Access to Gender-Affirming Care and Transgender Mental Health: Evidence from Medicaid Coverage[*]

Samuel Mann[†] Travis Campbell[‡] Duc Hien Nguyen[§]

August 7, 2022

Abstract

Using variation in the coverage of gender-affirming care under Medicaid, we provide the first evidence of increasing access to gender-affirming care on the mental health of transgender people. We use data from the 2014-2020 Behavioral Risk Factors Surveillance Systems paired with a triple-difference design that leverages state-level differences in timing and availability of Medicaid coverage for gender-affirming care and income-based Medicaid eligibility thresholds. Results demonstrate that Medicaid coverage of gender-affirming care meaningfully improves the mental health of transgender people. We also provide suggestive evidence that this is driven by increased uptake of gender-affirming care.

Keywords: Transgender, Gender Affirming Care, Health, Mental Health, Medicaid

JEL Codes: I13, I14, I18, I31, J15, K38

Conflict of Interest: The authors declare they have no conflict of interest.

Funding information: No funding was received for this work.

[*]We thank Gilbert Gonzales, Laura Nettuno, Benjamin Harrell, and Cameron Deal for helpful comments on a previous draft. We also thank seminar participants at the Discrimination and Diversity Workshop 2022, the 29th International Association for Feminist Economics, the Queer Populations, Policies and Perspectives Conference, the AEA's LGBTQ+ Virtual Seminar Series, and Vanderbilt University for helpful comments. All remaining errors are our own.

[†]Corresponding Author. Email: samuel.j.mann@vanderbilt.edu. Vanderbilt University, Global Labour Organization.

[‡]Southern Oregon University

[§]University of Massachusetts, Amherst.

1. Introduction

A broad literature documents that transgender and gender non-conforming individuals have significantly worse health outcomes than their cisgender counterparts. Transgender and gender non-conforming individuals have worse physical, mental, and overall self-rated health (White Hughto et al., 2015; James et al., 2016; Downing and Przedworski, 2018; Lagos, 2018; Carpenter et al., 2020; Campbell and Rodgers, 2022; Hughes et al., 2022). Recent work analyzing a large sample of transgender individuals highlighted that 40% of transgender people in the US had attempted suicide, nine times the rate of cisgender suicide attempts (James et al., 2016).

Prior work in Public Health has analyzed the relationship between gender-affirming care and transgender health, with the aim of identifying specific medical practices that may improve the health of transgender people. Gender-affirming care (GAC) aims to diminish the primary and secondary sex characteristics of sex assigned at birth, and to engender and/or enhance primary and secondary sex characteristics of one's gender identity. GAC involves the initiation of gender-affirming hormone therapy (GAHT) or gender-affirming surgery (GAS) (Metzger and Boettger, 2019). Analyzing the relationship between take up of GAC and health for transgender people in a systematic review of 28 observational studies conducted in Europe, Murad et al. (2010) found that after receiving GAC, 78% reported significant improvement in psychological health and 80% reported significant improvement in quality of life.[1] It is important to note that most of these reviewed studies however relied on small convenience samples with typically less than 100 participants, and lacked an appropriate control group, which gives doubt to the generalisability of their findings.

To overcome sample size limitations, more sophisticated studies have used large-scale administrative data. For example, Dhejne et al. (2011) analyzed Swedish administrative data between 1973 and 2003 and identified 324 transgender people who had undergone GAS. They found that compared to a matched cisgender sample, transgender people who underwent GAS still had higher mortality risk, suicidal behaviour, and psychiatric morbidity. In other words, GAS failed to close the transgender-cisgender health gap. Using the same data but focusing on the 2005-2015 period, Bränström and Pachankis (2020a) analyzed all people who had been diagnosed with gender dysphoria and found that years since completion of GAS was positively associated with better mental health outcomes. However, when comparing transgender individuals who had not received GAC to transgender individuals who had, estimated coefficients were statistically indistinguishable from zero (Bränström and Pachankis, 2020b).

[1] Similar findings were documented in Dhejne et al. (2016) and White Hughto and Reisner (2016) reviews.

GAC may have positive mental health effects given its ability to reduce gender dysphoria. Gender dysphoria refers to the distress caused by gender incongruence, i.e., distress that results from the mismatch between one's felt or self-identifying gender and their sex assigned at birth (American Psychiatric Association, 2013). People with gender dysphoria have much higher levels of depression, anxiety, and suicidality than people with gender congruence (Dhejne et al., 2016). As such, the Endocrine Society lists GAC as the primary treatment for gender dysphoria given its ability to enhance the sex characteristics of one's gender identity, thus reducing gender dysphoria (Tangpricha et al., 2017). Increasing access to GAC may therefore improve the mental health of transgender people who gain access to treatment.

For many transgender people, undertaking GAC is an important step in their transitioning process, however GAC is often extremely expensive and therefore inaccessible for many transgender individuals.[2] The costs associated with GAC therefore likely make GAC inaccessible for low-income transgender people that live in states that do not cover GAC under public insurance programs such as Medicaid. However, in 2016, the Centers for Medicare and Medicaid Services (CMS) refused to make a national coverage determination for GAC under Medicaid due to the evidence on the benefits of GAC being inconclusive. To justify its refusal, the CMS referred to previous research as being of "low quality" due to small sample sizes, a lack of an appropriate control group, and an inability to deal with confounding factors such as selection due to study design.

In practice, we exploit variation in the coverage of GAC under Medicaid within a triple difference design. We compare the mental health differential between low-income (treated) and high-income (control) transgender individuals in states that cover GAC (treated) to those that do not cover GAC (control), before and after the coverage of GAC under Medicaid. In doing so we make a causal evaluation of the effect of access to GAC on mental health for the first time. Our baseline estimates show that introducing GAC coverage under Medicaid leads to a meaningful reduction in the number of poor mental health days among low-income transgender people. Additionally, we provide suggestive evidence that these improvements are driven by increased uptake of GAC.

[2] For this paper, we use the term gender-affirming care (GAC) to refer to both GAHT and GAS. We do not distinguish between GAS and GAHT for two reasons. First, state policy that includes GAC includes both GAS and GAHT, thus the identification strategy cannot distinguish between GAS and GAHT. Second, the data we use cannot distinguish between GAS and GAHT. See Section 2 for more details on our data source (the BRFSS).

2. Data Description and Summary Statistics

Nearly all commonly used socioeconomic and healthcare surveys conflate gender and sex into a single question, thus preventing the identification of transgender individuals. One exception to this is the Behavioral Risk Factor Surveillance System (BRFSS) survey, which we use as our main data source (Centers for Disease Control and Prevention (CDC), 2020). The BRFSS is a representative survey of the US population, fielded every year by state health departments and compiled by the CDC.

Since 2014 the BRFSS has included an optional module that asks respondents their sexual orientation and gender identity (SOGI). We pool data covering the period 2014-2020.[3] Over the seven-year period covered in our sample, 43 states administered the SOGI module in at least one year. We identify transgender participants from the question "Do you consider yourself to be transgender?".[4] In total, we identify 6,598 transgender-identified respondents in our data. Among them, there are 2,883 MtF, 2,338 FtM, and 1,377 GNC individuals. In our current work, we consider all transgender respondents as one group, because our reduced-form model partitions this already-small sample further by Medicaid eligibility at the state level (see Section 3 for more details).

2.1. Determining Medicaid eligibility for BRFSS respondents

The BRFSS core questionnaire does not include a question on the respondent's primary source of health insurance. Instead, this question is in an optional module on Health Care Access that many states did not administer. Only 18% of our sample has data regarding their primary source of healthcare insurance, among which nearly 8% access their healthcare primarily through Medicaid. As such, we use income data and state eligibility cutoffs to identify a sample of individuals that are likely eligible for Medicaid.

Medicaid eligibility is determined by comparing an individual's poverty ratio against an annual, state-specific standard from Medicaid.gov. We obtain data on the annual state-specific Medicaid eligibility threshold from the Kaiser Family Foundation, and we estimate respondents' poverty ratio using BRFSS data. The poverty ratio is calculated as the ratio of the respondent's income relative to the federal poverty level (FPL), expressed as % FPL. The federal poverty level is the amount of a tax unit's annual modified adjusted gross income (MAGI) below which the tax unit is officially considered to be living in poverty.[5] Every year,

[3] The BRFSS is the only multi-year representative health survey in the US that allows the identification of both transgender and cisgender populations at a state level.

[4] As discussed in Carpenter et al. (2020), the BRFSS approach to gender identity significantly limits the possibility of false positives.

[5] A tax unit includes all individuals who file taxes together on the same tax return, such as a married

the Department of Health and Human Services publishes a base FPL for a single adult and an increment that scales the poverty threshold linearly with the number of members in their tax unit. The published FPL is used to determine financial eligibility for many need-based federal programs, as well as Medicaid.

It is important to emphasize that the FPL (from which the poverty ratio and Medicaid eligibility income threshold are derived) is calculated using MAGI and tax unit size. Therefore, precisely calculating Medicaid eligibility requires administrative tax records. Since we do not have access to BRFSS respondents' tax records, we use self-reported household income[6] and household size as proxies for MAGI and tax unit size. Specifically, we define the poverty ratio for BRFSS respondents as the ratio of self-reported household income relative to their state's FPL for the survey year, adjusted for household size. This means that our estimates of Medicaid eligibility are imprecise.

The imprecision of our poverty ratio measure creates a trade-off. Based on our poverty ratio estimate, we need to categorize respondents as low-income (eligible for Medicaid) or high-income (ineligible for Medicaid) when Medicaid status is unknown. By choosing a classification threshold below their actual Medicaid eligibility threshold, we could ensure that we do not erroneously categorize respondents who are in fact ineligible for Medicaid as low-income. However, this would also severely limit our low-income sample, as many Medicaid-eligible respondents would be incorrectly assigned high-income status. A high classification threshold, in contrast, would result in a larger low-income sample, at the cost of incorrectly including some Medicaid ineligible respondents. Using the exact cutoff may create bias as it is likely that at the cutoff there is some amount of endogenous labour supply switching (Simon et al., 2017). We resolve this trade-off using a receiver-operating characteristic (ROC) curve. Developed during the 1950s as a diagnostic for military predictions, ROC curves have not only become a common diagnostic tool to correctly classify subjects into two subgroups, but they also provide an intuitive and data-driven method for choosing a classification threshold for dichotomous classifications (Zweig and Campbell, 1993), a now standard practice for research at the intersection of machine learning and medicine (e.g. Gangloff et al., 2021; Raghu and Sriraam, 2018).

The trade-off between correctly classifying the small Medicaid-eligible sample as low-income and potentially inundating this small sample with false positives is illustrated by Appendix Figure A.1. The curve depicts the share of Medicaid recipients correctly classified as low-income (true positive rate) and the share of low-income classifications that are Medicaid

couple filing jointly and their dependents. MAGI refers to adjusted gross income plus supplementary social security income, nontaxable interest income, and foreign earned income and housing expenses.

[6] Household income was reported in categories, and we used the midpoint of each self-reported income category.

nonrecipients (false positive rate) for various classification thresholds. The sample is limited to those with known Medicaid status in Medicaid expansion states.[7] Since a perfect classifier would have a true positive rate of one and a false negative rate of zero, we calculate the optimal classification threshold for Medicaid eligibility by minimizing the distance to the top-left corner of the ROC plot.[8] Our calculation shows that the optimal classification threshold is the original Medicaid eligibility threshold plus 52% FPL. At this optimal classification threshold, the true positive rate is 0.79 and the false positive rate is 0.28. In comparison, had we used the zero cutoff (i.e., the state's actual Medicaid eligibility threshold), the true positive rate would be 0.59 and the false positive rate would be 0.17. To be clear, this procedure increases the share of Medicaid recipients classified as low-income at a cost of incorrectly classifying some Medicaid nonrecipients as low-income.[9] However, this is in line with work on Medicaid expansion which has used cutoffs larger than the exact cutoff to overcome issues with bunching and endogenous labor supply switching at the cutoff (Simon et al., 2017).

2.2. State-variation in GAC coverage under Medicaid

Low-income transgender people who are eligible for Medicaid are not guaranteed access to GAC, as this also depends on whether their state's Medicaid policies provide coverage for GAC. Bakko and Kattari (2020) reported that Medicaid insurance was associated with a greater probability of being denied GAC, compared to private health insurance plans. This is unsurprising given that there is currently no federal law that guarantees access to GAC. Insurance coverage for GAC is left to individual states, and different states have enacted different mandates. Some states have passed private healthcare non-discrimination acts and explicit inclusions of transgender-related healthcare under state plans. In other states, there are explicit transgender exclusions, which allow private and public insurance providers to refuse coverage of GAC as part of their insurance plans.

Our data for state Medicaid policies on GAC comes from the Movement Advancement Project (2022). As of 2020, 22 US states and the District of Columbia cover GAC under

[7] As mentioned, Medicaid status is known if the states chose to use the optional Health Care Access module during the survey year. This subsample consists of 289,000 respondents (18% of the overall BRFSS sample).

[8] The low prevalence of Medicaid recipients favors a low false positive rate at a cost of a higher true positive rate when indifferent to false positives and false negatives (Zweig and Campbell, 1993). For our application, this is not the case. The low prevalence is offset by the cost of incorrectly classifying the small Medicaid-eligible sample as high-income when the transgender sample is already scarce.

[9] This is similar to other approaches to identifying Medicaid eligibility, see for example, Simon et al. (2017), who included a higher threshold than the state cutoff allows one to reduce the likelihood that results are not being driven by endogenous switchers at the cutoff (i.e. people reducing their labor supply to become eligible for Medicaid. However, unlike others that choose arbitrary values for this exercise, we use a data-driven approach. Nonetheless, in Section 4.1 we demonstrate that using other cutoffs does not impact our quantitative or qualitative story and in fact our ROC curve-based approach leads to the most conservative estimate.

Medicaid (see Appendix Figure A.2).[10] The first state to include coverage of GAC under Medicaid was Vermont, in 2008.[11]

In contrast, 17 US states currently do not have an explicit policy regarding Medicaid coverage for gender-affirming care (Movement Advancement Project, 2022). In these states, some services may be approved for coverage (Zaliznyak et al., 2021), but transgender people seeking access to GAC often face significant barriers. The lack of specificity and transparency makes merely verifying whether specific GAC treatments are eligible for coverage an extremely time-consuming process (Zaliznyak et al., 2021; Mallory and Tentindo, 2019). Even where GAC could be covered, treatment is generally restricted to hormone therapy while the more costly gender-affirming surgery procedures are not included.

Finally, 11 US states currently exclude GAC from Medicaid coverage explicitly.[12] Such exclusionary restrictions mean that low-income transgender people who do not have private health insurance plans are often unable to afford GAC, except through crowdfunding or self-financing (Kimseylove et al., 2021). In some cases, the lack of access to cost-effective and safe transitioning options has driven low-income transgender people towards illicit and dangerous practices such as the injection of adulterated silicone liquid (Wallace, 2010).

2.3. Main health

To assess the impact of GAC on transgender patients, we focus on two main mental health outcomes in the BRFSS questionnaire. Respondents were asked to indicate for how many days during the past 30 days their mental health was not good. Our primary outcome variable, named *bad mental health days*, is based on the answer to this question and is in the unit of number of days (ranging from 0 to 30). Our second outcome variable creates a binary indicator that takes the value 1 if the individual reports 14 or more days of poor mental health in the preceding 30 days and zero otherwise. This outcome, named *frequent mental distress*, follows the Centers for Disease Control and Prevention (2004)'s definition of frequent mental distress. While we acknowledge that these outcomes are subjective self-reports, prior work has verified their validity (Hsia et al., 2020; Pierannunzi et al., 2013) and their close relationship with more objective measures of health such as mental health diagnoses (Cree et al., 2020).

Table 1 reports the mean difference in these outcomes among low-income and high-income

[10] It should be noted that Wisconsin, New Hampshire, and Hawaii had switched from excluding GAC coverage to including GAC coverage under Medicaid during our sample period (2014 - 2020).

[11] The 7 grey states have not included SOGI questions in the BRFSS. Three explicitly include GAC, one explicitly excludes GAC, and three do not have an explicit policy regarding GAC under Medicaid.

[12] This count did not include Wisconsin, New Hampshire, and Hawaii. As mentioned, historically these three states also had excluded GAC coverage from Medicaid, but they switched to including GAC during our sample period.

transgender and cisgender respondents, in state and years prior to GAC coverage under Medicaid. In states and years where GAC was not covered under Medicaid, low-income transgender respondents had significantly more days with bad mental health and a significantly greater incidence of frequent mental distress than their low-income cisgender counterparts and high-income transgender counterparts.

3. Econometric Framework

We use a triple difference design, that compares trends in the low-income transgender population's mental health in states where Medicaid covers GAC (the treated group) with the high-income transgender population in the same states (the first control group) and with both the high- and low-income transgender populations in states where Medicaid does not cover GAC (the second and third control groups). Triple difference design deviates from traditional difference-in-differences, which compares the pre- and post-policy trends in an outcome between states with and without the policy. In a triple difference model, the outcome is instead the difference between the treatment and control group (Olden and Møen, 2020) – in this case, the difference in mental health outcomes between high-income and low-income transgender individuals. This conceptualization not only clarifies the counterfactual (the relative health of the transgender population in states where Medicaid covers gender-affirming care, had this policy not taken effect), but also allows for data-driven counterfactuals, as will be made clear below. This research design can credibly estimate the impact of the policy under the assumption of parallel trends in the relative mental health of the transgender population.

There are three major challenges to difference-in-differences approaches. First, the administration of the policy is staggered across 2014-2019, which may bias difference-in-differences in the presence of time-variant heterogeneity (Goodman-Bacon, 2021). We address this issue by stacking each event, ensuring already treated states cannot be used as controls for future treated states (Baker et al., 2021; Cengiz et al., 2019).[13] Second, difference-in-differences is only valid if the treated group's counter-factual trend is parallel with the control group's trend after the policy is administered. While this assumption cannot be directly tested, we bolster its credibility by balancing the pre-policy trends between the treated states and

[13] We create an individual dataset for every treated state that includes said treated state and all control units with non-missing data, aligning event-time at zero. This resulted in 10 control states and 11 treated states comprising our final sample. We then stack all event-specific datasets. The final estimate is a weighted average of the event-specific triple difference estimates, which are contemporaneous and therefore robust to said bias.

the control states within each event using synthetic difference-in-differences (Arkhangelsky et al., 2021). Third, states that choose to cover GAC may be systematically different in their treatment of transgender people, for example, other transgender laws such as hate-crime laws may be passed at a similar time to GAC coverage. Furthermore, high-income transgender individuals may be systematically different than their low-income counterparts, biasing comparisons across the income eligibility threshold for Medicaid, as previously discussed. To account for this, we make use of a triple difference model under the following assumption: we assume that the bias when differencing across the location and timing of the policy equals the bias when differencing across the income eligibility threshold and the timing of the policy.[14]

We use triple differences with dynamic treatment effects for our baseline estimates. As is standard, we test for selection bias by allowing the trends in relative mental health to deviate between the treated and control states for three years prior to the policy. The baseline specification follows:

$$Y^*_{e,s,t} = \mu + \sum_{k=-3}^{3} \beta_k D_{k,e,s,t} + X^{*\prime}_{e,s,t}\kappa + \alpha_{e,s} + \delta_{e,t} + \epsilon_{e,s,t} \tag{1}$$

where Y^* is the health outcome of the transgender population differenced across Medicaid eligibility status in state i during event-year t within event e, D_k takes value one during event-year k for states where Medicaid covers gender-affirming care and zero otherwise, X^* is a vector of time variant controls differenced across Medicaid eligibility status, $\alpha_{e,s}$ are event-state fixed effects, and $\delta_{e,t}$ are event-year fixed effects.[15] The baseline specification controls for survey type, race, marital status, age, and population. The standard errors are clustered by state, the level the policy is assigned, accounting for possible correlation within a state in changes in mental health. The main identifying assumption is parallel trends in the relative outcome.

With the regression estimate at hand, we estimate the impact of the policy over the entire event window as follows: $\sum_{k=0}^{3} \beta_k/4 - \sum_{k=-3}^{-1} \beta_k/3$.

The baseline estimator applies weights to balance pre-policy trends in the relative outcome, within each event, across treatment status. Following Arkhangelsky et al. (2021), the weights optimize the following problem for each event, separately:

$$\hat{w}_{e,s,t} = \arg\min_{w} \sum_{s<C}\sum_{t<0} (Y^*_{e,C,t} - w_{e,s}Y^*_{e,s,t})^2 \quad s.t. \ \sum_{s<C} w_{e,s} = 1,\ 0 < w_{e,s} < 1 \tag{2}$$

[14] Olden and Møen (2020) show that the difference between two biased difference-in-differences estimators will be unbiased if the bias is the same in both estimators.

[15] Olden and Møen (2020) prove triple differences is equivalent to difference-in-differences if the third difference is taken prior. Note, our outcome is differenced by Medicaid eligibility status, denoted by the *, which is why we use event specific two-way fixed effects without interactions.

where Y^* denotes the health outcome, differenced across Medicaid status. $s = 1, \ldots, C-1$ enumerates the control states within each event and $s = C$ denotes the single control states in each event, applying a ridge penalty so that we do not overemphasize a small number of control states. This estimator is doubly robust. The estimator is consistent if weights are correctly penalized, even if Equation 1 is incorrectly specified. The estimator remains consistent, albeit inefficient, if Equation 1 is correctly specified.

3.1. Sample and covariate balance

The final sample is a stack of event-specific panel datasets. Each panel is an aggregate of the individual level data by state, year, and income (high- versus low- income). We restrict the sample to working-age respondents (ages 18-64) with non-missing data for household size and household income. The panels are balanced within each event. Each event consists of one treated state and all control states with non-missing data for both the low- and high-income transgender population every year the treated state is observed. If a control state meets the above conditions for multiple treated states, then it is included in multiple stacks. Within each event, time is aligned with the administration of the policy, so year zero always denotes the first year of the policy. Our final sample of treated and control states is mapped in Appendix Figure A.3.[16]

The pre-treatment covariance balance is presented in Appendix Table A.1. The observed differences between control and treated states are small and are largely statistically indistinguishable. The joint F-test demonstrates that the states are remarkably similar in terms of observable characteristics.[17]

4. Effects of Gender Affirming Care Coverage Under Medicaid on Transgender Mental Health

The results suggest that covering gender-affirming care through Medicaid is associated with a reduction in the number of poor mental health days and incidence of frequent mental distress among low-income transgender people (see Figure 1 and Table 2 for our baseline

[16]Three of the ten control states have not expanded Medicaid: Georgia, Kansas, and Texas. The respondents in these states are nonetheless partitioned into low- and high-income groups as if they had expanded Medicaid to 138% FPL under the assumption that time-variant gains from Medicaid expansion do not drive the results. Falsification tests provided later support this assumption.

[17]Another concerning source of selection bias that could act as a threat to our econometric setup is if the policy predicts the inclusion of the SOGI module in the BRFSS, or alternatively, if the inclusion of the SOGI module in the BRFSS predicts the inclusion of the policy. Appendix Table A.2 demonstrates that this is not the case.

estimates). While negative coefficients are documented in the entire post-policy period in Figure 1, the estimates do not reach conventional levels of statistical significance until two years after the policy; this is unsurprising given that initiating and realizing the benefits of GAC is a lengthy process; for example, it generally takes one to three years for the physical changes associated with GAHT to occur (i.e. feminization or masculinization) and transgender individuals wishing to undergo GAS are required to have been undergoing GAHT for at least one year prior (Coleman et al., 2012). Our baseline estimates indicate that two years after the policy, the incidence of frequent mental distress among low-income transgender people reduced by at least 0.5 percentage points or 1.3% from a baseline of 39.7%. In terms of poor mental health days, the policy was associated with at least 1.65 fewer poor mental health days among low-income transgender people after three or more years. This is equivalent to a reduction of at least 14.6% fewer poor mental health days relative to the pre-policy mean of 11.3 days.[18]

Overall, these results indicate that the introduction of gender-affirming care coverage under Medicaid significantly improves the mental health of transgender people that are likely eligible for Medicaid. These estimates are broadly consistent with the prior literature on the correlation between gender-affirming care and mental health, which documents that GAC is associated with significant improvements in mental health (see *inter alia*: Murad et al., 2010; Colton Meier et al., 2011; White Hughto and Reisner, 2016; Glynn et al., 2016; Rosenberg et al., 2019; Metzger and Boettger, 2019; Hughto et al., 2020).

4.1. Robustness

Results from several companion analyses designed to address the robustness of our core finding that the introduction of gender-affirming care coverage under Medicaid improves the mental health of low-income transgender people can be found in the appendix. The results pass both the high-income transgender falsification tests (Appendix Table A.3) and cisgender falsification tests (Appendix Table A.4). Additionally, Appendix Figure A.4 demonstrates that our results are robust to a quadruple difference model (where we leverage additional temporal, geographic, and income level variation for cisgender people). We also demonstrate that our main results are not driven by gains in access to care or insurance coverage among low-income transgender people (Appendix Table A.5). We document similar results when dropping one event at a time (Appendix Table A.6), and our results are robust to using alternative Medicaid eligibility cut-offs (Appendix Table A.7) following Simon et al. (2017).

[18]In additional analyses, we have re-estimated our main results excluding the year 2020 (given that if the Covid pandemic had a disproportionate impact on low-income transgender people then results may be biased by this). Doing so does not meaningfully change results. These results are available upon request.

Additional analyses demonstrate that our results are primarily driven by comparisons between treated states and those states that explicitly do not cover GAC rather than those states that do not have an explicit policy regarding GAC (Appendix Table A.8).

5. Take up of Gender Affirming Care

Our main finding indicates that introducing GAC coverage under Medicaid is associated with a significant reduction in bad mental health days. A natural interpretation of this finding is that increased GAC access leads to increased uptake of GAC among low-income transgender people, who could not afford GAC without Medicaid coverage. To test whether increased access to GAC did indeed lead to increased uptake of GAC, we use prescription drug data from the Medicaid State Drug Utilization Data (SDUD).[19] This data contains the universe of prescription drugs dispensed under Medicaid and is compiled by the Centers for Medicare and Medicaid Services. We identify all brand-named and generic drugs used for GAHT following Proctor et al. (2016). This allows us to create a state-by-year panel of the total number of 1) prescriptions filled for drugs used for GAHT, 2) all other prescriptions filled, and 3) Medicaid beneficiaries. Results from a stacked difference-in-differences model with event-specific synthetic control weights analogous to Equation 1 are provided in Figure 2 and Appendix Table A.9.[20] For interpretability, we convert the estimates to percentage changes by dividing them by the average outcomes for the treated group, one year prior to treatment.

Results presented in Figure 2a demonstrate that coverage of GAC leads to a significant increase in the uptake of drugs that are used for GAHT. There is no evidence of any changes prior to the policy but following the policy introduction, the coefficients are positive and statistically significant (averaging around 9.5% posttreatment). If our estimate is correct, the policy is responsible for 380 thousand more hormone prescriptions, because, one year prior to the policy, the 21 treated states had on average 190 thousand hormonal prescriptions through Medicaid. This estimate seems reasonable: between .6% to 1.6% of the US population is transgender (Herman et al., 2017; Brown, 2022), of which around 13% is on Medicaid (James et al., 2016), implying that the uptake of hormone prescriptions roughly equals the transgender

[19] Unfortunately, we cannot test whether coverage of GAC under Medicaid also led to changes in the uptake of GAS. While SDUD data allow us to identify drug utilization of Medicaid beneficiaries there is no comparable data for surgical procedure utilization of Medicaid beneficiaries; this would be needed to test the effect of GAC coverage under Medicaid on the uptake of GAS.

[20] Unfortunately, the SDUD data does not include the demographics of the beneficiaries that fill these prescriptions, as such we cannot identify whether the people filling these prescriptions are transgender. This is however the best available data on the drug utilization of Medicaid beneficiaries.

population with Medicaid.[21] This is strong suggestive evidence that the improvement in mental health outcomes for low-income transgender people following GAC coverage under Medicaid is channeled through increased uptakes of GAC.

A caveat to this analysis is that many of the drugs used for GAHT are also used for other purposes, such as hormone replacement therapy to relieve symptoms associated with menopause. As such, one might be concerned that the observed increase in the uptake of GAHT drugs might be due to utilization by non-transgender populations to treat menopause or other purposes non-related to gender-affirmation. We believe this is unlikely to be the case. While it is not possible to explicitly test this hypothesis, given that SDUD data do not include any demographic characteristics of patients, we can test whether the policy (GAC coverage under Medicaid) was associated with broad changes in drug utilization behavior. To do so, we repeat the analysis with a second outcome variable: prescription drug fills for all non-GAHT drugs. The results are presented in Figure 2b and demonstrate that coverage of GAC under Medicaid did not change the utilization of non-GAHT drugs.

Transgender people in the US are more likely to be in poverty than cisgender people (Carpenter et al., 2020), yet their Medicaid coverage rate is lower (James et al., 2016). Furthermore, the transgender population has lower insurance coverage (Campbell and Rodgers, 2022). The introduction of GAC coverage under Medicaid may therefore affect the health of the transgender population not only by increasing access to GAC, but by increasing Medicaid enrollment more generally. While we do find a small, positive association between the policy and Medicaid enrollment, the association is fairly precise yet statistically insignificant (see Appendix Table A.9). These findings are consistent with access to GAC, rather than Medicaid in-of-itself, driving the mental health improvements found in Section 4.

6. Conclusions

The results presented in this paper add to a growing body of research that documents that gender-affirming care significantly improves the health of transgender individuals. The current work overcomes issues present in prior work by exploiting policy variation and eligibility within a reduced form model. This responds to recent calls from the Centers for Medicare and Medicaid Services for research that makes use of more robust methodological approaches to evaluate the effects of gender-affirming care on transgender individuals (see Jensen et al., 2016) .

[21] If the current US population of 329.5 million, .6%-1.6% of the US population is transgender, and 13% of the transgender population is on Medicaid, then there are roughly between 257 thousand and 685 thousand transgender Medicaid enrollees.

Our results demonstrate that making gender-affirming care available to low-income transgender people improves their mental health. These results are especially important for ongoing policy debates regarding whether gender-affirming care should be covered by insurance programmes given that transgender populations have significantly worse mental health than their cisgender counterparts, with around 40% of transgender people attempting suicide, compared to only around 4.6% of the cisgender population (James et al., 2016). Our results indicate that the availability of gender-affirming care may help to reduce these mental health disparities.

Our work provides the first robust economic evaluation of the effect of Medicaid coverage of gender-affirming care on the health outcomes of low-income transgender people. As is necessary due to the policy variation exploited, we can only discuss these effects within the low-income transgender population. Future work should use alternative variations to provide causal evidence on the effect of gender-affirming care on the wider transgender population.

References

American Psychiatric Association (2013). *Diagnostic and statistical manual of mental disorders*. American Psychiatric Publishing, Arlington, VA, 5 edition.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review*, 111(12):4088–4118.

Baker, A., Larcker, D. F., and Wang, C. C. (2021). How much should we trust staggered difference-in-differences estimates? *Available at SSRN 3794018*.

Bakko, M. and Kattari, S. K. (2020). Transgender-related insurance denials as barriers to transgender healthcare: differences in experience by insurance type. *Journal of general internal medicine*, 35(6):1693–1700.

Bränström, R. and Pachankis, J. E. (2020a). Reduction in mental health treatment utilization among transgender individuals after gender-affirming surgeries: a total population study. *American journal of psychiatry*, 177(8):727–734.

Bränström, R. and Pachankis, J. E. (2020b). Toward rigorous methodologies for strengthening causal inference in the association between gender-affirming care and transgender individuals' mental health: response to letters. *American Journal of Psychiatry*, 177(8):769–772.

Brown, A. (2022). About 5from their sex assigned at birth.

Campbell, T. and Rodgers, Y. v. d. M. (2022). Health insurance coverage and health outcomes among transgender adults in the united states. *Health Economics*.

Carpenter, C. S., Eppink, S. T., and Gonzales, G. (2020). Transgender status, gender identity, and socioeconomic outcomes in the United States. *ILR Review*, 73(3):573–599.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454.

Centers for Disease Control and Prevention (2004). Self-reported frequent mental distress among adults–united states, 1993-2001. *MMWR. Morbidity and mortality weekly report*, 53(41):963–966.

Centers for Disease Control and Prevention (CDC) (2014-2020). Behavioral risk factor surveillance system survey data. Atlanta, Georgia: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention. Available at https://www.cdc.gov/brfss/annual_data/annual_data.htm.

Coleman, E., Bockting, W., Botzer, M., Cohen-Kettenis, P., DeCuypere, G., Feldman, J., Fraser, L., Green, J., Knudson, G., Meyer, W. J., et al. (2012). Standards of care for the health of transsexual, transgender, and gender-nonconforming people, version 7. *International journal of transgenderism*, 13(4):165–232.

Colton Meier, S. L., Fitzgerald, K. M., Pardo, S. T., and Babcock, J. (2011). The effects of hormonal gender affirmation treatment on mental health in female-to-male transsexuals. *Journal of gay & lesbian mental health*, 15(3):281–299.

Cree, R. A., Okoro, C. A., Zack, M. M., and Carbone, E. (2020). Frequent mental distress among adults, by disability status, disability type, and selected characteristics—united states, 2018. *Morbidity and Mortality Weekly Report*, 69(36):1238.

Dhejne, C., Lichtenstein, P., Boman, M., Johansson, A. L., Långström, N., and Landén, M. (2011). Long-term follow-up of transsexual persons undergoing sex reassignment surgery: cohort study in sweden. *PloS one*, 6(2):e16885.

Dhejne, C., Van Vlerken, R., Heylens, G., and Arcelus, J. (2016). Mental health and gender dysphoria: A review of the literature. *International review of psychiatry*, 28(1):44–57.

Downing, J. M. and Przedworski, J. M. (2018). Health of transgender adults in the US, 2014–2016. *American journal of preventive medicine*, 55(3):336–344.

Gangloff, C., Rafi, S., Bouzillé, G., Soulat, L., and Cuggia, M. (2021). Machine learning is the key to diagnose covid-19: a proof-of-concept study. *Scientific reports*, 11(1):1–11.

Glynn, T. R., Gamarel, K. E., Kahler, C. W., Iwamoto, M., Operario, D., and Nemoto, T. (2016). The role of gender affirmation in psychological well-being among transgender women. *Psychology of sexual orientation and gender diversity*, 3(3):336.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Herman, J. L., Flores, A. R., Brown, T. N., Wilson, B. D., and Conron, K. J. (2017). *Age of individuals who identify as transgender in the United States*. eScholarship, University of California.

Hsia, J., Zhao, G., Town, M., Ren, J., Okoro, C. A., Pierannunzi, C., and Garvin, W. (2020). Comparisons of estimates from the behavioral risk factor surveillance system and other national health surveys, 2011- 2016. *American Journal of Preventive Medicine*, 58(6):e181–e190.

Hughes, L. D., King, W. M., Gamarel, K. E., Geronimus, A. T., Panagiotou, O. A., and Hughto, J. M. (2022). Differences in all-cause mortality among transgender and non-transgender people enrolled in private insurance. *Demography*.

Hughto, J. M., Gunn, H. A., Rood, B. A., and Pantalone, D. W. (2020). Social and medical gender affirmation experiences are inversely associated with mental health problems in a US non-probability sample of transgender adults. *Archives of sexual behavior*, 49(7):2635.

James, S. E., Herman, J. L., Rankin, S., Keisling, M., Mottet, L., and Anafi, M. (2016). The report of the 2015 u.s.transgender survey.

Jensen, T. S., Chin, J., Rollins, J., Koller, E., Gousis, L., and Szarama, K. (2016). Gender dysphoria and gender reassignment surgery. Centers for Medicare & Medicaid Services (CMS). Administrative File: CAG #00446N.

Kimseylove, C., Edwards, T., and Inwards-Breland, D. (2021). Effect of medicaid expansion on the crowdfunding behavior of transgender adolescents. *Sexuality Research and Social Policy*, 18(3):564–574.

Lagos, D. (2018). Looking at population health beyond “male” and “female”: Implications of transgender identity and gender nonconformity for population health. *Demography*, 55(6):2097–2117.

Mallory, C. and Tentindo, W. (2019). Medicaid coverage for gender-affirming care. Los Angeles, CA: Williams Institute, UCLA School of Law. Available: https://williamsinstitute.law.ucla.edu/wp-content/uploads/Medicaid-Gender-Care-Oct-2019.pdf.

Metzger, N. Y. and Boettger, S. (2019). The effect of testosterone therapy on personality traits of trans men: a controlled prospective study in germany and switzerland. *Psychiatry research*, 276:31–38.

Movement Advancement Project (2022). Movement advancement project. Available at http://doi.org/10.5281/zenodo.4479837.

Murad, M. H., Elamin, M. B., Garcia, M. Z., Mullan, R. J., Murad, A., Erwin, P. J., and Montori, V. M. (2010). Hormonal therapy and sex reassignment: A systematic review and meta-analysis of quality of life and psychosocial outcomes. *Clinical endocrinology*, 72(2):214–231.

Olden, A. and Møen, J. (2020). The triple difference estimator. *NHH Dept. of Business and Management Science Discussion Paper*, (2020/1).

Pierannunzi, C., Hu, S. S., and Balluz, L. (2013). A systematic review of publications assessing reliability and validity of the behavioral risk factor surveillance system (brfss), 2004–2011. *BMC medical research methodology*, 13(1):1–14.

Raghu, S. and Sriraam, N. (2018). Classification of focal and non-focal eeg signals using neighborhood component analysis and machine learning algorithms. *Expert Systems with Applications*, 113:18–32.

Rosenberg, S., Tilley, P. M., and Morgan, J. (2019). "I couldn't imagine my life without it": Australian trans women's experiences of sexuality, intimacy, and gender-affirming hormone therapy. *Sexuality & Culture*, 23(3):962–977.

Simon, K., Soni, A., and Cawley, J. (2017). The impact of health insurance on preventive care and health behaviors: evidence from the first two years of the aca medicaid expansions. *Journal of Policy Analysis and Management*, 36(2):390–417.

Tangpricha, V., Hannema, S. E., Irwig, M. S., Meyer III, W. J., Safer, J. D., and Hembree, W. C. (2017). 2017 american association of clinical endocrinologists/endocrine society update on transgender medicine: case discussions. *Endocrine Practice*, 23(12):1430–1436.

Wallace, P. M. (2010). Finding self: a qualitative study of transgender, transitioning, and adulterated silicone. *Health Education Journal*, 69(4):439–446.

White Hughto, J. M. and Reisner, S. L. (2016). A systematic review of the effects of hormone therapy on psychological functioning and quality of life in transgender individuals. *Transgender health*, 1(1):21–31.

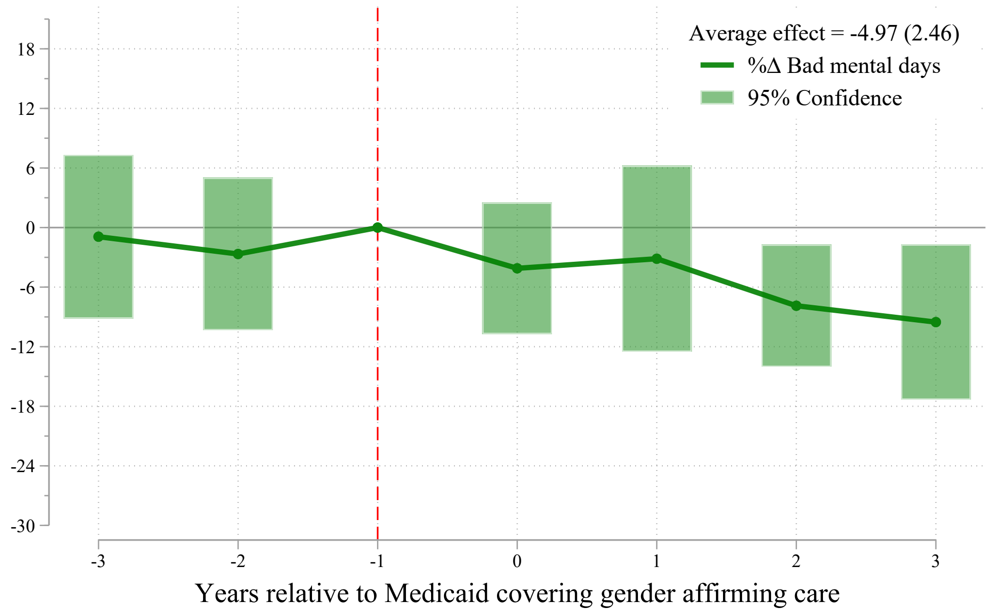
White Hughto, J. M., Reisner, S. L., and Pachankis, J. E. (2015). Transgender stigma and health: A critical review of stigma determinants, mechanisms, and interventions. *Social science & medicine*, 147:222–231.

Zaliznyak, M., Jung, E. E., Bresee, C., and Garcia, M. M. (2021). Which US states' medicaid programs provide coverage for gender-affirming hormone therapy and gender-affirming genital surgery for transgender patients?: A state-by-state review, and a study detailing the patient experience to confirm coverage of services. *The Journal of Sexual Medicine*, 18(2):410–422.

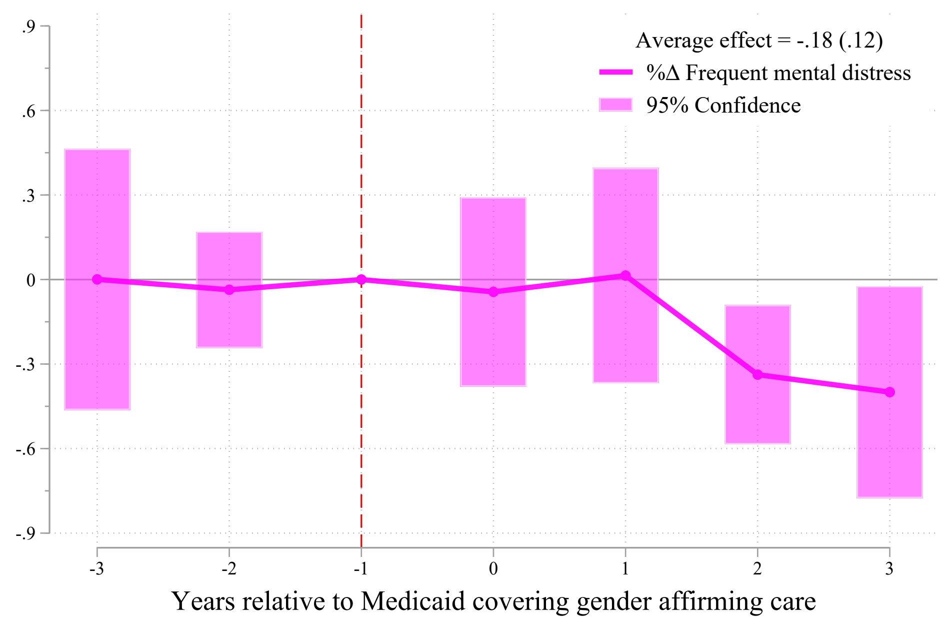
Zweig, M. H. and Campbell, G. (1993). Receiver-operating characteristic (ROC) plots: a fundamental evaluation tool in clinical medicine. *Clinical Chemistry*, 39(4):561–577.

List of Figures

Figure 1: Dynamic Impact of Medicaid Covering Gender-Affirming Care on Mental Health



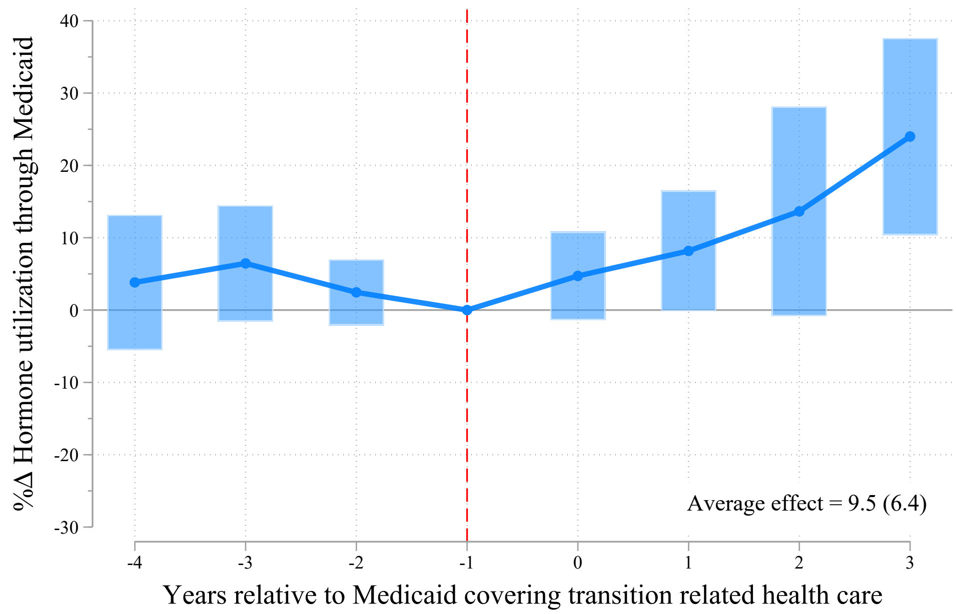
(a) Bad mental health days



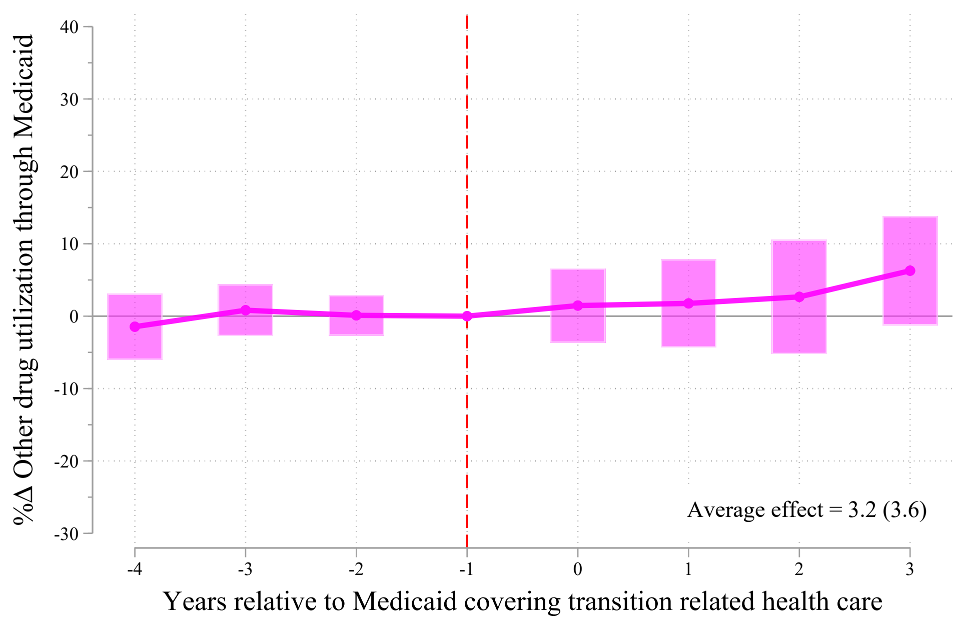
(b) Frequent mental distress

Notes: This figure depicts our estimates for the stacked triple differences with synethic control weights detailed in Section 3. The outcome of the regression is either 1) the average number of self-reported bad mental health days or 2) the share of respondents who report having fourteen or more bad mental health days over the past thirty days. The regression includes event state and event-time fixed effects and controls for survey type, race, marital status, age, and population. The shaded area in each figure is the 95% confidence interval based on robust standard errors clustered by state. The coefficients are converted to percentage changes; they are scaled by the pretreatment average outcome among the treated states.

Figure 2: Drug Utilization with Medicaid



(a) Hormone prescriptions



(b) Other prescriptions

Notes: The figures show the estimates of the stacked difference-in-difference model given by Equation 1 with event-specific synthetic control weights. The outcomes are the total number of prescriptions covered by Medicaid, either hormonal prescriptions or all others. The regressions include event-state and event-time fixed effects and control for Medicaid expansion. The shaded area in each figure is the 95% confidence interval based on robust standard errors clustered by state.

List of Tables

Table 1: Pre-treatment Health Averages by Transgender Status and Medicaid Eligibility

	(1) Low-income transgender	(2) High-income transgender	(3) Low-income cisgender	(4) High-income cisgender
Bad mental health days	7.75[a]	4.2[a]	5.55[a]	2.98[a]
Observations	245	226	79,298	163,603
Frequent mental distress	.303[ab]	.11[a]	.181[ab]	.084[a]
Observations	245	226	79,298	163,603

Notes: [a] denotes statistically significant difference across income within gender, [b] denotes statistically significant difference across gender within income (p<.05). This table displays pretreatment means by income group and transgender status for the sample under age 64. P-values are based on robust standard errors that are clustered by primary sampling unit. Sampling weights are applied.

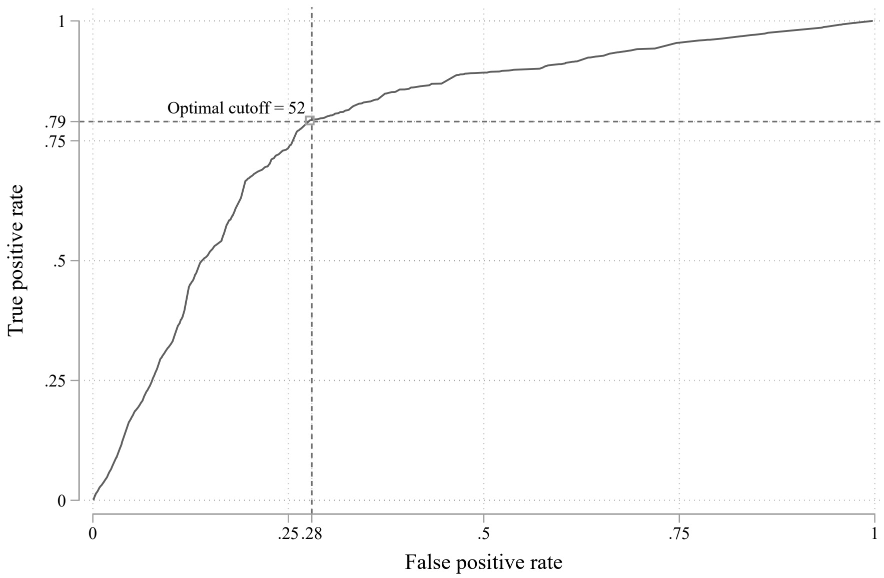
Table 2: Impact of Medicaid Covering Gender-Affirming Care on Mental Health

	(1) Bad mental health days	(2) Frequent mental distress
Overall impact of policy	-4.97^{*}	$-.18$
	(2.46)	(.12)
Impact over last two years	-7.5^{**}	$-.36^{**}$
	(2.82)	(.15)
Event-state fixed effects	✓	✓
Event-year fixed effects	✓	✓
Demographic controls	✓	✓
Pre-policy average outcome	11.3	.397
Low-income transgender people	1,215,080	1,215,080
Treated states	11	11
Control states	13	13
Observations	228	228

*Notes: *p<0.10,**p<0.05,***p<0.01.* This table reports the benchmark estimates detailed in Section 3. All regressions include event-state fixed effects and event-year fixed effects and control for survey type, race, marital status, age, and population. The regressions are a triple differences, across Medicaid eligibility, the timing of the policy, and the location of the policy. Robust standard errors are clustered by state and reported in parenthesis.

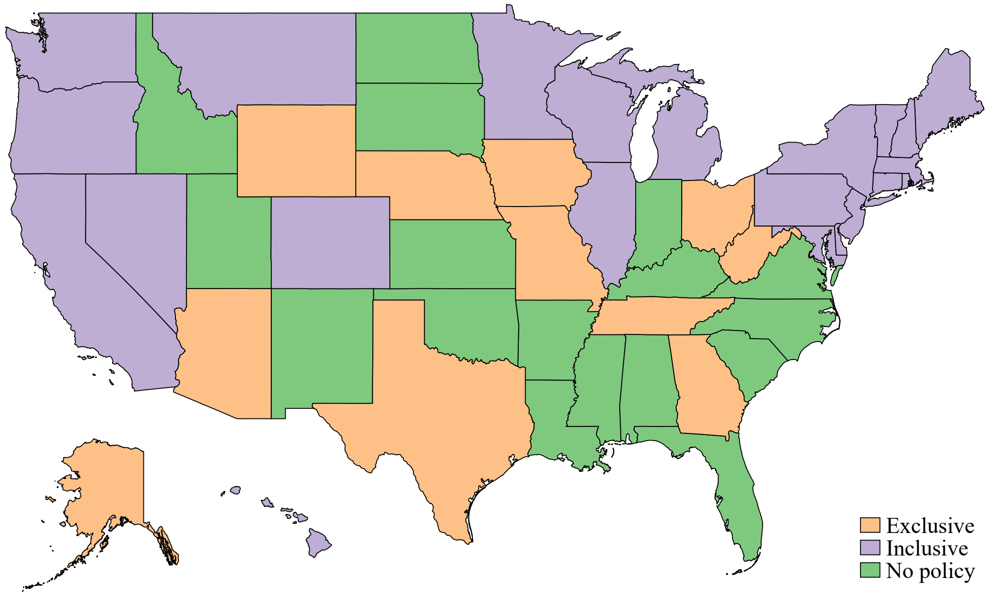
A. Appendix – Additional Tables and Figures

Figure A.1: Receiver Operating Characteristic Plot



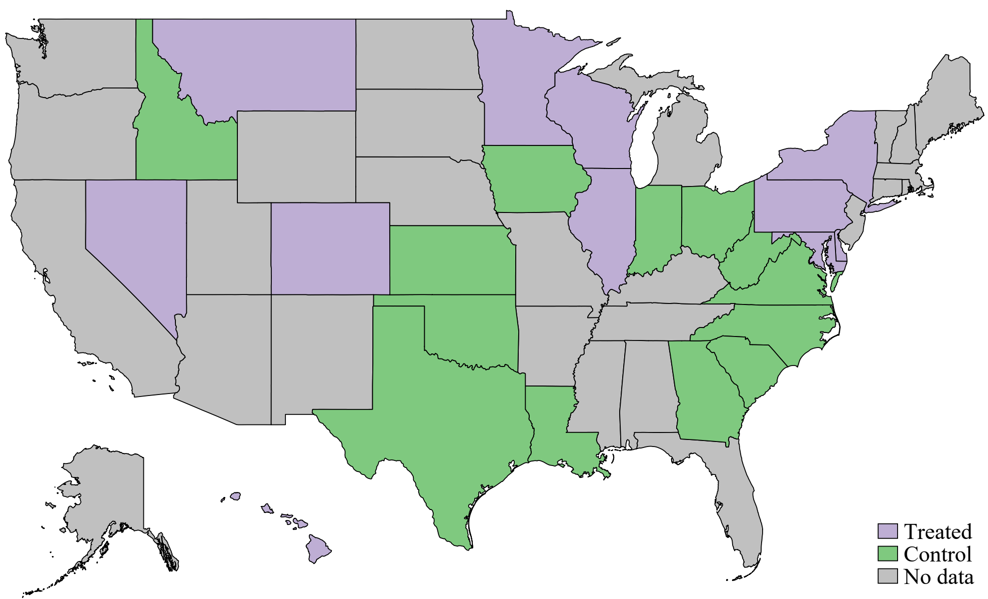
Notes: This figure depicts the true positive rate and false positive rate for the subsample of BRFSS respondents whose Medicaid status is elicited for various poverty ratio thresholds. The optimal cutoff is poverty ratio that minimizes the distance to the top left corner, a perfect classifier.

Figure A.2: Map of Treatment Status



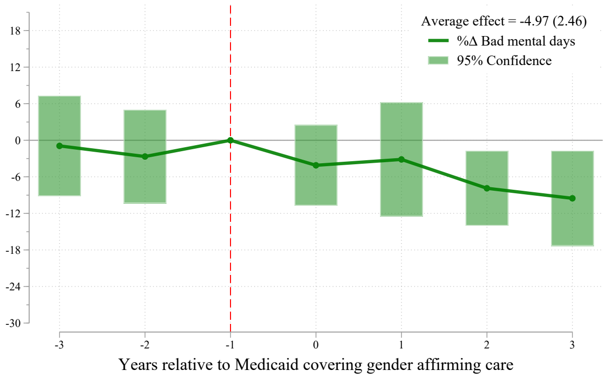
Notes: This figure maps each state's decision whether or not to cover gender-affirming care under Medicaid as of 2020, according to the Movement Advancement Project (2022). States policies can either explicitly cover gender affirming care (purple), explicitly exclude such care (orange), or not have an explicit policy towards such care (green).

Figure A.3: Map of Treatment Status for Final Sample

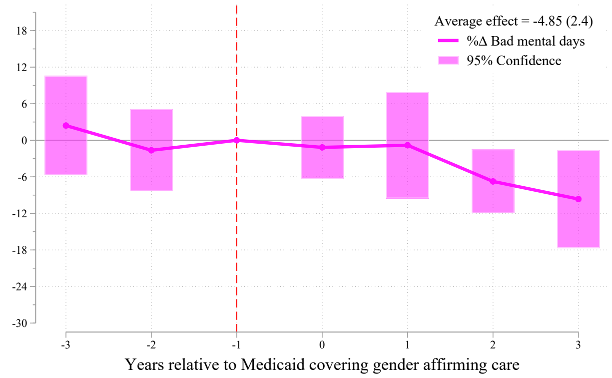


Notes: This figure maps the treatment status of our final sample. Each treated state (purple) must have changed its Medicaid policy form either an exclusive or inexplicit policy to a policy inclusive of gender affirming care care at some point between 2014 and 2019. Further, we must have data on both the low- and high-income transgender population for at least one year before and after the change in the policy. The control states (green) must have a Medicaid policy that is inexplicably or exclusive of gender affirming care for the entire sample. We must also have data for the control state for low- and high-income transgender populations for all years we observe the treated state for at least one event. All states that do not meet either of these criteria are shaded grey.

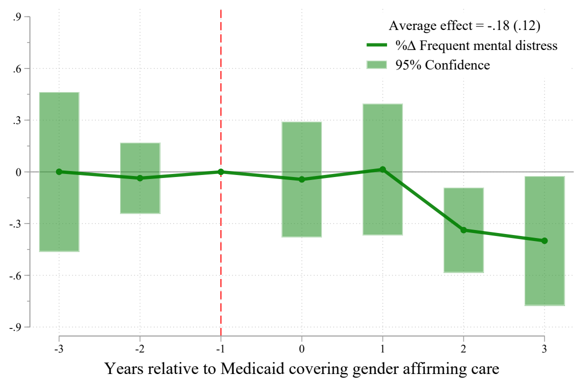
Figure A.4: Alternative Estimator for the Evolution of Medicaid Covering Gender Affirming Care's Impact on Mental Health



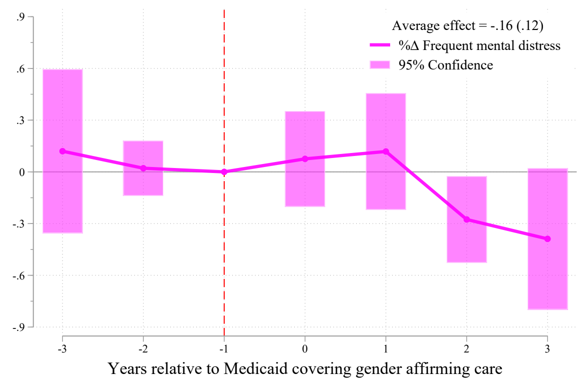
(a) Bad mental health days, triple differences



(b) Bad mental health days, quadruple differences



(c) Frequent mental distress, triple differences



(d) Frequent mental distress, quadruple differences

Notes: The figures show the estimates of the stacked triple difference model given by Equation 1. The outcome of each regression is either 1) the average number of self-reported bad mental health days over the past thirty days or 2) the share of respondents who report having fourteen or more bad mental health days over the past thirty days. All specifications include event state and event-time fixed effects and control for survey type, race, marital status, age, and population. The shaded area in each figure is the 95% confidence interval based on robust standard errors clustered by state. Figures A.4a and A.4c difference the outcome by Medicaid eligibility status prior to the regression and estimating the synthetic unit weights. Figures A.4b and A.4d differences the outcome by Medicaid eligibility status and transgender status prior to both the regression and estimating the synthetic unit weights.

Table A.1: Pre-treatment Covariate Balance for Low Income Transgender Population by Treatment Status

	(1) Treated	(2) Control	(3) Difference
Bad mental health days	7.75	9.35	−1.6 (1.63)
Frequent mental distress	.307	.329	−.023 (.073)
Insurance coverage	.764	.653	.111 (.074)
Couldn't see doctor due to cost	.214	.323	−.11* (.062)
Federal poverty level	95.1	99.6	−4.55 (7.18)
White population share	.495	.552	−.057 (.104)
Black population share	.0848	.208	−.123* (.064)
Parental status	.471	.4	.071 (.056)
Sex	.525	.552	−.028 (.071)
LGB status	.345	.31	.035 (.087)
Survey type	.626	.683	−.057 (.086)
Employment	.375	.336	.039 (.063)
Unemployment	.239	.357	−.118* (.066)
College educational attainment	.0777	.0699	.008 (.019)
High school educational attainment	.702	.626	.076 (.074)
Couple status	.437	.372	.065 (.07)
Age	37.8	37.7	.085 (2.21)
Population	1,532	2,034	−502 (707)
$F_{18,\,396}$	1.07	1.07	1.07
States	11	13	

Notes: This table displays average pretreatment means by treatment status: states where Medicaid covers gender-affirming care (treated) and for states where Medicaid does not cover gender-affirming care (control). Robust standard errors are reported in parenthesis. The row F statistics reports the joint F-test for difference in means based on robust standard errors.

Table A.2: Association between Treatment Status and Inclusion of LGBTQ Module and Medicaid Expansion Status

	(1)	(2)	(3)
LGBTQ module	-0.0459		-0.0497
	(0.0499)		(0.0522)
Medicaid expansion		-0.0237	-0.0468
		(0.102)	(0.107)
Constant	0.301***	0.293***	0.335***
	(0.0264)	(0.0682)	(0.0863)
Observations	350	350	350
Number of States	50	50	50
Years	2014-2020	2014-2020	2014-2020
State fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓

*Notes:*p<0.10,**p<0.05,***p<0.01.* This table reports the coefficients from a regression of an indicator for treatment status on an indicator for the state choosing to use the optional LGBTQ module on their BRFSS survey and an indicator for Medicaid expansion. All regressions include state fixed effects and year fixed effects. Robust standard errors are clustered by state and reported in parenthesis.

Table A.3: The Impact of Medicaid Covering Gender Affirming Care on High-Income Transgender Mental Health

	(1)	(2)
Outcome	Bad mental health days	Frequent mental distress
Overall impact of policy	2.22 (1.59)	.005 (.086)
Event-state fixed effects	✓	✓
Event-year fixed effects	✓	✓
Demographic controls	✓	✓
Pre-policy average outcome	7.01	.321
Annual high-income transgender people	885,704	885,704
Treated states	11	11
Control states	13	13
Observations	228	228

Notes: **p<0.10,**p<0.05,***p<0.01.* This table provides our estimates for the stacked difference-in-differences with synethic control weights (by state and time) using only the high-income transgender sample, who are likely ineligible for Medicaid. The outcome of the regression is average number of self-reported bad mental health days or the share of the population that reports have 14 or more bad mental health days. The regressions include event-state and event-time fixed effects and control for survey type, race, marital status, age, and population. Robust standard errors are clustered by state and reported in parenthesis.

Table A.4: The Impact of Medicaid Covering Gender Affirming Care on Cisgender Mental Health

	(1)	(2)
Outcome	Bad mental health days	Frequent mental distress
Overall impact of policy	−.065 (.08)	−.003 (.004)
Event-state fixed effects	✓	✓
Event-year fixed effects	✓	✓
Demographic controls	✓	✓
Pre-policy average outcome	6.07	.202
Annual low-income cisgender people (millions)	56.3	56.3
Treated states	20	20
Control states	28	28
Observations	3,277	3,277

*Notes: *p<0.10,**p<0.05,***p<0.01.* This table provides our estimates for the stacked triple differences with synethic control weights detailed in Section 3 using the full cisgender sample (both high- and low-income). Since the cisgender sample will inundate the relatively small transgender sample when transgender status is not known, we use data for each state regardless of their decision to the the Sexual Orientation and Gender Identity Module. The outcome of the regression is average number of self-reported bad mental health days or the share of the population that reports have 14 or more bad mental health days. The regressions include event-state and event-time fixed effects and control for survey type, race, marital status, age, and population. Robust standard errors clustered by state.

Table A.5: Impact of Medicaid Covering Gender-Affirming Care on Insurance Coverage and Access to Care

	(1)	(2)	(3)	(4)
Sample	Cisgender	Cisgender	Transgender	Transgender
Outcome	Insurance Coverage	Couldn't see doctor due to cost	Insurance Coverage	Couldn't see doctor due to cost
Overall impact of policy	$-.005$	$.001$	$-.387^{***}$	$.087$
	(.007)	(.005)	(.077)	(.107)
Event-state fixed effects	✓	✓	✓	✓
Event-year fixed effects	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Pre-policy average outcome	.808	.224	.759	.241
Annual low-income people (millions)	56.3	56.3	.235	.235
Treated states	20	20	11	11
Control states	28	28	13	13
Observations	3,277	3,277	228	228

*Notes: *p<0.10,**p<0.05,***p<0.01.* This table reports the benchmark estimates detailed in Section 3. All regressions include event-state fixed effects and event-year fixed effects and control for survey type, race, marital status, age, and population. The regressions are a triple differences, across Medicaid eligibility, the timing of the policy, and the location of the policy. Robust standard errors are clustered by state and reported in parenthesis. Annual low-income people refers to the average number of people we predict as Medicaid eligible within each state, aggregated across states.

Table A.6: Event heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Event removed	Full	CO	DE	HI	IL	MD	MN	MT	NV	NY	PA	WI
Bad mental health days												
Overall impact of policy	-4.97^{*}	-5.13^{*}	-3.03	-5.62^{**}	-5.29^{**}	-5.97^{**}	-5.52^{*}	-2.79	-7.08^{***}	-3.81	-4.33	-6.37^{**}
	(2.46)	(2.62)	(2.54)	(2.69)	(2.4)	(2.67)	(2.89)	(2.23)	(2.22)	(2.37)	(2.63)	(2.54)
Frequent mental distress												
Overall impact of policy	$-.18$	$-.19$	$-.127$	$-.211^{*}$	$-.203$	$-.198$	$-.182$	$-.064$	$-.284^{***}$	$-.124$	$-.162$	$-.261^{**}$
	(.119)	(.128)	(.137)	(.12)	(.127)	(.13)	(.137)	(.106)	(.095)	(.115)	(.124)	(.108)
Event-state fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Event-year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Treated states	11	10	10	10	10	10	10	10	10	10	10	10
Control states	13	11	13	13	12	13	13	13	13	13	13	10
Observations	912	804	832	840	828	832	840	832	848	840	840	784

Notes: *$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.* This table reports the benchmark estimates detailed in Section 3, dropping one event in our sample at a time. All regressions include event-state fixed effects and event-year fixed effects and control for survey type, race, marital status, age, and population. The regressions are a triple differences, across Medicaid eligibility, the timing of the policy, and the location of the policy. Robust standard errors are clustered by state and reported in parenthesis.

Table A.7: Alternative Medicaid Thresholds

	(1)	(2)	(3)	(4)	(5)
Medicaid cutoff	Baseline	138	150	200	250
Bad mental health days					
Overall impact of policy	-4.97^{*}	-1.85	-4.89^{*}	-6.05^{**}	-1.27
	(2.46)	(2.32)	(2.5)	(2.69)	(3.48)
Frequent mental distress					
Overall impact of policy	$-.18$	$-.091$	$-.104$	$-.249^{**}$	$-.086$
	(.119)	(.11)	(.098)	(.119)	(.113)
Event-state fixed effects	✓	✓	✓	✓	✓
Event-year fixed effects	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Low-income transgender people	1,215,080	913,296	945,611	1,167,289	1,289,844
Treated states	11	11	11	11	10
Control states	13	13	13	13	11
Observations	228	228	228	220	193

*Notes: *p<0.10,**p<0.05,***p<0.01.* This table reports the benchmark estimates detailed in Section 3; however, each column uses alternative FPL cutoffs for likely Medicaid eligibility. All regressions include event-state fixed effects and event-year fixed effects and control for survey type, race, marital status, age, and population. The regressions are a triple differences, across Medicaid eligibility, the timing of the policy, and the location of the policy. Robust standard errors are clustered by state and reported in parenthesis.

Table A.8: Subsetting controls by policy type

	(1)	(2)	(3)
Control group	Full	No policy	Exclusive
Bad mental health days			
Overall impact of policy	-4.97^{*}	-3.38	-6.39^{**}
	(2.46)	(3.14)	(2.74)
Frequent mental distress			
Overall impact of policy	$-.18$	$-.113$	$-.189$
	(.119)	(.164)	(.143)
Event-state fixed effects	✓	✓	✓
Event-year fixed effects	✓	✓	✓
Demographic controls	✓	✓	✓
Low-income transgender people	1,215,080	940,758	931,258
Treated states	11	11	11
Control states	13	9	5
Observations	912	596	524

Notes: *$p<0.10$, **$p<0.05$, ***$p<0.01$. This table reports the benchmark estimates detailed in Section 3; however, each subsets the controls group by their Medicaid policy (both inexplicit and exclusive, only inexplicit, or only exclusive). All regressions include event-state fixed effects and event-year fixed effects and control for survey type, race, marital status, age, and population. The regressions are a triple differences, across Medicaid eligibility, the timing of the policy, and the location of the policy. Robust standard errors are clustered by state and reported in parenthesis.

Table A.9: Impact of Medicaid Covering Gender-Affirming Care on Medicaid Utilization

	(1) Total hormone prescriptions through Medicaid	(2) Total other prescriptions through Medicaid	(3) Total Medicaid enrollees
Impact of policy (%Δ)	9.45 (6.37)	3.17 (3.63)	2 (1.87)
Event-state fixed effects	✓	✓	✓
Event-year fixed effects	✓	✓	✓
Medicaid expansion control	✓	✓	✓
Pre-policy average outcome	190,718	13800013	1,338,947
Treated states	21	21	21
Control states	33	33	33
Observations	3,897	3,897	3,897

*Notes: *p<0.10,**p<0.05,***p<0.01.* This table reports stacked difference-in-difference estimates for the impact of Medicaid covering gender-affirming care on Medicaid utilization. All regressions include event-state fixed effects and event-year fixed effects and control for an event-Medicaid expansion status interaction. The regression is weighted to balance pre-policy trends in the outcome between the treated and control group. Robust standard errors are clustered by state and reported in parenthesis.