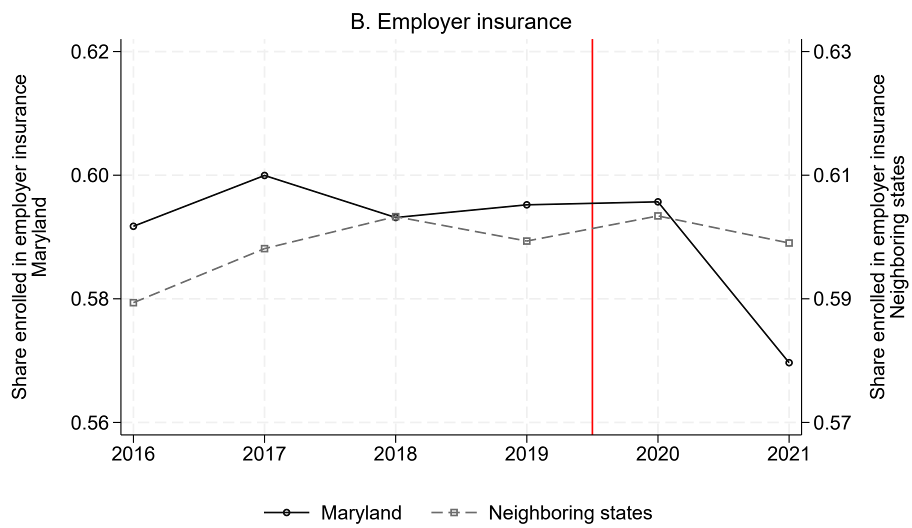
Figure 6: Distribution of Family Income of Taxpayers who Checked the Box



This figure shows distribution of family income regarding individuals who checked the box. The sample includes taxpayers with positive family income who checked the box in either 2021 or 2022.

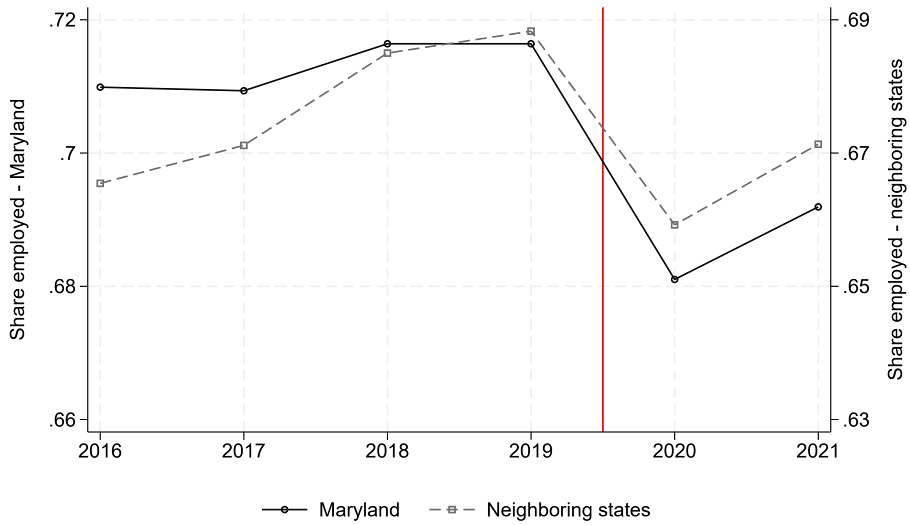
Figure 7: Medicaid and Employer Insurance Enrollment, Raw Trends





This figure shows raw trends in share enrolled in Medicaid and employer insurance for Maryland and neighboring states. Panel A shows trends for Medicaid and Panel B shows trends for employer insurance. The sample consists of individuals aged 18-64 with family income less than $70,000.

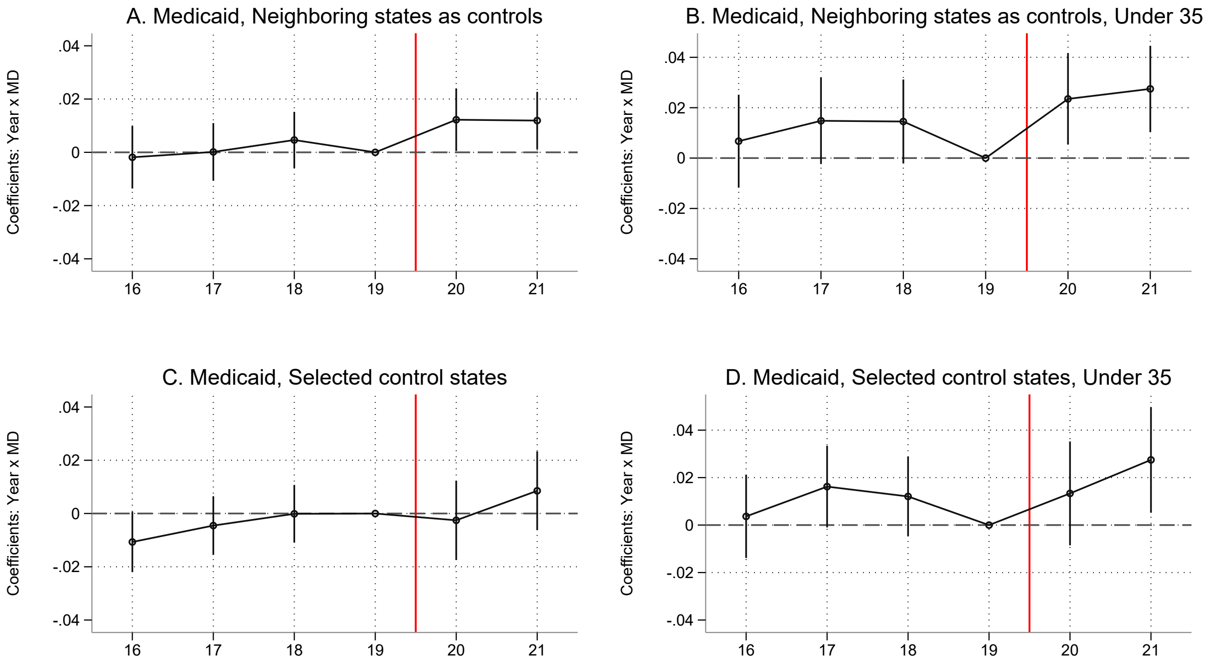
Figure 8: Employment, Raw Trends



This figure shows raw trends in employment for Maryland and neighboring states. The sample consists of individuals aged 18-64 with family income less than $70,000.

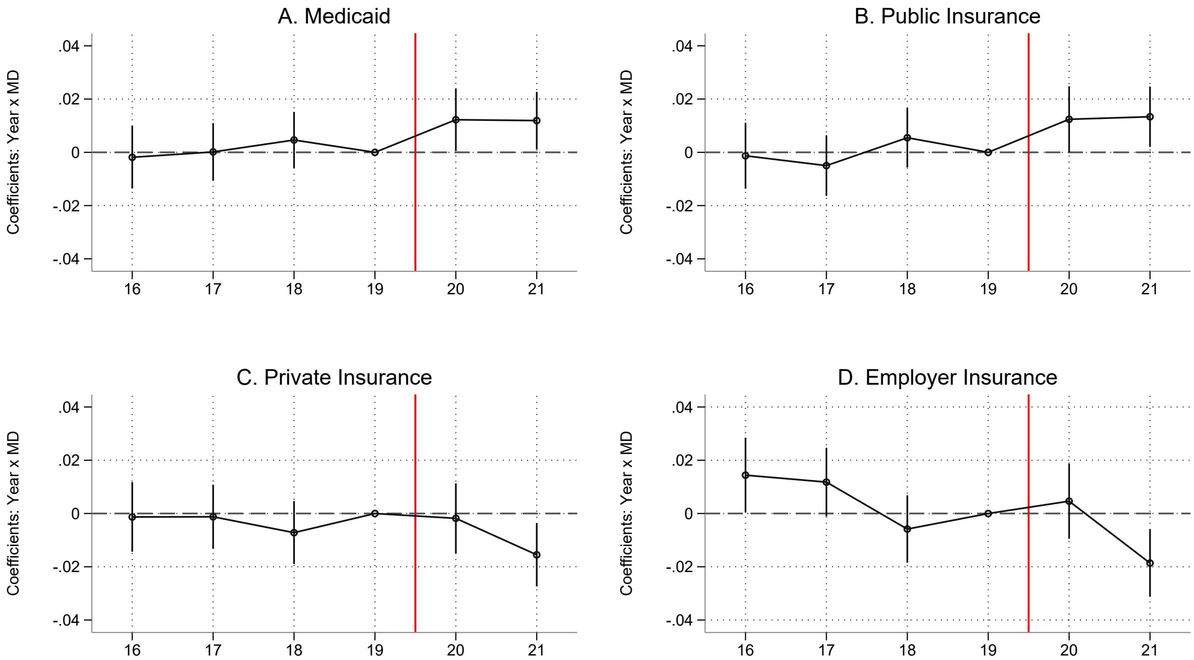
Tables

Figure 9: Event Study on Medicaid Enrollment Around Checkbox Implementation



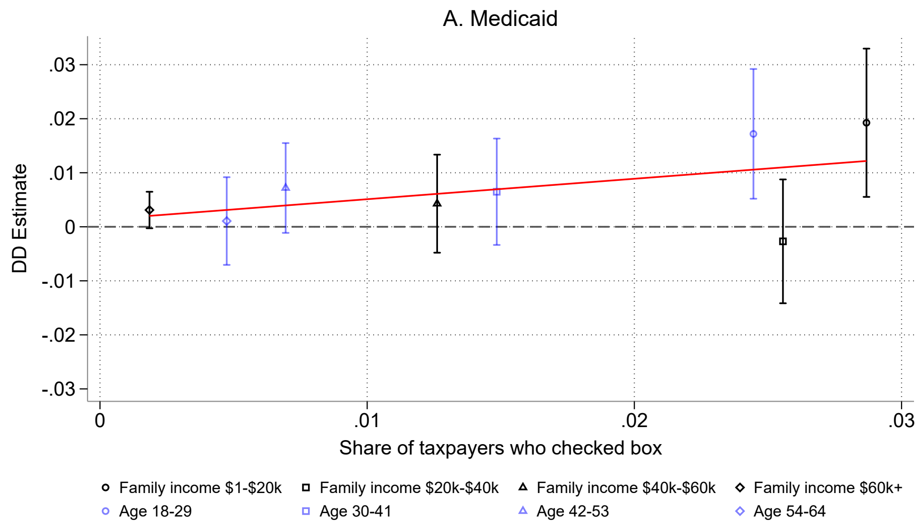
This figure shows event study plots on Medicaid enrollment in Maryland. The vertical red line represents when the checkbox was implemented. Panel A is the benchmark case where control states are neighboring states of District of Columbia, Pennsylvania, West Virginia, and Delaware. Panel B restricts the sample to individuals aged under 35. Panel C excludes West Virginia and includes New Jersey in the control group. Panel D uses the same control group as Panel C and uses individuals aged 18 to 34. State fixed effects, year fixed effects, and state-year demeaned unemployment are included. Demographic controls include dummies of age group, sex, education level, race, and marital status. Individuals aged 18-64 with family income under $70,000 are included in the sample. Robust standard errors are used.

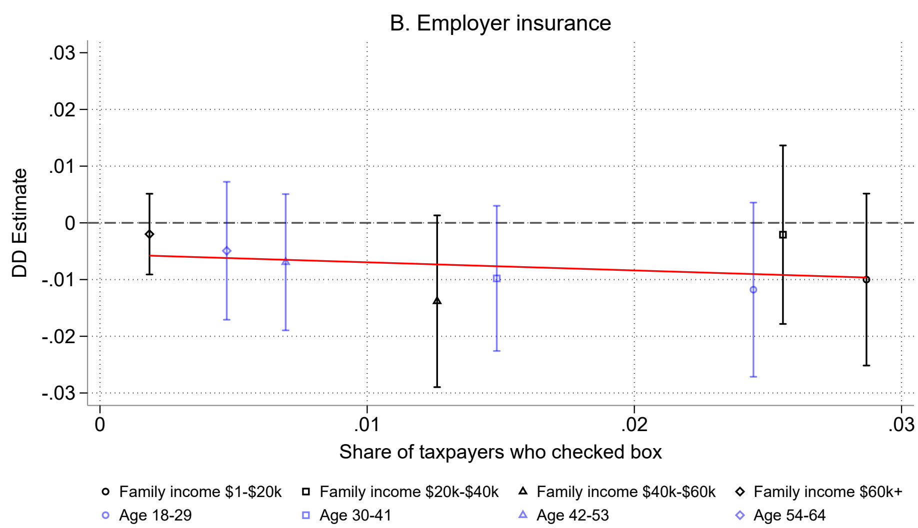
Figure 10: Event Study on Different Types of Insurance Around Checkbox Implementation



This figure shows event study plots for Medicaid, public insurance, private insurance, and employer insurance. The vertical red line represents when the checkbox was implemented. Panel A represents results for Medicaid; Panel B shows results for all public insurance (Medicaid, Medicare, Department of Veterans Affairs insurance); Panel C is for private insurance (employer provided, purchased from private companies, Tricare or other military health care); Panel D plots results for employer-provided insurance. The control states include neighboring states of District of Columbia, Pennsylvania, West Virginia, and Delaware. State fixed effects, year fixed effects, and state-year demeaned unemployment are included. Demographic controls include dummies of age group, sex, education level, race, and marital status. Individuals aged 18-64 with family income under $70,000 are included in the sample. Robust standard errors are used.

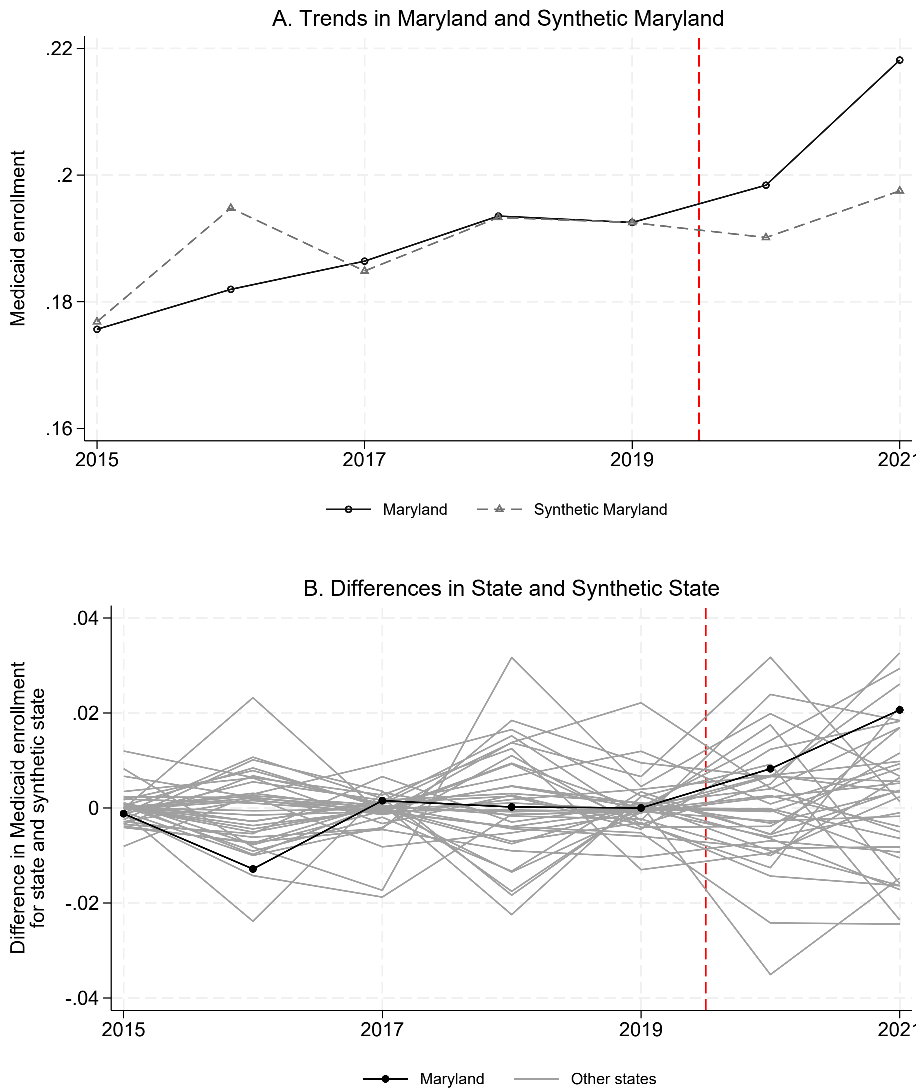
Figure 11: DiD Estimates Plotted Against Shares of Individuals who Checked the Box





This figure shows difference-in-difference estimates and share of taxpayers who checked box by different age and family income groups. The y axis shows difference-in-difference estimates from regressions by group using the baseline difference-in-difference specification. The x axis shows proportion of individuals who checked the box by group. The number of individuals who checked the box are calculated using MHBE data of years 2021 and 2022. The total population by group is estimated through ACS data using year 2021. The red line indicates a fitted line between the difference-in-difference point estimates and share of taxpayers who checked the box.

Figure 12: Effect on Medicaid Enrollment, Synthetic Control Method



In this figure, Panel A shows trends in share enrolled in Medicaid for Maryland and synthetic Maryland. Panel B shows differences in state and synthetic state for Maryland alongside that of all other states in the donor pool. The matching uses years from 2015 to 2019. The variables used include Medicaid enrollment in 2015, 2017, and 2019 and the averages of age, race, college education, family income, marital status, and income restriction of Medicaid from 2015 to 2019. Individuals aged 18-64 with a family income less than $70,000 are included in the sample.

Table 1: Summary Statistics for Maryland and Control States

	(1) Maryland	(2) Control States
Medicaid	0.20	0.21
	(0.40)	(0.41)
Public Insurance	0.23	0.25
	(0.42)	(0.43)
Any Insurance	0.89	0.90
	(0.31)	(0.30)
Private Insurance	0.71	0.70
	(0.46)	(0.46)
Employer Insurance	0.59	0.60
	(0.49)	(0.49)
Age	39.4	40.3
	(14.1)	(14.3)
Sex	0.51	0.50
	(0.50)	(0.50)
College	0.59	0.54
	(0.49)	(0.50)
Black	0.35	0.14
	(0.48)	(0.35)
Married	0.36	0.39
	(0.48)	(0.49)
Adjusted Gross Income	25602	24422
	(22770)	(22356)
Observations	152,019	473,652

Note: This table shows summary statistics for Maryland and control states. Control states include neighboring states of District of Columbia, Pennsylvania, West Virginia, and Delaware. The variables include ratio of individuals enrolled in different types of insurance, age, ratio male, ratio college educated, ratio of Black individuals, and ratio married. The sample consists of individuals in the age range of 18-64 with a family income of less than $70,000 from 2016 to 2021.

Table 2: DiD Estimates on Medicaid, Other Insurance Variables, and Employment

	(1) Medicaid	(2) Public ins.	(3) Private ins.	(4) Employer ins.	(5) Employment
Panel A: Neighboring states as controls					
post(2020) X Maryland	0.011***	0.013***	-0.006*	-0.012***	-0.007*
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
N	625671	625671	625671	625671	625671
Mean	0.21	0.24	0.70	0.60	0.68
Panel B: Selected controls					
post(2020) X Maryland	0.011***	0.012***	-0.006*	-0.011***	-0.006
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
N	792123	792123	792123	792123	792123
Mean	0.19	0.23	0.70	0.60	0.69
Panel C: Neighboring states as controls, Under 35					
post(2020) X Maryland	0.016***	0.018***	-0.008	-0.015**	-0.012*
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
N	243222	243222	243222	243222	243222
Mean	0.21	0.22	0.70	0.60	0.69
Panel D: Selected controls, Under 35					
post(2020) X Maryland	0.015***	0.016***	-0.009	-0.016**	-0.006
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
N	313035	313035	313035	313035	313035
Mean	0.20	0.21	0.70	0.60	0.69

Note: This table shows difference-in-difference regression results for enrollment in Medicaid, public insurance (Medicaid, Medicare, Department of Veterans Affairs insurance), private insurance (employer provided, purchased from private companies, Tricare or other military health care), employer insurance, and employment. Panel A uses neighboring states as the control group and includes all age groups; Panel B excludes West Virginia and adds New Jersey to the control group; Panel C uses neighboring states as the control group and restricts to individuals aged under 35; Panel D excludes West Virginia, adds New Jersey, and restricts to under 35. I use years of 2016-2021, where 2020 is period of treatment. State fixed effects, year fixed effects, and state-year demeaned unemployment are included. State-year demeaned unemployment are not included in the last column where employment is the outcome variable. Demographic controls include dummies for age groups, sex, education level, race, marital status. Individuals aged 18-64 with family income under $70,000 are included in the sample. Robust standard errors are used. Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3: Control States Used in Constructing Synthetic Maryland

State	Weight
District of Columbia	0.286
Georgia	0.176
Iowa	0.290
New Hampshire	0.113
New York	0.005
Wisconsin	0.131

Note: This table shows control states used in constructing the hypothetical Maryland. The matching uses years from 2015 to 2019. The variables used include Medicaid enrollment in 2015, 2017, and 2019 and the averages of age, race, college education, family income, marital status, and income restriction of Medicaid from 2015 to 2019. Individuals aged 18-64 with a family income less than $70,000 are included in the sample.

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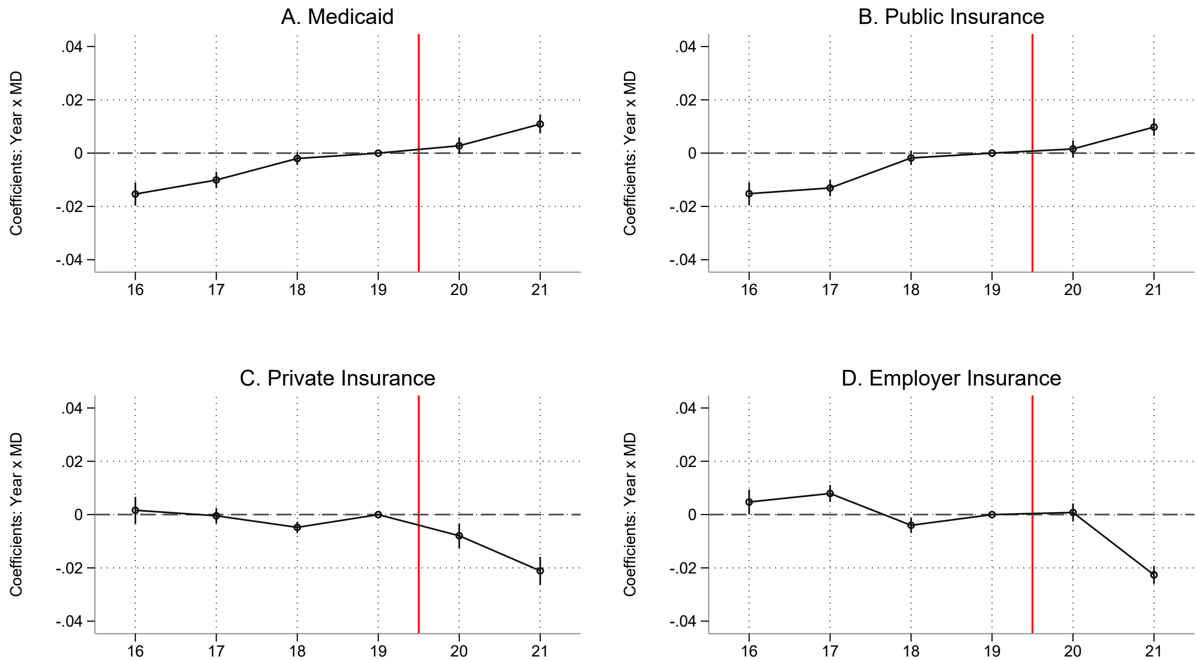
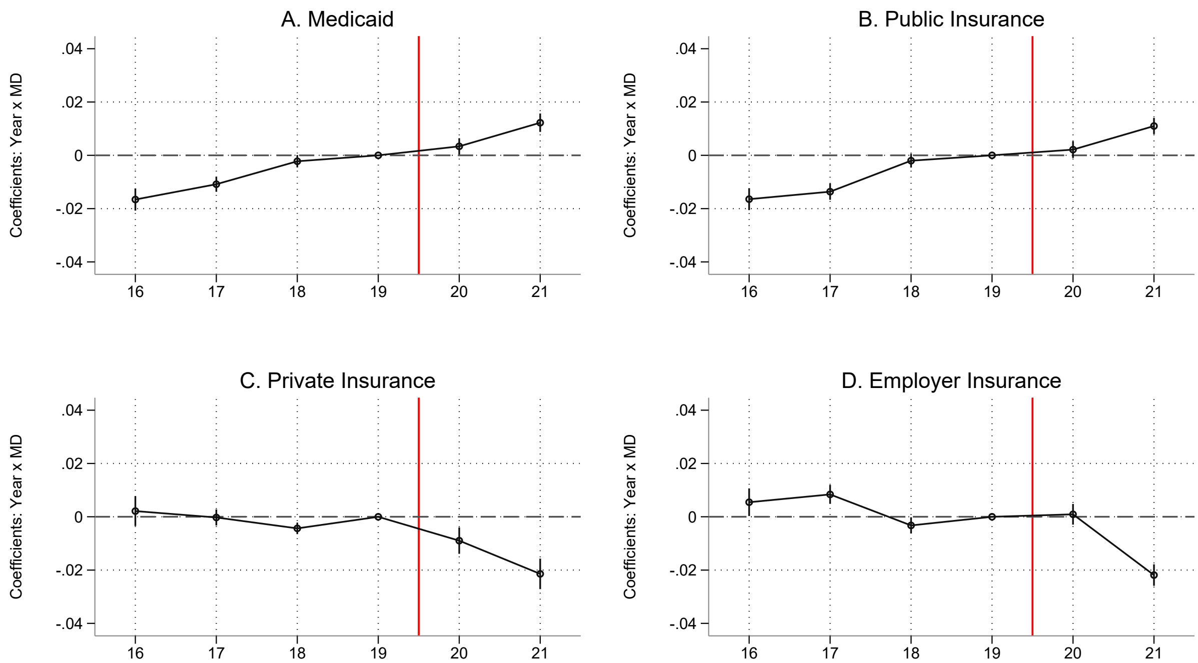
A Appendix Figures and Tables

Figure A1: Event Study for Different Types of Insurance - All Other States as Control Group



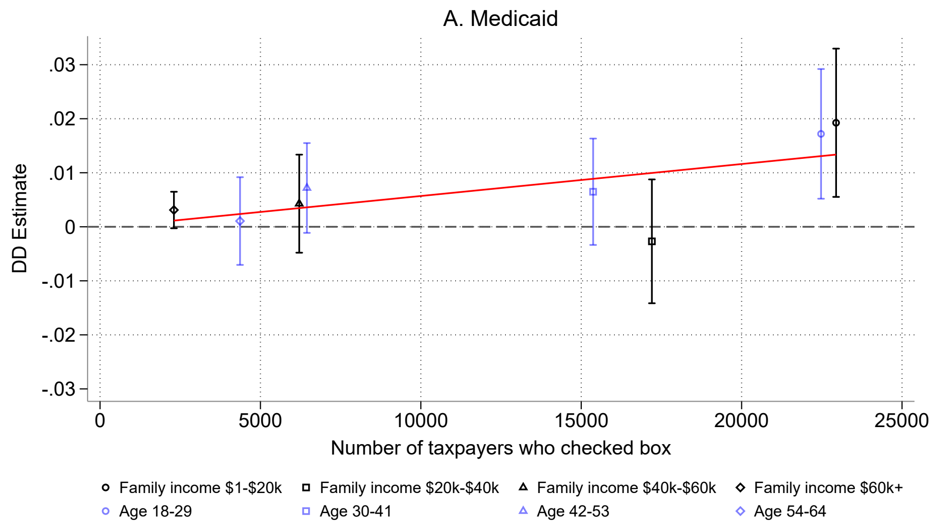
This figure shows event study plots for Medicaid, public insurance, private insurance, and employer insurance. The vertical red line represents when the checkbox was implemented. Panel A represents results for Medicaid; Panel B shows results for all public insurance (Medicaid, Medicare, Department of Veterans Affairs insurance); Panel C is for private insurance (employer provided, purchased from private companies, Tricare or other military health care); Panel D plots results for employer insurance. The control states include all states excluding Maryland. State fixed effects, year fixed effects, and state-year demeaned unemployment are included. Demographic controls include dummies for age group, sex, education level, race, marital status, and state. Individuals aged 18-64 with a family income under $70,000 are included in the sample. Standard errors are clustered at state-level.

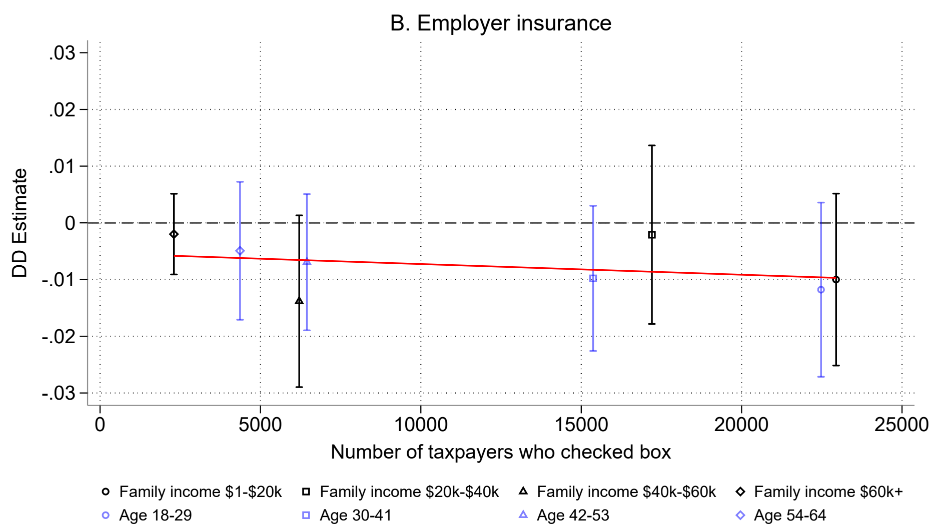
Figure A2: Event Study for Different Types of Insurance - All Other States Excluding States with Other Medicaid Expansion Policies as Control Group



This figure shows event study plots for Medicaid, public insurance, private insurance, and employer insurance. The vertical red line represents when the checkbox was implemented. Panel A represents results for Medicaid; Panel B shows results for all public insurance (Medicaid, Medicare, Department of Veterans Affairs insurance); Panel C is for private insurance (employer provided, purchased from private companies, Tricare or other military health care); Panel D plots results for employer-provided insurance. The control states include all states excluding Maryland, and states which enacted the ACA Medicaid expansion after 2014. This excludes 11 states of Virginia, Indiana, Alaska, Pennsylvania, Montana, Louisiana, Maine, Idaho, Utah, Nebraska, and Oklahoma. State fixed effects, year fixed effects, and state-year demeaned unemployment are included. Demographic controls include dummies for age group, sex, education, race, marital status, and state. Individuals aged 18-64 with a family income under $70,000 are included in the sample. Standard errors are clustered at state-level.

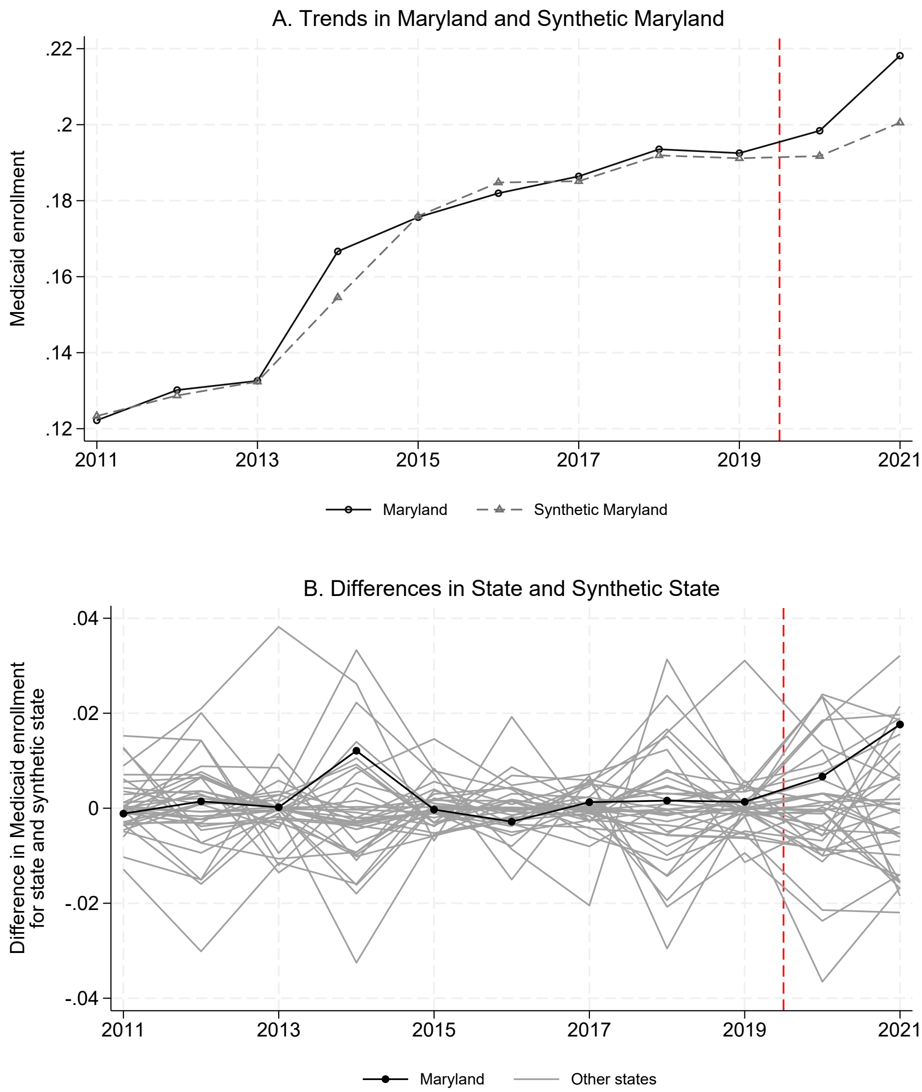
Figure A3: DiD Estimates Plotted Against Numbers of Individuals who Checked the Box





This figure shows difference-in-difference estimates and numbers of taxpayers who checked the box by different age and family income groups. The y axis shows difference-in-difference estimates from regressions by group using the baseline difference-in-difference specification. The x axis shows how many taxpayers checked the box by group in years 2021 and 2022. The red line indicates a fitted line between the difference-in-difference point estimates and the number of taxpayers who checked the box.

Figure A4: Effect on Medicaid Enrollment, Synthetic Control Method



In this figure, Panel A shows trends in share enrolled in Medicaid for Maryland and synthetic Maryland. Panel B shows differences in state and synthetic state for Maryland alongside that of all other states in the donor pool. The matching uses years from 2011 to 2019. The variables used include Medicaid enrollment in 2011, 2013, 2015, 2016, 2017, and 2019 and the averages of age, race, college education, family income, marital status, and income restriction of Medicaid from 2011 to 2019. Individuals aged 18-64 with a family income less than $70,000 are included in the sample.