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Revisiting The Effect of the Affordable Care Act Medicaid Expansion on Migration *†

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Abstract

We revisit the impact of the Affordable Care Act's Medicaid expansion on interstate migration to determine the longer-run effects of the policy. Using American Community Survey data from 2010-2019 and a difference-in-differences (DiD) research design, we test for changes in migratory trends between expansion and non-expansion states. In contrast with prior findings examining short-run effects, we find evidence of increased migration from non-expansion-to-expansion states among those with Medicaid coverage after the policy change. Staggered DiD methods indicate that increases in net migration to expansion states are driven by reduced out-migration from expansion states.

JEL codes: I13, J11, I38
Keywords: Migration, Medicaid Expansion, Welfare Magnet, Public Policy

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1 Background

The Patient Protection and Affordable Care Act (ACA), passed in 2010, is the most substantial change in U.S. healthcare policy since the implementation of Medicaid and Medicare in the 1960s. The policy includes a variety of mandates and provisions intended to increase access to health insurance among Americans. One such provision, Medicaid expansion, called for expanding program eligibility from 100% to 138% of the federal poverty level (FPL) across all states. In 2012, the Supreme Court ruled that each state had the right to decide whether to expand eligibility for Medicaid programs (Musumeci, 2012). This ruling created variation in Medicaid expansion decisions across states, with 26 states and the District of Columbia expanding their program eligibility in 2014 and 24 states choosing not to expand.[1]

An earlier study of ACA Medicaid expansion determined whether variation in state expansion decisions led individuals to migrate from non-expansion-to-expansion states in the short-run to gain access to Medicaid (Goodman, 2017). For example, low-income, childless individuals who remained ineligible for Medicaid in non-expansion states may have become eligible for Medicaid in expansion states following the policy. Nearly 20% of the U.S. population relies on Medicaid for their health insurance, and the monetary value of gaining access to Medicaid is substantial (Keisler-Starkey and Bunch, 2021). For the year 2019, state-level estimates of per-capita expenditures on ACA Medicaid expansion range from \$1,647 (Arkansas) to \$13,966 (North Dakota), with a median of \$6,709 across the 35 states surveyed (Medicaid, n.d.). These benefits are especially large in relation to federal poverty guidelines. In 2019, 138% of the FPL was \$17,236 for families with one person and \$35,535 for families of four (Office for the Assistant Secretary for Planning and Evaluation, 2019). Thus, it is plausible that low-income individuals faced an increased incentive to migrate into expansion states following ACA Medicaid expansion. Early work relates this potential migratory response to the "welfare magnet" hypothesis, the idea that individuals' migration decisions are influenced by the generosity of the welfare system in the area of destination (Giulietti, 2014).

[1] Since 2014, several additional states have expanded their Medicaid programs. As of January 2022, 38 states and the District of Columbia (i.e., 39 states including D.C.) have expanded their Medicaid programs (Kaiser Family Foundation, 2022).

Goodman's (2017) original work on the relationship between ACA Medicaid expansion and migration finds little evidence of increased net migration into expansion states among low-income individuals in 2014. We revisit the topic now that additional post-policy data is available to determine the longer-run impacts of the policy. We use data from the American Community Survey (ACS) spanning the years 2010-2019 and follow Goodman's (2017) identification strategy in the spirit of differences-in-differences (DiD) to estimate changes in net migration from non-expansion-to-expansion states following the policy implementation. To better account for variation in the timing of state Medicaid expansion decisions, we employ multiple treatment-control group assignment strategies as well as utilize Callaway and Sant'Anna's (2021) recently developed staggered DiD methodology.

We contribute to the existing literature and extend the work of Goodman (2017) in several ways. First, we include post-policy data beyond 2014, which was the only wave of post-ACA Medicaid expansion data available at the time of Goodman's (2017) work. By utilizing post-policy data spanning 2014-2019, we are able to better exploit the staggered rollout of Medicaid expansion in the years following 2014. Additionally, because it may take time for individuals to learn about the differences in state Medicaid policies, coordinate the logistics of a move, and secure the resources required to move (Kaplan and Schulhofer-Wohl, 2017), changes in migratory trends may not be immediately apparent by 2014. Along these lines, we explore whether migratory effects following ACA Medicaid expansion become more evident over time.

Second, the Medicaid expansion literature typically focuses on those with income below a certain level or those with less than a high school education to target the population most likely to be impacted by the policy (Goodman, 2017; Schwartz and Sommers, 2014; Alm and Enami, 2017). We follow this traditional approach by analyzing a sample of individuals with family incomes at or below 138% of the FPL; however, we also focus on a second sample of individuals - those with Medicaid coverage in any given year. The Medicaid-covered sample allows us to test for changes in migratory trends among individuals benefiting from their current state's Medicaid program, or those most likely to be impacted by changes in Medicaid policy. We argue that migratory trend changes among those covered by Medicaid may better target the impacts of the policy change compared to the low-income sample as some individuals do not enroll in Medicaid coverage, despite eligibility, for reasons including lack of awareness, negative stigma, and churn (Orgera, Rudowitz and Damico, 2021; Congressional Budget Office, 2020).

Third, the Medicaid expansion literature often uses a time-invariant approach to treatment-control group assignment and standard DiD estimation. We follow this approach while also using two alternative treatment-control group assignment strategies along with recently developed DiD methods that account for variation in treatment timing. Our alternative treatment-control group assignments include: (i) dropping early and late expansion states, which leaves 34 states (Black et al., 2019), and (ii) including only new (original) and never expanding states, leaving 21 states total (Courtemanche, Marton and Yelowitz, 2019). Exploring differences across group assignment strategies is important due to the varied timing and nature of states expanding Medicaid as well as differences in pre-ACA Medicaid generosity. Lastly, we use the Callaway and Sant'Anna (2021) estimator to fully exploit the staggered rollout of ACA Medicaid expansion over the years 2014-2019.[2]

Migration tied to Medicaid expansion may impact states and society as a whole through several channels. First, migration tied to Medicaid expansion increases the population that benefits from the program. Access to Medicaid during early childhood positively impacts both health and economic outcomes later in life (Boudreaux, Golberstein and McAlpine, 2016; Goodman-Bacon, 2021b; Miller and Wherry, 2019; Kaestner et al., 2017). Access to Medicaid is also associated with better financial well-being (Jackson, Agbai and Rauscher, 2021; Hu et al., 2018). Second, Medicaid expansion shifts the disincentive to work more in expansion states from individuals near 100% of the FPL to those near 138% of the FPL (Moffitt, 2015). The option to potentially increase one's income and retain or gain Medicaid coverage (up to 138% of the FPL) could lead to non-expansion-to-expansion state migration (Moffitt, 2015). Third, states are increasingly financially responsible for the costs associated with Medicaid expan-

[2] Recent advances in the DiD literature show that two-way fixed effects (TWFE) estimates are biased when different units are treated at different times (Goodman-Bacon, 2021a; Borusyak and Jaravel, 2017; Kim and Wang, 2019; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Athey and Imbens, 2021). Therefore, we also use Callaway and Sant'Anna's (2021) staggered DiD estimator to explicitly account for variation in treatment timing to assess the impact of the staggered rollout of ACA Medicaid expansion.

sion. Thus, increased migration to expansion states in the longer term may lead to additional expenses to cover more Medicaid enrollees.[3]

Overall, among the low-income sample, we find mixed evidence of increased net migration from non-expansion-to-expansion states following 2014. When following a time-invariant treatment assignment that includes all states, we find no evidence of migratory trend changes following the policy. When using more targeted treatment assignment approaches, dropping early and late expansion states (leaving 34 states), and including only new and never expanding states (21 states), we find some evidence of migratory trend changes. Specifically, we estimate a 10% - 38% increase in average net migration to expansion states after the policy among those with low-income. Among the sample of Medicaid-covered individuals, we find stronger evidence of migratory trend changes following the policy. We estimate an increase in net migration from non-expansion-to-expansion states of 0.31 to 0.55 percentage points (pp) after 2014 among individuals with Medicaid. These estimates correspond to a 26% - 99% increase in average net migration into expansion states, or an additional 2,600 - 3,000 migrants for the sample.[4] Thus, individuals with Medicaid coverage in expansion states are significantly more likely to have recently migrated from a non-expansion state following the policy change.

We supplement our main analysis by exploring policy heterogeneity across demographic and household characteristics: race, gender, family structure, and health status. We find that changes in migratory behavior are larger among Hispanics, males, single adults, childless adults, and those without a disability. Migration responses for low-income adults without children are particularly interesting as eligibility gains from ACA Medicaid expansions were largest for childless adults (McMorrow et al., 2017). We also conduct an event study to estimate year-by-year policy effects and to visually assess the standard parallel trends assumption. The event study results show that increased net migration from non-expansion-to-expansion states persisted for several years after the ACA, but dropped off by the year 2019. Last, due to the staggered

[3]The incremental costs associated with ACA Medicaid expansions were initially funded 100% by the federal government, with the federal government's share of incremental expenses steadily decreasing to 90% by 2020 (Lee and Winters, 2021).

[4]The additional 2,600 - 3,000 migrants are only relative to the ACS sample and are likely higher for the full population.

nature of Medicaid expansion across time, we utilize methods from the emerging "variation in treatment timing" DiD literature. The staggered DiD results reveal a modest increase in migration from non-expansion-to-expansion states and a large decrease in migration from expansion-to-non-expansion states, particularly among the Medicaid-covered sample. Thus, additional post-policy data reveals that ACA Medicaid expansions did impact migratory patterns from non-expansion-to-expansion states, particularly for individuals with Medicaid coverage.

The remainder of the paper is organized as follows: Section 2 provides background information on the welfare magnet hypothesis and migration in response to Medicaid expansion. Section 3 describes three treatment-control group assignment approaches for Medicaid expansion. Section 4 discusses the data and sample selection criteria, while Section 5 describes the the econometric methods. Section 6 details the results, and, finally, Section 7 concludes.

2 Medicaid and Migration

2.1 The Welfare Magnet

The welfare magnet hypothesis centers on the idea that low-income individuals face incentives to migrate to locations with more generous welfare benefits or public assistance programs. Research on the welfare magnet is mixed overall. In a review of the early literature on this topic, Moffitt (1992) noted that studies from the 1960s and early 1970s generally found no evidence of the welfare magnet (Gallaway, Gilbert and Smith, 1967; Sommers and Suits, 1973; Fields, 1979), while others in the late 1970s and 1980s found evidence supporting the hypothesis (Hutchens, Jakubson and Schwartz, 1989; Bane and Ellwood, 1983; Danziger et al., 1982). The divergent results are due to differences in data aggregation; early studies typically use a high level of data aggregation, while later studies often disaggregate the data by demographic characteristics such as gender, race, or marital status (Moffitt, 1992). As Cebula (1979) explains, it is important to target the population that is eligible for welfare or public assistance programs rather than including all individuals in the analysis.

As welfare programs and policies have changed over the years, research on the welfare magnet and the impacts of public programs continues to evolve. Hanson and Hartman (1994) emphasize that low-income individuals are unlikely to move at all, including moving to states for more generous public assistance. Further, Allard and Danziger (2000) find little evidence that single-parent households in the U.S. migrated to states with higher welfare benefits in the aftermath of federal welfare reform in 1996.

A few studies specifically analyze the welfare magnet for unmarried mothers, a population likely to receive welfare benefits. Kaestner, Kaushal and Van Ryzin (2003) study the migration of low-educated, unmarried mothers in response to state and federal welfare policy changes that added time-limited benefits, financial sanctions for non-compliance, and work eligibility rules. The authors find that welfare reform reduced interstate migration but increased intrastate migration for low-educated, unmarried women with children, emphasizing the importance of migrating for economic or employment reasons rather than welfare benefit differences (Kaestner, Kaushal and Van Ryzin, 2003). Gelbach (2004) also studies low-educated, never-married mothers, and finds that those who move across states are more likely to move to a state with higher welfare benefits. Similarly, Bailey's (2005) results also support the welfare magnet for poor, unmarried mothers as welfare generosity does impact migration. These studies highlight the potential heterogeneous nature of the welfare magnet as some groups are more likely to move for access to public insurance or welfare programs.

2.2 Medicaid Expansion

Medicaid, one of the largest social welfare programs in the country, has expanded since its implementation in the 1960s to provide health insurance to low-income individuals, children, pregnant women, and people with disabilities (Rudowitz, Garfield and Hinton, 2019).[5] The latest round of Medicaid expansions, those tied to the ACA, extended eligibility to childless adults and increased the income threshold for eligibility from under 100% to 138% of the FPL. The ACA policy initially called for Medicaid expansion nationwide, but the Supreme Court later ruled that the decision to expand Medicaid was ultimately up to each state (Musumeci, 2012). As of January 2022, 38 states and the District of Columbia have adopted ACA Medicaid expansion, up from 26 states and D.C. that initially expanded in 2014 (Kaiser Family

[5] See point 3 in Rudowitz, Garfield and Hinton (2019) for a brief summary of Medicaid coverage over time.

Foundation, 2022).

2.2.1 Migration and Medicaid Expansion

A specific area of the welfare magnet literature focuses on the relationship between Medicaid expansion and migration. Cebula and Clark (2013) find a positive effect of Medicaid generosity on interstate migration from 2000 to 2008. Schwartz and Sommers (2014) study four states, Arizona, Maine, Massachusetts, and New York, that expanded their Medicaid programs to include childless adults prior to the ACA. The authors do not find significant evidence of migration in response to expanding Medicaid eligibility. Alm and Enami (2017) study the relationship between migration and the 2006 Massachusetts Health Care Reform (MHCR), a program that influenced the design of ACA Medicaid expansion. Alm and Enami's (2017) findings highlight the regional nature of migration responses, even within a given state. Cities in Massachusetts closest to the state border, within 5 miles, experienced significant low-income population growth (18-25 pp) after the MHCR policy change. In contrast, cities more than 15 miles from the state border experienced virtually no change in their low-income population growth (Alm and Enami, 2017).

Goodman (2017), the first to study ACA Medicaid expansion and migration, uses a model in the spirit of DiD to analyze the change in migration into expansion states from non-expansion states compared to migration in the opposite direction. Goodman (2017) finds a negligible impact with an upper bound increase of 0.18 percentage points in net migration to expansion states, noting that ACA Medicaid expansions did not meaningfully impact migration. Given the timing of Goodman's work, it was only possible to analyze changes in migration flows in the initial year of the policy change. As Goodman (2017) notes, there is still room for future research using "data from an additional year of the ACS...to uncover any longer-run effects that are not visible in the short run" (p.236). Thus, we revisit the question of how ACA Medicaid expansions impacted migratory trends now that more time has elapsed since the policy implementation in 2014.

2.2.2 Other Impacts of Medicaid Expansion

Related areas of the welfare magnet literature explore impacts of Medicaid expansion beyond migration, such as health behaviors or labor supply. The primary motivation behind Medicaid expansions, including those tied to the ACA, is to increase health insurance coverage and access to healthcare. Expanding adult eligibility for Medicaid can also spillover to increase enrollment for the adult's already-eligible children, what is known as the "woodwork effect" (Sacarny, Baicker and Finkelstein, 2022). Miller and Wherry (2019) study the long-run impacts of Medicaid coverage; the authors find that individuals with mothers who had access to Medicaid prenatal coverage experienced a lower likelihood of chronic conditions and fewer hospitalizations related to obesity or diabetes as adults. Similarly, adults with Medicaid eligibility or exposure during early childhood experience significant improvements in health, linked to higher health care utilization and reductions in mortality and disability (Boudreaux, Golberstein and McAlpine, 2016; Goodman-Bacon, 2021b; Thompson, 2017). Declines in disease-related mortality and hospitalizations later in life are particularly pronounced for black individuals (Wherry and Meyer, 2016; Wherry et al., 2018).

Evidence on health insurance coverage and healthcare access specific to the ACA also suggests that ACA Medicaid expansions increased health insurance coverage (Kaestner et al., 2017). The share of residents with insurance increased by nearly 3 pp more in states that expanded Medicaid compared to states that did not expand Medicaid (Courtemanche et al., 2017). Similarly, Courtemanche et al. (2018) find that the ACA significantly improved healthcare access across all states, with the gains in Medicaid expansion states exceeding those in non-expansion states. ACA Medicaid expansions also increased Medicaid coverage for those with income less than 138% of the federal poverty level (Courtemanche, Marton and Yelowitz, 2019) and health insurance coverage for the self-employed (Lee and Winters, 2021). Despite the increases in Medicaid coverage in response to the ACA, Schmidt, Shore-Sheppard and Watson (2020) do not find a meaningful change in Supplemental Security Income (SSI) or Social Security Disability Insurance (SSDI) applications.

Medicaid coverage also impacts economic outcomes beyond health care coverage and utilization, including labor outcomes, education, financial well-being, and marriage. For some, primarily white individuals, Medicaid eligibility in early childhood increased employment and decreased reliance on disability transfer programs later in life (Goodman-Bacon, 2021b). Brown, Kowalski and Lurie (2020) show that young adults, ages 19 to 28, with greater Medicaid eligibility during childhood experience higher college enrollment and pay more in taxes; women also experience increased wages. In contrast, participation in Medicaid as an adult typically has a negative impact on labor supply (Dague, DeLeire and Leininger, 2017), particularly among women (Moffitt and Wolfe, 1992; Winkler, 1991). In the aftermath of Medicaid or welfare program eligibility contractions, individuals typically increase their labor supply (Garthwaite, Gross and Notowidigdo, 2014; Borjas, 2003). There is also a strong connection between Medicaid coverage and financial well-being. Medicaid expansion or greater access to Medicaid decreased the number of unpaid bills, debt sent to collection agencies, new medical debt, and likelihood of bankruptcy (Gross and Notowidigdo, 2011; Hu et al., 2018; Finkelstein et al., 2012). Medicaid coverage is also associated with higher savings, retirement account, and mortgage balances (Jackson, Agbai and Rauscher, 2021). Similarly, the loss of Medicaid coverage in Tennessee is associated with declines in personal financial well-being (Argys et al., 2020). Recently, Medicaid expansion has been linked to increased child support payments made to custodial parents, indicating that Medicaid expansion increased the financial ability of non-custodial parents (Bullinger, 2021). ACA Medicaid expansion also led to decreased marriage rates among working-aged adults, likely due to decreased reliance on spousal health insurance coverage (Hampton and Lenhart, 2022), and decreased medical divorce among college-educated individuals ages 50-64 (Slusky and Ginther, 2021).

The literature reveals a strong connection between Medicaid and health care coverage, access, and utilization. However, evidence on the relationship between Medicaid and migration remains mixed. We revisit Goodman's (2017) initial findings on the migration response to the first year of ACA Medicaid expansion now that more data is available to determine the longer-run impacts of the policy. We also explore the heterogeneous impacts of the program expansions across demographic characteristics, use three approaches to treatment-control assignment, and incorporate newly developed DiD models to account for variation in treatment timing.

3 Medicaid Expansion Group Assignment

Any study of Medicaid expansion requires the determination of treatment and control group assignment, which hinges on the timing of ACA Medicaid expansion decisions across states. ACA Medicaid expansions began in 2014 and have increased in number since. Such variation in treatment timing makes treatment-control group assignment difficult. Figure 1 illustrates the timing of ACA Medicaid expansion across states from 2014-2019. As part of the ACA, 26 states and D.C. expanded Medicaid in 2014, 3 states expanded in 2015, 2 states expanded in 2016, and 2 states expanded in 2019.[6] The figure also reveals a regional pattern to ACA Medicaid expansions. States in the northeast and west regions are more likely to adopt ACA Medicaid expansions compared to states in the midwest or south. We ultimately use three different group assignment approaches, outlined below, that become progressively more restrictive, to balance sample size with the timing and nature of state Medicaid expansion decisions.

3.1 The Time-Invariant Approach

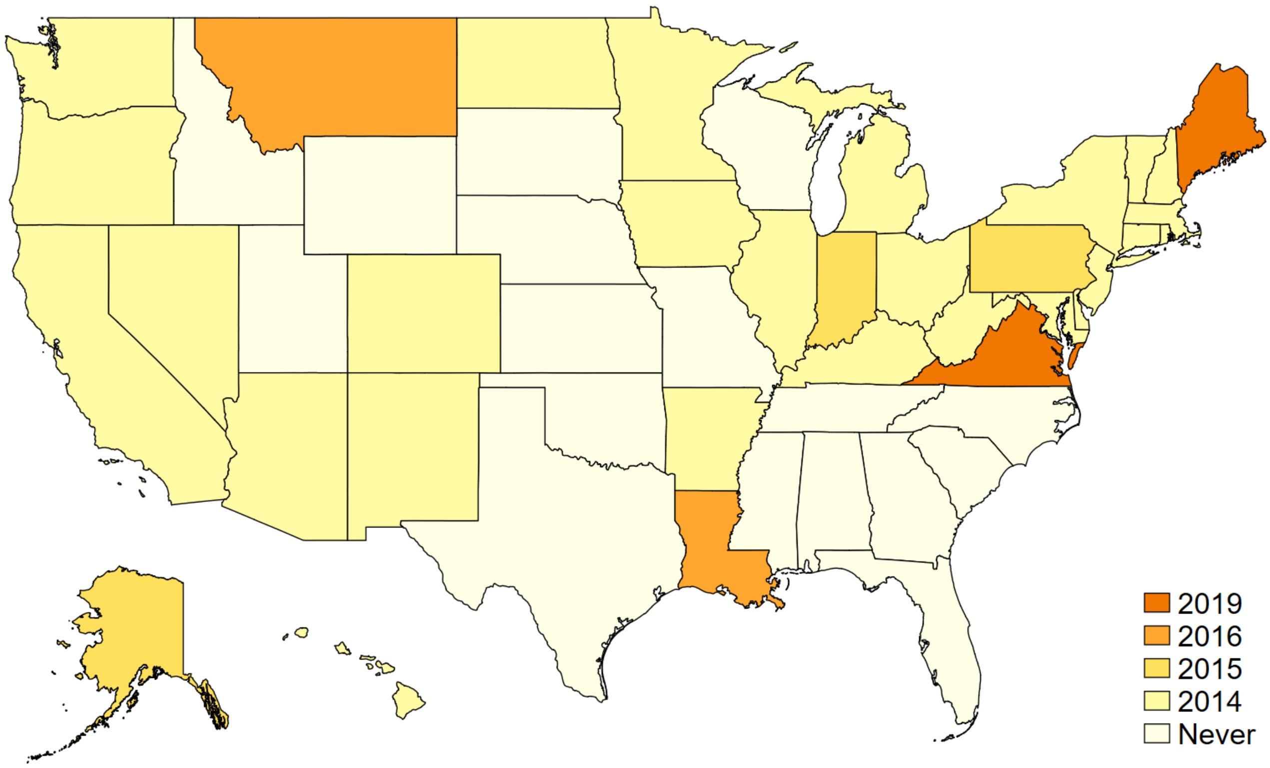
Many ACA Medicaid expansion studies rely on a time-invariant approach to treatment assignment, assigning the 26 states and D.C. that expanded Medicaid in 2014 to the treatment group, and the remaining 24 states that did not expand in 2014 to the control group (for example, see Courtemanche et al. (2017, 2018)).[7] Goodman (2017), whose methodology we follow closely, also follows this time-invariant approach. Panel (a) of Figure 2 provides a visual illustration of expansion versus non-expansion states using the time-invariant approach. Although the time-invariant approach is the most straightforward and includes all states (including D.C.),[8] it is limited in that it fails to account for states with generous pre-ACA Medicaid programs, a majority of which further expanded Medicaid as part of the ACA, and it permanently charac-

[6] Idaho, Missouri, Nebraska, Oklahoma and Utah expanded in 2020. Since we utilize data from 2010-2019, we treat these 2020 expanding states as non-expansion states in the analysis.

[7] Kaestner et al. (2017) use a variation of the time-invariant approach, but they categorize five states with prior comprehensive expansions to include childless adults in the control group.

[8] For simplicity, we treat D.C. as its own state for treatment-control group assignment purposes. Thus, the total possible number of states included in the analysis is 51.

Figure 1: Timing of ACA Medicaid Expansions, 2014 - 2019



Source: Kaiser Family Foundation.
Note: Figure shows the staggered rollout of Medicaid expansion decisions following the passage of the ACA. The figure includes all 50 states and D.C. Each color in the figure represents the particular year that a given state expanded Medicaid. Five states that expanded in 2020 are included in the "Never" category.

terizes later expanding states as members of the control group, ignoring policy variation from 2015-2019. Thus, estimated policy effects using the time-invariant approach are likely to be biased towards zero.

3.2 Dropping Early and Late Expansion States

Our second treatment assignment approach better accounts for states that expanded their Medicaid programs before and after 2014 by dropping early and late expansion states. We follow Black et al. (2019) by dropping 10 states with expansions prior to 2014: Hawaii (1994); Delaware and Vermont (1996); New York (2001); Massachusetts (2006); Wisconsin (2009); and California, Connecticut, D.C., and Minnesota (2010). Additionally, we drop 7 states that expanded Medicaid in the years 2015 - 2019: Alaska, Indiana, and Pennsylvania (2015); Louisiana and Montana (2016); and Maine and Virginia (2019) (Kaiser Family Foundation, 2022). Panel (b) of Figure 2 provides a visual illustration of expansion versus non-expansion states after dropping early and late expanders. While this approach only includes 34 states in the analysis, and hence is more limited in terms of statistical power, it offers a "cleaner" treatment-control group comparison that better isolates the impact of ACA Medicaid expansion, which may reveal migratory effects not discernible using the time-invariant approach.

3.3 Only New and Never Expansion States

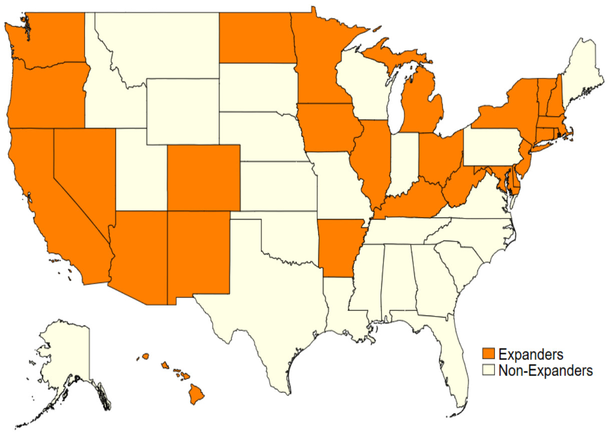
For the third treatment assignment approach, we follow Courtemanche, Marton and Yelowitz (2019) and limit the sample to new and never expanding states. New expansion states are those who expanded Medicaid for the first time ever in 2014, while never expansion states are those that, as of 2019, never expanded Medicaid. Panel (c) of Figure 2 provides a visual illustration of expansion versus non-expansion decisions including only new and never expansion states. Among the 9 new expansion states, none offered Medicaid coverage to any subgroup (other than pregnant women) with income above 138% of the FPL prior to the ACA. Among the 12 never expansion states, the income eligibility threshold for Medicaid was between 17-54% of the FPL for adult caretakers in families, and no state extended coverage to childless adults. Overall, all 21 states under this approach had weak health insurance safety nets for working-age adults prior to the ACA (Courtemanche, Marton and Yelowitz, 2019). While this group assignment strategy is the most restrictive, as it drops over half of U.S. states from the analysis, it better isolates the states most likely to be impacted by the ACA Medicaid expansions and offers the cleanest counterfactual via the control group.

4 Data and Sample Selection

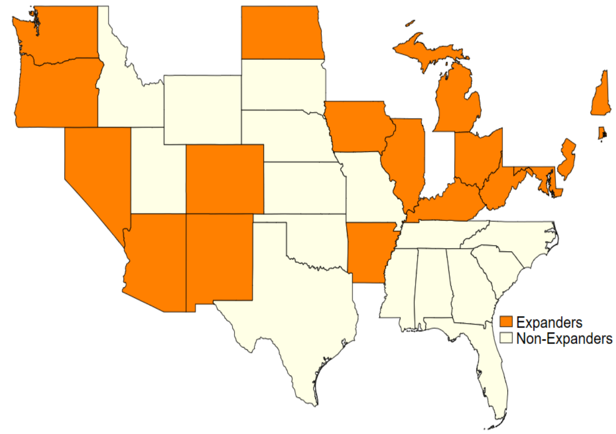
We use data from the American Community Survey (ACS) for years 2010 to 2019 (U.S. Census Bureau, n.d.). The ACS is an ongoing annual survey maintained by the U.S. Census Bureau that samples approximately 1 percent of Americans each year and is weighted to be representative

Figure 2: Medicaid Expansion Treatment Assignment Approaches

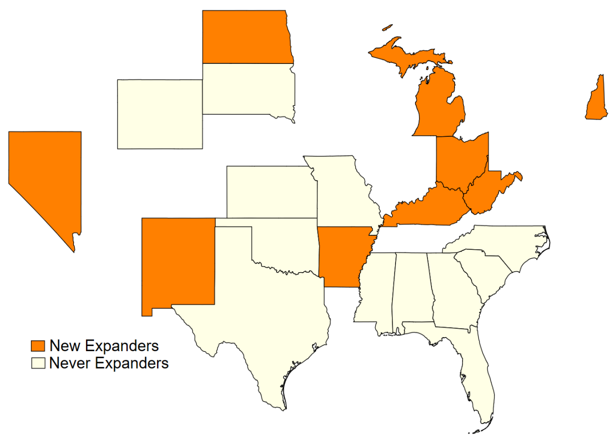
(a) Time-Invariant, All States



(b) Drop Early and Late Expanders, 34 States



(c) Only New and Never Expanders, 21 States



Source: Kaiser Family Foundation.
Notes: Figure shows states included in treatment (expansion) and control (non-expansion) groups for three treatment assignment approaches. Panel (a) displays the time-invariant approach using all 50 states and D.C. The second approach, displayed in Panel (b), drops early and late expansion states, leaving 34 states. The last approach, displayed in Panel (c), keeps only new and never expansion states, leaving 21 states. Expansion states are in orange and non-expansion states are in cream.

of the U.S. population.[9] The ACS is well-suited to study the impact of Medicaid expansion on interstate migration for three reasons. First, unlike many other publicly available datasets,

[9]The ACS data is maintained in two separate records that may be merged together for each calendar year: the housing files and the person files. We obtain each set of files from the Census Bureau File Transfer Protocol (FTP) site and pool data from the one-year Public Use Microdata Sample (PUMS) files between the years 2010 and 2019. To avoid concerns related to the Great Recession, we omit data from years prior to 2010. Additionally, due to the COVID-19 pandemic, we also do not include data from 2020. The Census Bureau additionally acknowledges the potential issues related to post-COVID-19 data and refer to the 2020 wave as *2020 ACS 1-Year Experimental Estimates.*

the ACS includes state Federal Information Processing System (FIPS) codes, which allow us to identify residence in all 50 states and the District of Columbia. While the ACS data is cross-sectional, and we cannot observe the same person or family in multiple waves, the dataset does include migration-related variables that identify an individual's state of residence in both the survey year and the prior year. Such variables are necessary to determine whether someone has recently migrated across states and further allow us to identify an individual's origin and destination states following a decision to migrate. Second, the ACS has a rich set of demographic and socioeconomic-related characteristics, which are important determinants of one's ability and willingness to migrate. Third, the ACS is appealing due to its large sample size, surveying over 3 million people in any given year.

In the analysis, we make several sample selection decisions, which closely follow Goodman (2017), to better target the individuals most likely to be impacted by Medicaid expansion. First, we limit the sample to working-aged adults between ages 18 and 64 since individuals qualify for Medicare at age 65.[10] Second, we drop members of the active-duty military who are covered by TRICARE. Third, as lawfully present immigrants are generally not eligible for Medicaid until five years after they receive permanent resident status, and undocumented immigrants are ineligible for the program, we drop all immigrants who arrived in the U.S. within five years of the interview year. Finally, we generally focus on two subsamples to better target those impacted by changes in Medicaid policy: (1) individuals with family earnings less than or equal to 138% of the FPL, and (2) individuals with Medicaid coverage.

Table 1 presents descriptive statistics for our full sample without imposing any socioeconomic-related restrictions across the three treatment-control group assignment strategies. The table shows sample means for individuals living in non-expansion and expansion states, following the time-invariant treatment assignment approach (all states) in columns (1) and (2), dropping early and late expanders (34 states) in columns (3) and (4), and including only new and never expanders (21 states) in columns (5) and (6).[11] From the table, the proportion of individuals

[10] As Goodman (2017) notes, while some individuals are dually eligible for both Medicare and Medicaid, this subgroup is unaffected by ACA Medicaid expansion.

[11] Appendix Tables A1 and A2 display analogous means specific to the two subsamples: those with family earnings less than or equal to 138% of the FPL and those with Medicaid coverage.

Table 1: Summary Statistics

	All States		*34 States*		*21 States*	
Variable	**(1) Non-Exp.**	**(2) Expansion**	**(3) Non-Exp.**	**(4) Expansion**	**(5) Non-Exp.**	**(6) Expansion**
Migrated Regions	0.014	0.010	0.008	0.008	0.003	0.006
Medicaid Coverage	0.107	0.152	0.101	0.142	0.100	0.155
Age	42.313	42.176	42.286	42.576	42.510	42.776
Male	0.489	0.493	0.486	0.492	0.487	0.494
Black	0.141	0.084	0.154	0.087	0.165	0.085
White	0.797	0.783	0.782	0.832	0.772	0.857
Hispanic	0.087	0.12	0.107	0.073	0.124	0.048
Immigrant	0.041	0.082	0.045	0.047	0.052	0.024
% FPL	319.74	341.41	316.32	336.42	317.73	313.07
Married	0.532	0.514	0.538	0.538	0.529	0.531
Family Size	2.746	2.819	2.772	2.768	2.756	2.723
Number of Children	0.621	0.615	0.628	0.629	0.608	0.615
High School Degree	0.289	0.255	0.278	0.277	0.274	0.316
Some College	0.337	0.339	0.344	0.342	0.346	0.343
Bachelor's Degree or More	0.275	0.321	0.272	0.297	0.276	0.245
Unemployment Rate	5.912	6.471	6.204	6.641	6.094	6.539
Maximum EITC	0.030	0.184	0.014	0.086	0.016	0.045
Poverty Rate	14.538	13.325	15.192	13.202	15.275	14.937
Observations	8,054,018	9,183,495	6,715,959	6,121,345	4,736,145	2,133,656

Notes: American Community Survey 1-year Public Use Microdata Sample files, 2010–2019. Summary statistics for three treatment assignment approaches: time-invariant including all states in columns (1) and (2), dropping early and late expanders including 34 states in columns (3) and (4), and only new and never expanders including 21 states in columns (5) and (6).

migrating is small with 0.3 - 1.4% of individuals recently moving into non-expansion states, and 0.6-1.0% recently moving into expansion states.[12] Additionally, there are some differences in observable characteristics between individuals living in expansion versus non-expansion states. First, individuals living in non-expansion states are more likely to be black. Additionally, those living in non-expansion states are less likely to have immigrated from another country, and generally have lower income with respect to the federal poverty level, with the exception of the most limited sample including 21 states. Finally, individuals living in non-expansion states are generally less educated, again with the exception of the most limited sample of 21 states. Before imposing any socioeconomic-related sample restrictions, the sample of all states contains over 8 million individuals living in non-expansion states and over 9 million in expansion states.

[12] We follow Goodman (2017) in defining a "region-mover" as someone that moves from a non-expansion-to-expansion state, or vice versa. We outline this approach in Section 5.

5 Econometric Methods

5.1 Difference-in-Differences Research Design

We primarily follow Goodman's (2017) empirical approach to capture net migration induced by ACA Medicaid expansion. Goodman (2017) uses a model in the spirit of difference-in-differences (DiD) to compare migration from non-expansion to expansion states relative to migration from expansion to non-expansion states, both before and after the 2014 policy change.[13] We initially follow time-invariant group assignment as outlined in Section 3.1, which includes all 50 states and D.C. We also use the two alternative, more restrictive, treatment assignment approaches, dropping early and late expanders and only new and never expanders, which are discussed in Section 3.2 and 3.3, respectively.

Goodman's (2017) model is outlined as:

$$y_{irt} = \beta \times nonexp_r \times post_t + \lambda_t + \mu_r + +\varepsilon_{rt}, \tag{1}$$

where i indexes individuals, r indexes origin region, and t indexes time. The dependent variable y captures interregion migration and takes on a value of 1 if an individual moved from one "region" to the other in the prior 12 months, and 0 otherwise. The term region defines two sets of states, non-expansion or expansion. $nonexp_r$ is an indicator for an origin state in the non-expansion region, and $post_t$ is a post-2014 dummy variable. $nonexp_r$ takes on a value of 1 for the following types of individuals: (1) one who migrates from a non-expansion state to an expansion state; (2) one who lives in a non-expansion state and does not migrate (or migrates and remains in the same state); and (3) one who migrates from one non-expansion state to another non-expansion state. The interaction between $nonexp_r$ and $post_t$ captures migration from non-expansion-to-expansion regions (states) both before and after 2014. Each model also includes fixed effects, where λ_t represents year fixed effects, and μ_r represents origin-

[13] Prior to Goodman (2017), the "welfare magnet" literature typically measures the treatment effect on migration inflows into states with more generous public assistance (or expansion states), and migration outflows from states with less generous public assistance (or non-expansion states), separately. For examples of earlier work, see Gelbach (2004); Fiva (2009); Schwartz and Sommers (2014).

and destination-state fixed effects.[14] All regression models are estimated via linear probability methods and are weighted using ACS sample weights, with standard errors clustered at the origin-state level.[15]

Some specifications also include control variables that may influence one's decision to migrate across regions. As the likelihood of migrating likely decreases with age, we control for both age and age-squared. We also include indicator variables for whether an individual is non-Hispanic black, non-Hispanic white, and Hispanic, whether a person immigrated to the U.S. from another country, and whether an individual is married. Further, as those with higher levels of education are more likely to migrate, we include dummy variables for whether one has a high school degree or less, some college, or a bachelor's degree or more. Finally, to account for state-year-level factors that may influence migration, we include controls for state-year unemployment rates, state-year Earned Income Tax Credit (EITC) rates (as a percentage of the federal amount), and state-year poverty rates.

In Equation (1), β captures the extent to which non-expansion-to-expansion migration increased after the policy change in 2014 relative to the increase in expansion-to-non-expansion migration. While not a traditional DiD specification, the model is similar in nature in the sense that non-expansion states play the role of the "treatment group," and expansion states play the role of the "control group." As stated by Goodman (2017), the above equation is analogous to a DiD regression, and hence identification relies on an assumption of parallel pretrends between the treatment and control groups. In other words, a causal interpretation requires that non-expansion-to-expansion migration followed the same trend as expansion-to-non-expansion migration prior the 2014 policy.

[14]Goodman (2017) only includes origin-state fixed effects. Due to the complicated "push" and "pull" nature of migratory behavior, we believe it is important to mitigate concerns of unobservable characteristics at both the origin-state level and the destination-state level. For that reason, our preferred specifications include both origin- and destination-state fixed effects. Results with varying levels of fixed effects are qualitatively similar and available upon request.

[15]We estimate additional models utilizing multi-level clustering. Each model is estimated using the Stata module "reghdfe," which allows for both high-dimensional fixed effects and multi-way clustering. For more on this, see Correia (2019). Results when clustering at multiple levels are qualitatively similar and available upon request.

5.2 Event Study

In addition to the main analysis, we also adopt a traditional event study framework that allows policy effects to vary across time. The event study approach, also utilized by Goodman (2017), is also commonly used to more formally assess the standard parallel pre-treatment trends assumption. We estimate an event study model testing year-by-year effects of Medicaid expansion on migratory behavior. The event study model is outlined by:

$$y_{irt} = \lambda_t + \mu_r + \sum_{s \neq 2013} \beta_s \times nonexp_r \times 1(year_t = s) + \varepsilon_{rt}. \tag{2}$$

In Equation (2), each β_s coefficient captures the difference between non-expansion-to-expansion migration and migration in the opposite direction, relative to that in the 2013 wave, which is omitted from the model as the reference category. The event study specification allows us to not only test for persistence of the policy by allowing policy effects to vary by year in the post-policy period, but also determines whether pre-treatment trends between expansion and non-expansion states were similar. Estimated β_s coefficients for the years prior to 2014 that are statistically indistinguishable from zero lend support to the standard pre-treatment parallel trends assumption.

5.3 Variation in Treatment Timing

We complement our primary methodology with the recently developed estimator of Callaway and Sant'Anna (2021), which accounts for variation in treatment timing and properly assesses the impact of a staggered policy rollout, such as ACA Medicaid expansion. Given concerns related to exploiting only appropriate policy variation, the authors propose an approach to implement DiD methods in situations of differential treatment timing. The Callaway and Sant'Anna (2021) estimator is outlined as:

$$ATT(g,t) = E\left[\left(\frac{G_g}{E[G_g]} - \frac{\hat{p}(X)C}{E\left[\frac{\hat{p}(X)C}{1-\hat{p}(X)}\right]}(Y_t - Y_{g-1})\right)\right], \tag{3}$$

where $\hat{p}(X)$ is the generalized propensity score, G_g is an indicator for whether an observation is first treated in period g, and C is an indicator for whether an observation belongs in the comparison (never treated) group. Each ATT presented in our results section is obtained using the doubly robust inverse probability weighting (dripw) estimator, which incorporates control variables using a combination of both a regression-based approach and a reweighting approach.[16]

We use two different strategies to assign states to the treatment versus control group here. First, we continue to use all 50 states and D.C. (All States). States that expanded Medicaid in 2014 - 2019, including those with prior Medicaid expansions, are included in the treatment group for the year of and years after expansion, while states that did not expand Medicaid from 2014-2019 are included in the control group or the never treated group. While this approach includes all 50 states and D.C., it is no longer time-invariant. Further, this approach includes some states that expanded Medicaid prior to 2014 in the control group, which could be problematic. Therefore, we also use a second approach that drops early expansion states from the analysis, leaving 41 states. Since the staggered DiD model accounts for states adopting Medicaid expansion in different years, the treatment group changes from year to year.[17]

We also use Callaway and Sant'Anna's (2021) event study framework for situations with variation in treatment timing. Their event study approach captures the time elapsed since policy treatment was first adopted and is outlined by:

$$\theta_{es}(e) = \sum_{g \in G} \mathbb{1}\{g + e \leq T\} P(G = g | G + e \leq T) ATT(g, g + e), \tag{4}$$

where $e = t - g$ denotes the amount of time elapsed since policy treatment, and T is the final time period of data (2019 in our case). The above aggregation of ATT captures the average effect of participating in the treatment e time periods after the treatment was adopted across all groups that are ever observed to have participated in the treatment for exactly e time periods (Callaway and Sant'Anna, 2021).

[16]Results from implementing the Callaway and Sant'Anna (2021) estimator are obtained using the CSDID command in Stata. See Rios-Avila, Sant'Anna and Callaway (2021) for more information on this recently developed Stata module. Further, see Sant'Anna and Zhao (2020) for additional background information regarding doubly robust estimators.

[17]For example, a state that expanded Medicaid in 2014 is in the treatment group for the years 2014 - 2019, while a state that expanded Medicaid in 2016 is in the treatment group for the years 2016-2019.

6 Results

6.1 Descriptive Trends in Migration

We first present descriptive figures showing trends in out-migration across time that allow us to visually assess the parallel trends assumption (i.e., whether migratory trends between non-expansion and expansion states are parallel prior to the policy change). In Section 6.5, we also present the event study results to formally test for parallel pre-trends. Figure 3 presents descriptive migratory trends across time for the two samples under study: those with family incomes less than 138% of the FPL (Panel A), and those with Medicaid coverage (Panel B). For each sample, we present migratory trends following each of the three treatment-control group assignment approaches: All States (Time-invariant), 34 States (Dropping Early and Late Expanders), and 21 States (Only New and Never Expanders). In each figure, solid lines represent the proportion of out-migration from non-expansion states (treatment group), and dashed lines represent the proportion of out-migration from expansion states (control group). The vertical line at 2014 signifies the initial year of ACA Medicaid expansion.

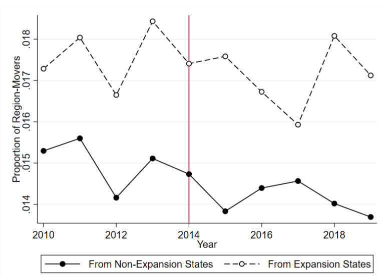
Beginning with the low-income sample in Panel A, pre-treatment trends appear somewhat parallel between the two groups across all three treatment assignment approaches. Using the time-invariant approach, (a) All States, little can be taken away regarding migratory changes in the post-policy period. When we drop early and late expanders, (b) 34 states, there is a modest decrease in out-migration from expansion states by 2016. This indicates that low-income individuals may be less likely to move out of expansion states for a short period after 2014. The decrease in out-migration from expansion states after 2014 is more noticeable when we only include new and never expanders ((c), 21 states). In this subfigure, there is also an increase in migration out of non-expansion states for a few years, indicating that some low-earning individuals may have migrated to expansion states in response to the policy.

When limited to only Medicaid-covered individuals (Panel B), pre-treatment trends again appear to be somewhat parallel between the two groups across all three treatment approaches. There is also a more discernible change in migratory trends after the policy among the Medicaid-covered sample. In each of the subfigures of Panel B, there is an increase in out-migration from

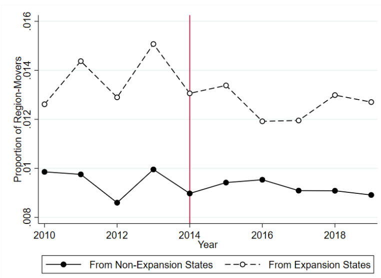
Figure 3: Interstate Migration Across Time: Descriptive Trends

Panel A. Below 138% FPL Sample

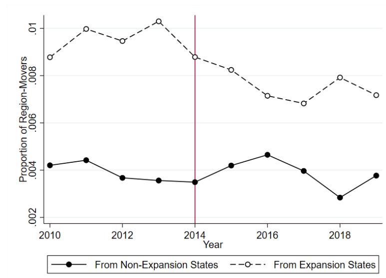
(a) All States



(b) 34 States

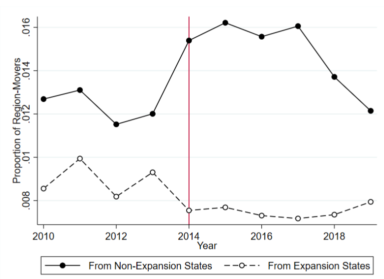


(c) 21 States

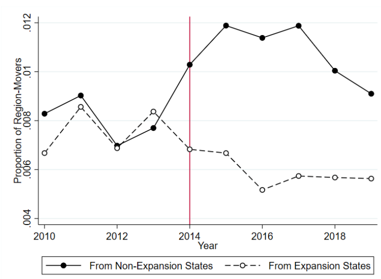


Panel B. Medicaid-Covered Sample

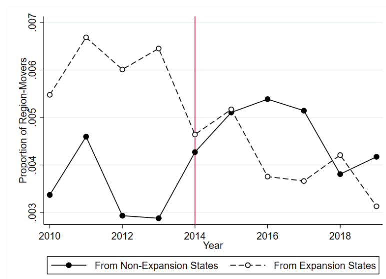
(d) All States



(e) 34 States



(f) 21 States



Notes: American Community Survey one-year Public Use Microdata Sample files, 2010-2019. Figure plots the proportion of individuals moving across regions over time for two samples, those below 138% of the FPL (Panel A), and those with Medicaid coverage (Panel B), and three treatment assignment approaches. All States is the time-invariant approach that includes all states and D.C.; 34 States drops early and late expansion states; 21 states includes only new and never expanding states. The solid line represents individuals moving from non-expansion-to-expansion states, while the dashed line represents those moving from expansion-to-non-expansion states. The vertical line at 2014 represents the year that ACA Medicaid expansion was initially implemented.

non-expansion states (solid line), starting after 2014 and persisting for several years in the post-policy period. This implies that there was an increase in the portion of Medicaid recipients within expansion states that moved to the state within the past 12 months after the policy change. While only descriptive in nature, it is possible that some individuals moved in response to changes in Medicaid policy. The subfigures in Panel B also show a decrease in out-migration from expansion states (dashed line) beginning after 2014. This implies that Medicaid-covered individuals in expansion states became less likely to move out of an expansion state after the policy change, possibly linked to the concern of losing Medicaid coverage. Overall, Figure 3 provides some descriptive evidence that ACA Medicaid Expansions in 2014 influenced migratory trends among low-income individuals and those with Medicaid coverage following 2014.

6.2 Impact of ACA Medicaid Expansion on Migration

While Figure 3 shows some evidence of migratory trend changes following ACA Medicaid expansion in 2014, particularly among Medicaid-covered individuals, the plots are merely descriptive and do not account for observable characteristics of the sample or additional factors that may influence migration. In this section, we present results from estimating Goodman's (2017) model in the spirit of DiD outlined by Equation (1). Table 2 presents the main results estimating the impact of ACA Medicaid expansion on migration. The first three columns of the table show results for the low-income sample, while the latter three columns show findings for the sample of Medicaid-covered individuals. The heading above each column indicates the treatment assignment approach, i.e., which set of states are included in a given regression model: all states (time-invariant), 34 states (dropping early and late expanders), or 21 states (only new and never expanders). As indicated at the bottom of the table, each specification includes state (both origin and destination) and year fixed effects as well as additional control variables.

Beginning with the low-income sample, the estimated coefficient of interest for all states (column 1) is negative and statistically insignificant, indicating no meaningful change in migratory trends following ACA Medicaid expansion. This result is in line with the main results of Goodman (2017). When dropping early and late expanding states in column (2), however, the estimated effect becomes positive in sign, larger in magnitude, and statistically significant at the 5% level; we estimate a 0.13 percentage point (pp) increase in net migration from non-expansion-to-expansion states when including 34 states. This translates to a 9.22% increase from the mean non-expansion out-migration rate of 1.41% in 2013, or 1,366 new "net-migrants" into expansion states following the policy change.[18] When further limiting to 21 states, new and never expanders in column (3), the estimated coefficient is even larger at 0.0026 and sta-

[18]To calculate the estimated increase in migrants, we multiply the estimated coefficient, β, by the relevant population of non-expansion states for the corresponding treatment assignment approach. For column (2), we multiply the coefficient of 0.0013 times the low-income sample population across the 34 states in the analysis of 1,050,375, for a total of 1,366. Goodman (2017) goes through a similar exercise but uses the upper bound of the 95% confidence interval. For column (2), the upper bound of the 95% CI is 0.0041, which corresponds with 4,307 new "net-migrants" into expansion states. The calculation for new net-migrants is only relative to the sample population and is likely much larger when scaled up to the full population.

Table 2: Impact of ACA Medicaid Expansion on Migration

Dependent Variable: Net Migration into Expansion States

	Below 138% FPL			***Medicaid-Covered***		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	All States	**34 States**	**21 States**	**All States**	**34 States**	**21 States**
Effect	-0.0005	0.0013	0.0026	0.0031	0.0053	0.0055
	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0010)
Observations	2,862,329	1,895,873	1,333,531	2,259,410	1,309,839	832,490
Sample Mean	0.0149	0.0141	0.0068	0.0119	0.0115	0.0055

Notes: American Community Survey 1-year Public Use Microdata Sample files, 2010–2019. Each column reports OLS estimates of the impact of ACA Medicaid expansion on interstate migration as outlined by Equation (1). The dependent variable is an indicator taking on a value of 1 if an individual either moves from a non-expansion-to-expansion state or from an expansion-to-non-expansion state and 0 otherwise. Columns (1)-(3) present results for a sample of individuals with family income at or below 138% of the FPL, while columns (4)-(6) present those for a sample of Medicaid-covered individuals. We use three different treatment assignment approaches: time-invariant including all states in Columns (1) and (4), dropping early and late expanders leaving 34 states in Columns (2) and (5), and only using new and never expanders leaving 21 States in Columns (3) and (6). Each specification includes origin and destination state fixed effects, year fixed effects, and additional controls. Robust standard errors clustered at the origin-state level are shown in parentheses.

tistically significant at the 1% level. This results in an increase of 38.24% from the mean in 2013 or 2,397 additional net-migrants into new expansion states following the policy. Taken together, we find some evidence of changes in migratory behavior after the policy among the low-income sample when using more targeted group assignment approaches.

Columns (4)-(6) of Table 2 present analogous results for the Medicaid-covered sample. Across all three treatment assignment approaches, each estimated coefficient is positive and significant at the 1% level for the Medicaid-covered sample. Further, the coefficients are two to four times larger in magnitude compared to those for the low-income sample. For all states, we estimate a 0.31 pp increase in net migration into expansion states following 2014 among the Medicaid-covered sample (column 4); this translates to a 26.05% increase from the mean non-expansion migration rate of 1.19 in 2013. The estimated effect again grows larger in magnitude when restricting the analysis to include fewer states. When limiting to 34 states in column (5), we estimate a 0.53 pp (46.09%) increase in net migration into expansion states, and when keeping only 21 states, the estimated effect increases to 0.55 pp (99.17%). Across the three treatment assignment approaches, the results translate to an additional 2,664 - 3,044 net migrations into expansion states after the policy change. Using the upper bound of the 95% confidence interval, 0.0076, for column (5) corresponds with 4,365 new net-migrants with Medicaid coverage into expansion states. Again, the estimated new net-migrants are only relative to the sample population and are likely larger when scaled to the full population. Overall, the results of Table 2 provide strong evidence of changes in migratory trends among the Medicaid-covered sample, and more nuanced effects among the low-income sample.

6.3 Heterogeneous Policy Effects

In this section, we test for potential heterogeneous effects of the Medicaid policy across a variety of different demographic and socioeconomic characteristics to better understand the dynamics of migration in response to the policy change. We explore differences across race, gender, and other family structure and health-related factors, such as marital status, presence of children, and disability status. Prior to the ACA, insurance rates differed across demographic characteristics. For example, Hispanics were less likely to be insured than white or black individuals (Artiga et al., 2021), and males were less likely to be insured than females (Becker and Babey, 2019). Individuals without insurance coverage may have a larger incentive to migrate for Medicaid. Childless adults were also generally excluded from Medicaid coverage prior to the policy change and likely have lower costs of migration in comparison to families with children. Thus, these additional analyses help us determine how different subgroups of the population responded to changes in Medicaid policy.

Table 3 shows results testing for policy heterogeneity across both gender and race/ethnicity across the three treatment assignment strategies and two subsamples. Each regression model continues to include both origin- and destination- state fixed effects, year fixed effects, and additional control variables. The results for the low-income sample are presented in columns (1) - (3) and those for the Medicaid-covered sample are presented in columns (4) - (6). A few patterns emerge from the table. First, the coefficients continue to be larger in magnitude and more statistically significant for the Medicaid-covered sample. Second, all demographic groups

Table 3: Impact of ACA Medicaid Expansion on Migration by Gender and Race/Ethnicity

Dependent Variable: Net Migration into Expansion States

	Below 138% FPL			***Medicaid-Covered***		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	All States	**34 States**	**21 States**	**All States**	**34 States**	**21 States**
Panel A: Male						
Effect	-0.0004	0.0013	0.0023	0.0044	0.0069	0.0054
	(0.0009)	(0.0009)	(0.0012)	(0.0010)	(0.0012)	(0.0010)
Panel B: Female						
Effect	-0.0007	0.0013	0.0028	0.0020	0.0041	0.0054
	(0.0007)	(0.0006)	(0.0008)	(0.0005)	(0.0006)	(0.0012)
Panel C: Black						
Effect	0.0028	0.0032	0.0047	0.0035	0.0050	0.0067
	(0.0012)	(0.0011)	(0.0015)	(0.0013)	(0.0012)	(0.0014)
Panel D: White						
Effect	-0.0014*	0.0006	0.0019	0.0032	0.0054	0.0051
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0012)
Panel E: Hispanic						
Effect	-0.0008	0.0011	0.0013	0.0051	0.0077	0.0070
	(0.0014)	(0.0015)	(0.0024)	(0.0022)	(0.0021)	(0.0032)

Notes: American Community Survey 1-year Public Use Microdata Sample files, 2010–2019. Each column reports OLS estimates of the impact of ACA Medicaid expansion on interstate migration by gender or race as outlined by Equation (1). The dependent variable is an indicator taking on a value of 1 if an individual either moves from a non-expansion-to-expansion state or from an expansion-to-non-expansion state and 0 otherwise. Columns (1)-(3) present results for a sample of individuals with family income at or below 138% of the FPL, while columns (4)-(6) present those for a sample of Medicaid-covered individuals. We use three different treatment assignment approaches: time-invariant including all states in Columns (1) and (4), dropping early and late expanders leaving 34 states in Columns (2) and (5), and only using new and never expanders leaving 21 States in Columns (3) and (6). Each specification includes origin and destination state fixed effects, year fixed effects, and additional controls. Robust standard errors clustered at the origin-state level are shown in parentheses.

show a positive and significant increase in net migration from non-expansion-to-expansion states after the policy, particularly for the Medicaid-covered sample.

There are also some notable differences in coefficient magnitudes across subgroups in Table 3. Focusing on our preferred specification in column (5), which balances sample size with the timing of Medicaid expansion decisions for the Medicaid-covered sample, we estimate a 0.69 pp increase in net migration to expansion states among males, compared to a 0.41 pp increase for females. As males were more likely to go without insurance prior to the 2014 policy (Becker and Babey, 2019), they face a larger incentive to migrate into an expansion state after the 2014 policy change. Additionally, gender differences in risk tolerance, caregiving responsibilities, and career mobility are well documented in the literature and likely impact the decision to migrate (Barber and Odean, 2001; Bernasek and Shwiff, 2001; Charness and Gneezy, 2012; Croson and Gneezy, 2009; Goldin, 2021; Cortes and Pan, 2018; Fitzenberger and Kunze, 2005; Lordan and Pischke, 2022).

We also observe differences across race and ethnicity; while estimated coefficients for non-Hispanic black and white individuals are relatively similar, they are larger for Hispanic individuals. For our preferred specification in column (5), we find an increase of 0.50 and 0.54 pp for black and white individuals, respectively, compared to a 0.77 pp increase in net migration into expansion states for Hispanics. Hispanic individuals were more likely to be uninsured prior to the ACA and thus faced a larger incentive to migrate into expansion states if eligible for coverage (Artiga et al., 2021; McMorrow et al., 2015). Together, the results in Table 3 suggest that males and Hispanics may be more willing and able to move across states in comparison to females and non-Hispanic white and black individuals. Our results also align with the fact that Hispanics experienced the largest decline in uninsured rates after the ACA (Artiga et al., 2021; McMorrow et al., 2015).

We also explore heterogenous policy effects across marital status, presence of children, and health status (Table 4). The coefficients continue to be larger in magnitude and highly significant for the Medicaid-covered sample, shown in columns (4)-(6), in comparison to those for the low-income sample presented in columns (1)-(3). Focusing on our preferred specification in column (5), we estimate a 0.62 pp increase ($p < 0.01$) in net migration into expansion states for single individuals, compared to a 0.27 pp increase ($p < 0.05$) for married adults. It is reasonable to assume that it is more difficult for married individuals to move across states as more individuals are impacted by the move compared to a single individual. Similarly, our preferred specification shows that the migratory response is much larger among childless adults, a 0.66 pp increase ($p < 0.01$), compared to individuals with children, a 0.21 pp increase ($p < 0.05$).

Table 4: Impact of ACA Medicaid Expansion on Migration by Household Characteristics

Dependent Variable: Net Migration into Expansion States

	Below 138% FPL			***Medicaid-Covered***		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	All States	**34 States**	**21 States**	**All States**	**34 States**	**21 States**
Panel A: Married						
Effect	-0.0016	-0.0008	0.0021	0.0002	0.0027	0.0027
	(0.0010)	(0.0011)	(0.0015)	(0.0009)	(0.0011)	(0.0019)
Panel B: Single						
Effect	-0.0003	0.0018	0.0027	0.0040	0.0062	0.0063
	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0010)
Panel C: Children						
Effect	-0.0006	0.0006	0.0023	0.0007	0.0021	0.002*
	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0014)
Panel D: Childless						
Effect	-0.0013	0.0009	0.0023	0.0037	0.0066	0.0065
	(0.0009)	(0.0008)	(0.0010)	(0.0009)	(0.0010)	(0.0014)
Panel E: Disability						
Effect	0.0006	0.0009	0.0026	0.0009	0.0025	0.0032
	(0.0011)	(0.0011)	(0.0010)	(0.0008)	(0.0010)	(0.0011)
Panel F: No Disability						
Effect	-0.0009	0.0014	0.0025	0.0040	0.0068	0.0070
	(0.0007)	(0.0006)	(0.0009)	(0.0008)	(0.0009)	(0.0015)

Notes: American Community Survey 1-year Public Use Microdata Sample files, 2010–2019. Each column reports OLS estimates of the impact of ACA Medicaid expansion on interstate migration by household characteristics as outlined by Equation (1). The dependent variable is an indicator taking on a value of 1 if an individual either moves from a non-expansion-to-expansion state or from an expansion-to-non-expansion state and 0 otherwise. Columns (1)-(3) present results for a sample of individuals with family income at or below 138% of the FPL, while columns (4)-(6) present those for a sample of Medicaid-covered individuals. We use three different treatment assignment approaches: time-invariant including all states in Columns (1) and (4), dropping early and late expanders leaving 34 states in Columns (2) and (5), and only using new and never expanders leaving 21 States in Columns (3) and (6). Each specification includes origin and destination state fixed effects, year fixed effects, and additional controls. Robust standard errors clustered at the origin-state level are shown in parentheses.

Similar to single adults, it is likely easier for childless individuals to move across states. Finally, individuals with a disability are less likely to migrate, 0.25 pp ($p < 0.05$) in comparison to those without a disability, ($p < 0.01$). It may be more difficult for individuals with a disability to move across states; other public assistance programs also exist for individuals with disabilities that may impact their migration response to the policy change. Overall, Tables 3 and 4 illustrate that some subgroups of the population are more likely than others to migrate in response to ACA Medicaid expansions.

6.4 Income Placebo

Variation in Medicaid expansion decisions across states plausibly provides an incentive for individuals in the lower tail of the income distribution to migrate into expansion states. In contrast, Medicaid expansion should not affect individuals who are not eligible for the program, those in the middle or upper tail of the earnings distribution. Intuitively, individuals with higher earnings, family income above 200% of the FPL, may act as a falsification or placebo group compared to the low-income sample. In this falsification analysis, each model again includes both origin- and destination-state fixed effects, year fixed effects, and additional controls.

Table 5 displays these heterogeneous effects across the income distribution. Panel A includes all states (time-invariant), Panel B includes 34 states (dropping early and late expanders), and Panel C includes 21 states (only new and never expanders). Similar to the main results for the low-income sample in Table 2, we do not see a strong migration response for those with family incomes between 50 - 138% of the FPL. The coefficient in column (1) is only positive and significant in Panel C, which uses the most restrictive treatment assignment approach and limits the analysis to 21 states. In contrast, the estimated coefficients in columns (3) and (4) for higher-income individuals are either statistically indistinguishable from zero or negative. While the majority of the negative coefficients are significant, this indicates a lower likelihood of migrating from non-expansion-to-expansion states. For the highest group of earners, those with income above 500% of the FPL, we estimate a 0.09 - 0.25 percentage point decline in net migration into expansion states, which is significant in both Panel B (5% level) and Panel C (10% level). Overall, we see no evidence of a meaningful migration response for the higher-income subgroups, which supports the falsification exercise. The results of Table 5 further support our main finding that low-income individuals, specifically those with Medicaid coverage, had an incentive to migrate into expansion states, while those with higher earnings had no such

Table 5: Impact of ACA Medicaid Expansion on Migration by Income

Dependent Variable: Net Migration into Expansion State				
	(1) **50-138%**	**(2)** **139-200%**	**(3)** **201-500%**	**(4)** **>500%**
Panel A: All States				
Effect	-0.0002	0.0003	-0.0018	-0.0009
	(0.0010)	(0.0009)	(0.0006)	(0.0006)
Observations	1,925,282	1,507,544	6,678,918	5,460,101
Panel B: 34 States				
Effect	0.0006	0.0006	-0.0018	-0.0021
	(0.0010)	(0.0009)	(0.0008)	(0.0009)
Observations	1,282,357	1,003,583	4,295,808	3,216,318
Panel C: 21 States				
Effect	0.0024	0.0001	-0.0025	-0.0025
	(0.0011)	(0.0010)	(0.0013)	(0.0015)
Observations	907,990	701,699	2,853,212	1,921,446

Notes: American Community Survey 1-year Public Use Microdata Sample files, 2010–2019. Each column reports OLS estimates of the impact of ACA Medicaid expansion on interstate migration across varying family income levels as outlined by Equation (1). The dependent variable is an indicator taking on a value of 1 if an individual either moves from a non-expansion-to-expansion state or from an expansion-to-non-expansion state, and 0 otherwise. Heterogeneous income effects are presented across each column. The panels represent three different treatment assignment methods: time-invariant including all states in Panel A, dropping early and late expanders leaving 34 states in Panel B, and only including new and never expanders leaving 21 states in Panel C. Each model includes origin- and destination-state fixed effects, year fixed effects, and additional controls. Robust standard errors clustered at the origin-state level are shown in parentheses.

incentive following ACA Medicaid expansion.

6.5 Traditional Event Study

Next, we present results from the event study model outlined by Equation (2) to formally assess whether the parallel pre-treatment trends assumption is satisfied and to examine policy heterogeneity across post-treatment years. Figure 4 displays the event study estimates for the low-income sample in Panel A and the Medicaid-covered sample in Panel B across the three treatment assignment approaches.[19] All regression models continue to include both fixed effects and additional control variables. The vertical axis represents the change in net migration into expansion states, while the horizontal axis shows the year. The vertical line at 2013 represents the omitted reference category, the year prior to ACA Medicaid expansion for most states. The solid black line shows the evolution of estimated coefficients, while the dashed lines are 95% confidence interval bands.

Across both panels, there is a noticeable increase in the magnitude of coefficients from before to after the policy, starting in 2014. Although several coefficients are positive and statistically significant at the 10% level for 2010, which could be picking up some early effects from the year the ACA was first passed, almost all of the coefficients for years 2011 and 2012 are statistically indistinguishable from zero. In contrast, the coefficient for 2014 becomes positive across all specifications. For the low-income sample in Panel A, the coefficient remains positive and significant in some of the post-policy years, particularly for the most restrictive treatment assignment approach that includes 21 states (new and never expanders). For the Medicaid-covered sample (Panel B), the coefficients are positive and statistically significant for all post-policy years. Further, the magnitudes of the coefficients over time follow an inverse U-shape, particularly for the Medicaid-covered sample in Panel B. The coefficients increase in magnitude from 2014 to 2017, then decline in magnitude in 2018 and 2019, although they remain positive and significant. The inverse U-shape is also seen among the low-income sample in Panel A, but the trend is not as pronounced, and some of the coefficients are indistinguishable from zero. Overall, the event study results support the parallel trends assumption and provide more validity to the results presented thus far. Moreover, the event study shows clear increases in net migration from non-expansion-to-expansion states, particularly for the Medicaid-covered sample.

6.6 Variation in Treatment Timing

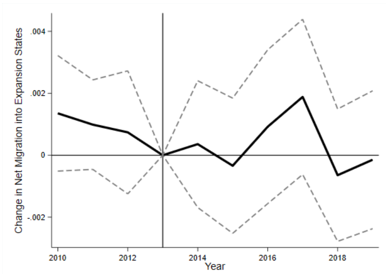
Finally, Table 6, along with Figures 5 and 6, presents results that account for variation in policy treatment timing using the Callaway and Sant'Anna (2021) estimator, which better accounts

[19]Table A3 in the appendix shows the corresponding numerical values for the event study results.

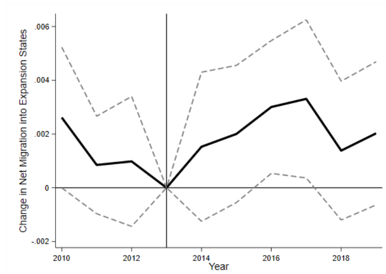
Figure 4: Interstate Migration Across Time: Event Study

Panel A. Below 138% FPL Sample

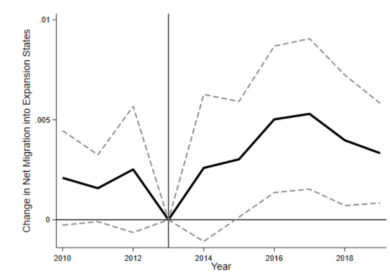
(a) All States



(b) 34 States

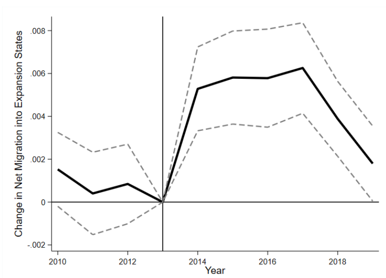


(c) 21 States

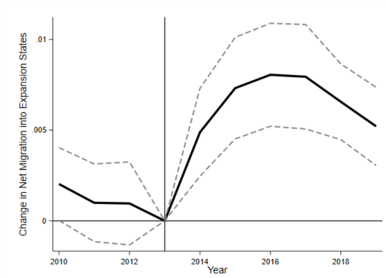


Panel B. Medicaid-Covered Sample

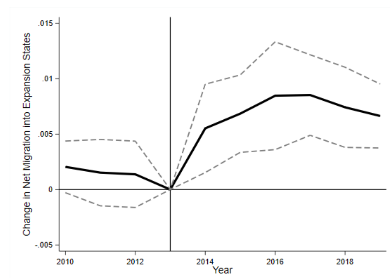
(d) All States



(e) 34 States



(f) 21 States



Notes:American Community Survey 1-year Public Use Microdata Sample files, 2010–2019. Each subfigure displays estimated coefficients from estimating the event study model outlined by Equation (2). The dependent variable is an indicator taking on a value of 1 if an individual either moves from a non-expansion-to-expansion state or from an expansion-to-non-expansion state, and 0 otherwise. Panel A presents results for a sample of individuals with family income at or below 138% of the FPL, while Panel B presents those for a sample of Medicaid-covered individuals. We use three different treatment assignment approaches: time-invariant including all states in subfigures (a) and (d), dropping early and late expanders leaving 34 states in subfigures (b) and (e), and only using new and never expanders leaving 21 states in subfigures (c) and (f). Robust standard errors are clustered at the origin-state level.

for the staggered rollout of Medicaid expansion over the years 2014-2019. Table 6 presents the aggregated group-time average treatment effects on the treated (ATT) estimating the impact of Medicaid expansion on migration, obtained from estimating equation (3). We separately examine impacts on migration out of non-expansion states (Panel A) and migration out of expansion states (Panel B). Columns (1)-(2) show results for the low-income sample, and columns (3)-(4) show those for Medicaid-covered individuals. While the Callaway and Sant'Anna (2021) estimator does allow us to exploit policy variation among states that expanded Medicaid in the years 2015-2019 (late expanders), it does not address the confounding issue of including states with generous pre-ACA Medicaid programs, most of which further expanded in 2014 as part of

Table 6: Impact of ACA Medicaid Expansion on Migration: Staggered DiD with Time Variant Treatment

	Below 138% FPL		*Medicaid-Covered*	
	(1)	**(2)**	**(3)**	**(4)**
	All States	**41 States**	**All States**	**41 States**
Panel A: Migration from non-expansion-to-expansion states				
Average Treatment Effect (ATT)	0.0001	0.0002	0.0004	0.0008
	(0.0003)	(0.0003)	(0.0002)	(0.0003)
Panel B: Migration from expansion-to-non-expansion states				
Average Treatment Effect (ATT)	-0.0144	-0.0226	-0.0133	-0.0226
	(0.0005)	(0.0006)	(0.0006)	(0.0007)

Notes: American Community Survey 1-year Public Use Microdata Sample files, 2010–2019. Each column reports estimated ATTs of the impact of ACA Medicaid expansion on interstate migration using the Callaway and Sant'Anna (2021) estimator outlined by Equation (3). The dependent variable in Panel A is an indicator taking on a value of 1 if an individual moves from a non-expansion-to-expansion state, and 0 otherwise. The dependent variable in Panel B is an indicator taking on a value of 1 if an individual moves from an expansion-to-non-expansion state, and 0 otherwise. Columns (1) and (2) present results for a sample of individuals with family income at or below 138% of the FPL, while columns (3) and (4) present those for a sample of Medicaid-covered individuals. Odd numbered columns include all states; even numbered columns drop 10 states with generous Medicaid programs prior to the ACA. Each ATT is obtained using the doubly robust inverse probability weighting (dripw) estimator using the CSDID command in Stata. Robust standard errors clustered at the origin-state level are shown in parentheses.

the ACA. The inclusion of such states into the treatment group will necessarily downward bias any policy effects. For this reason, we present results both for all states and when dropping early expanders (41 states).

Table 6, Panel A presents estimated ATT's assessing the impact of Medicaid expansion on migration from non-expansion-to-expansion states. For the low-income sample, estimated ATT's are positive in sign but statistically insignificant, indicating no impact of ACA Medicaid expansion on migration into expansion states. Among the Medicaid-covered sample, we estimate positive and significant impacts of Medicaid expansion on migration into expansion states. The effect is positive and larger in magnitude when dropping early expanding states (leaving 41 states). From Panel A, column (4), we estimate a 0.08 pp increase ($p < 0.05$) in migration from non-expansion-to-expansion states. This corresponds to a 200% increase above the mean low-income, non-expansion out-migration rate of 0.40 in 2013.

Table 6, Panel B presents estimated ATT's assessing the impact of Medicaid expansion on migration in the opposite direction, from expansion-to-non-expansion states. For both the low-income and Medicaid-covered samples, we estimate negative and statistically significant ATT's (all significant at the 1% level), indicating a reduction in migration into non-expansion states following Medicaid expansion. When dropping early expansion states (leaving 41 states), estimated ATT's are nearly identical for both the low-income and Medicaid-covered samples. For both samples, we estimate a 2.26 pp decrease in migration out of expansion states. This translates to a 109.71% reduction in migration into non-expansion states for the low-income sample and a 132.16% decrease for the Medicaid-covered sample. Taken together, the results of Table 6 provide nuanced evidence of increased migration from non-expansion-to-expansion states while providing stronger evidence of decreased migration from expansion-to-non-expansion states.

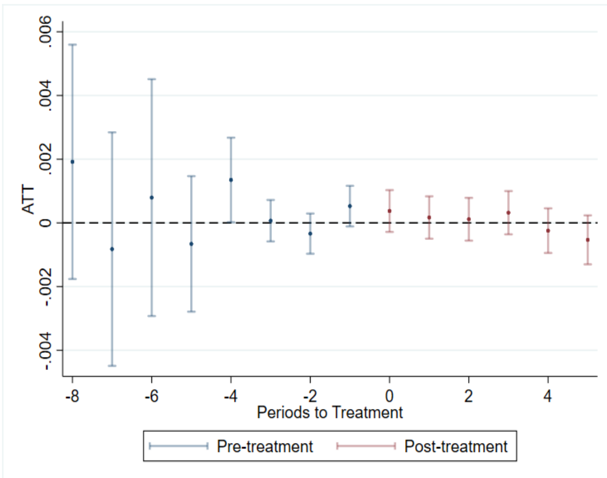
Corresponding event study estimates from Callaway and Sant'Anna's (2021) approach outlined by Equation (4) are presented in Figures 5 and 6. Figure 5 presents the estimated annual effects of Medicaid expansion on migration out of non-expansion states, while Figure 6 shows analogous plots for migration out of expansion states. In each figure, Panel A focuses on the low-income sample, while Panel B shows results for those covered by Medicaid. From Figure 5, Panel A, little can be taken away regarding out-migration from non-expansion states among the low-income sample. Estimated effects are all flat and statistically indistinguishable from zero for both the sample of all states or when dropping early expanders. For the Medicaid-covered sample, presented in Panel B, we estimate positive and statistically significant (at least at the 5% level) post-treatment policy effects that persist for up to four years after a given state's Medicaid expansion. This indicates that among Medicaid-covered individuals, Medicaid expansion induced out-migration from non-expansion states following the policy, at least in the short-run (1-4 years post-policy).

Finally, Figure 6 presents analogous plots estimating effects on migration out of expansion states. For both samples, event study estimates for migration from expansion-to-non-expansion states are more clear than those for migration in the opposite direction in the prior figure. In each subfigure of Figure 6, we estimate a clear decrease in out-migration from expansion states following Medicaid expansion. Further, the decline in out-migration persists for the entire

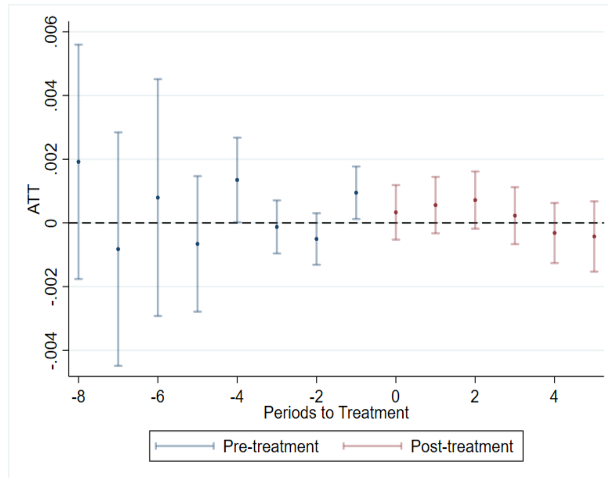
Figure 5: Migration from non-expansion-to-expansion states

Panel A. Below 138% FPL Sample

(a) All States

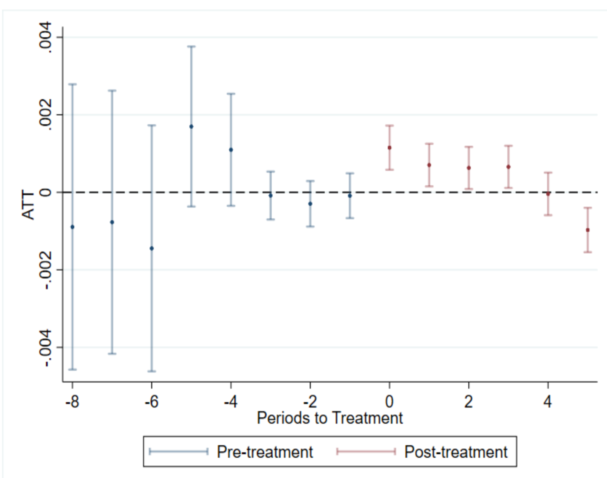


(b) 41 States

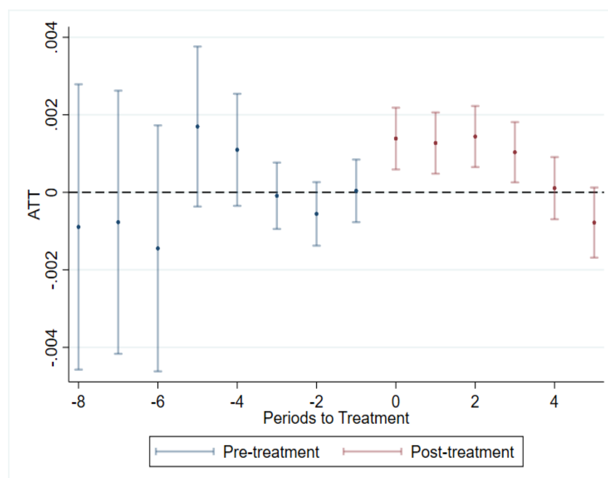


Panel B. Medicaid-Covered Sample

(c) All States



(d) 41 States



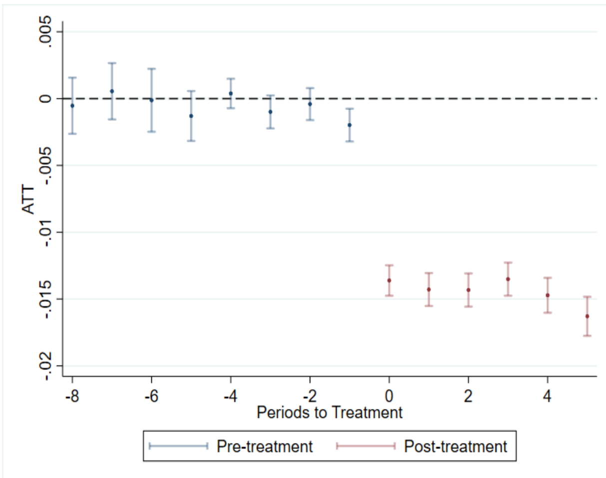
Notes: American Community Survey 1-year Public Use Microdata Sample files, 2010–2019. Each subfigure displays estimated coefficients from estimating the event study model following the approach of Callaway and Sant'Anna (2021) as outlined by Equation (4). The dependent variable is an indicator taking on a value of 1 if an individual moves from a non-expansion-to-expansion state, and 0 otherwise. Panel A presents results for a sample of individuals with family income at or below 138% of the FPL, while Panel B presents those for a sample of Medicaid-covered individuals. Subfigures (a) and (c) include all states, while subfigures (b) and (d) drop 10 states with generous Medicaid programs prior to the ACA. Each ATT is obtained using the doubly robust inverse probability weighting (dripw) estimator using the CSDID command in Stata. Robust standard errors are clustered at the origin-state level.

period under study. This indicates that after a state adopted ACA Medicaid expansion, both low-income individuals and those covered by Medicaid were significantly less likely to migrate

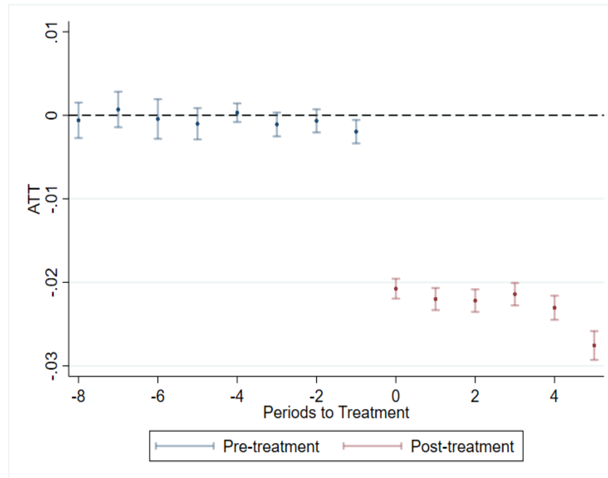
Figure 6: Migration from expansion-to-nonexpansion states

Panel A. Below 138% FPL Sample

(a) All States

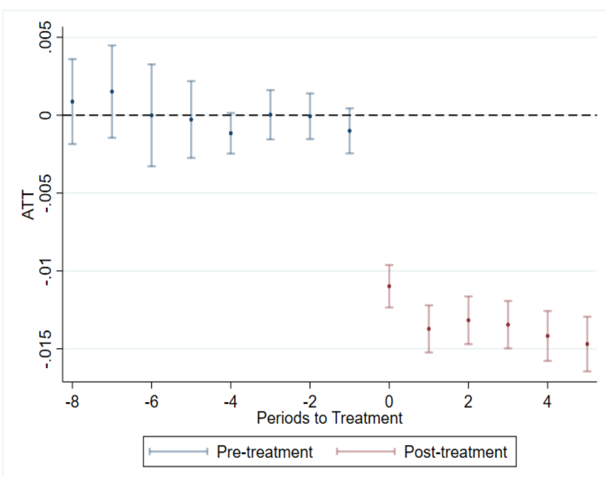


(b) 41 States

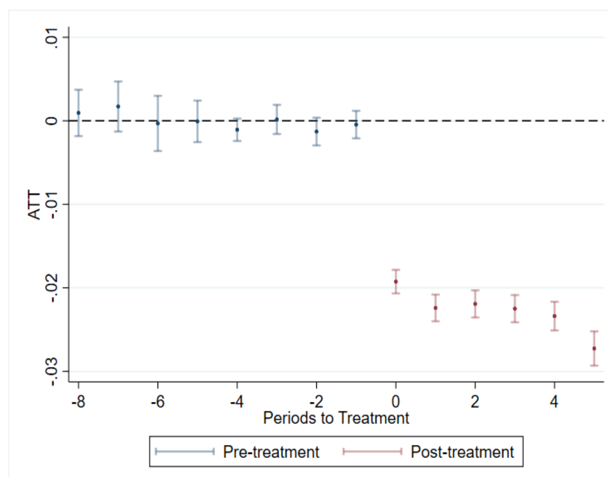


Panel B. Medicaid-Covered Sample

(c) All States



(d) 41 States



Notes: American Community Survey 1-year Public Use Microdata Sample files, 2010–2019. Each subfigure displays estimated coefficients from estimating the event study model following the approach of Callaway and Sant'Anna (2021) as outlined by Equation (4). The dependent variable is an indicator taking on a value of 1 if an individual moves from an expansion-to-non-expansion state, and 0 otherwise. Panel A presents results for a sample of individuals with family income at or below 138% of the FPL, while Panel B presents those for a sample of Medicaid-covered individuals. Subfigures (a) and (c) include all states, while subfigures (b) and (d) drop 10 states with generous Medicaid programs prior to the ACA. Each ATT is obtained using the doubly robust inverse probability weighting (dripw) estimator using the CSDID command in Stata. Robust standard errors are clustered at the origin-state level.

away from an expansion state and into a non-expansion state. Thus, Figures 5 and 6 illustrate that the increase in net migration from non-expansion-to-expansion states was largely driven by a decline in out-migration from expansion states. In other words, individuals eligible for and those with Medicaid coverage in expansion states were less likely to migrate to a non-expansion state after Medicaid expansion.

7 Conclusion

The decision to adopt ACA Medicaid expansion was ultimately left to each state, creating variation in expansion decisions across states. We revisit Goodman's (2017) initial work on Medicaid expansion and interregion migration now that several years of post-policy data are available. We use three treatment-control group assignment approaches and focus on two population subsamples to better target those most likely to be impacted by changes in Medicaid policy: those with incomes less than 138% of the FPL and individuals with Medicaid coverage. Among those with incomes below 138% of the FPL, we find mixed evidence of Medicaid expansion inducing migration from non-expansion-to-expansion states. We find no statistically significant effect when including all states, a 0.13 pp (9.22%) increase in net migration when dropping early and late expansion states (34 states), and a 0.26 pp (38.24%) increase when including only new and never expansion states (21 states). For our sample, this translates to approximately 1,300 - 2,500 new "net migrants" into expansion states following the policy. Using the median state per-capita expenditure of $6,709 on ACA Medicaid expansion (Medicaid, n.d.), this translates to over $16 million dollars in additional expense for Medicaid expansion states for our sample. As the estimates scale up to the full population, both the number of additional net migrants and additional expenditures likely increase substantially.

We find stronger evidence of migratory trend changes among the Medicaid-covered sample. Across all three treatment-control group assignment approaches, we estimate a positive and statistically significant increase (at the 1% level) in net migration from non-expansion to expansion states among the Medicaid-covered sample. As the treatment assignment approach becomes more restrictive, the coefficients of interest become larger in magnitude, ranging from a 0.31 to 0.55 pp (26% - 99%) increase in net migration to expansion states after the policy change. For the relevant sample population of less than 1,000,000, this translates to approximately 3,000 additional new "net migrants" to expansion states after the policy change, or over $20 million in additional Medicaid expenses for expansion states (Medicaid, n.d.). Thus, individuals with Medicaid coverage in expansion states are significantly more likely to have recently migrated from a non-expansion state after 2014. As this scales up to the full population likely to be impacted in the U.S., the additional expense to expansion states is likely to be significant.

In addition to the main results, we also explore policy heterogeneity across demographic and household characteristics. We find that males and Hispanic individuals are more likely to migrate from non-expansion to expansion states compared to females and (non-Hispanic) white and black individuals. Across household characteristics, our results show that single adults, adults without children, and adults without a disability are more likely to migrate than married adults, adults with children, and adults with a disability. The migratory effects continue to be larger among the Medicaid-covered sample. The ACA Medicaid expansions intentionally targeted expanding coverage eligibility to include childless adults. Our analysis shows that the expansions induced at least some childless adults to migrate to an expansion state, which is likely tied to the ability to attain Medicaid coverage in those states.

We also use two alternative models to analyze the impacts of ACA Medicaid expansion on interregion migration, an event study and a staggered difference-in-differences model to better account for the variation in Medicaid expansion adoption across states. The event study lends credibility to the parallel trends assumption as most of the pre-policy coefficients are insignificant, with the exception of 2010. For the post-policy period, we see a positive and significant impact on net migration that follows an inverse U-shaped pattern; the coefficients are positive, and increasing in magnitude for 2014 - 2017, and begin to decline in magnitude, while staying positive, for 2018 to 2019. The coefficients of interest continue to be larger for the Medicaid-covered sample and when using more restrictive treatment assignment approaches. The staggered DiD model breaks net migration down into two components: migration from non-expansion to expansion states (in-migration), and migration from expansion to non-expansion states (out-migration). We see that changes in net migration are largely driven by a strong decline in out-migration from expansion states. Less people are moving from expansion-to-non-expansion states, likely because they risk losing Medicaid coverage. For those with Medicaid coverage, we also see an increase in migration from non-expansion-to-expansion states, but the effect is smaller in size compared to the decline in out-migration from expansion states.

We contribute to the literature and extend Goodman's (2017) work in several ways. First, we examine the relationship between interregion migration and ACA Medicaid expansion beyond the first year after the policy change. Given that migration is costly, both in terms of time and financially, it is plausible that migration effects are more evident over a longer period of time. While Goodman (2017) didn't find significant increases in migration in 2014 for those below 138% of the FPL, we find that net migration continues to increase through 2017 and then begins to decline in 2018. Second, we complement the traditional approach of analyzing a low-income sample by using an alternative sample, those with Medicaid coverage, to target those most impacted by Medicaid policy. Migratory effects are significantly larger for the Medicaid-covered sample. Third, we also utilize three different treatment-control group assignment approaches and incorporate the new staggered DiD methods to better account for the variation in ACA Medicaid expansion decisions across states. Our results highlight the importance of targeting the sample most likely to be impacted by the policy change and using a treatment-control group assignment strategy that offers the cleanest counterfactual possible.

Our results also have important implications for policymakers as the ACA continues to be legally challenged and health policy evolves in the future. Our policy heterogeneity analysis across demographic and household characteristics illustrates that certain subgroups of the population were more likely to migrate in response to ACA Medicaid expansions than others, particularly the groups that had the most to gain from the policy change due to low insurance uptake rates, such as males or Hispanics, or previous exclusion from Medicaid eligibility regardless of income, such as childless adults. Given the overarching goal of the ACA to increase access to health insurance, Medicaid expansion is one channel of the policy that contributes to that goal. Our results reveal that Medicaid expansion induced some individuals to move to expansion states, who likely gained access to Medicaid from that move. While we are able to capture longer-term effects than Goodman's (2017) initial work, we are only able to observe effects through 2019. Future research can continue to explore even longer-run migration or other economic effects as more data becomes available. For example, do we see any changes in labor supply for individuals in expansion states now that they can earn up to 138% of the FPL without risking their eligibility for Medicaid?

References

Allard, Scott W., and Sheldon Danziger. 2000. "Welfare magnets: Myth or reality?" The Journal of Politics, 62(2): 350–368.

Alm, James, and Ali Enami. 2017. "Do government subsidies to low-income individuals affect interstate migration? Evidence from the Massachusetts Health Care Reform." Regional Science and Urban Economics, 66: 119–131.

Argys, Laura M, Andrew I Friedson, M Melinda Pitts, and D Sebastian Tello-Trillo. 2020. "Losing public health insurance: TennCare reform and personal financial distress." Journal of Public Economics, 187: 104202.

Artiga, Samantha, Latoya Hill, Kendal Orgera, and Anthony Damico. 2021. "Health Coverage by Race and Ethnicity, 2010-2019." The Kaiser Family Foundation.

Athey, Susan, and Guido W. Imbens. 2021. "Design-based analysis in difference-in-differences settings with staggered adoption." Journal of Econometrics.

Bailey, Michael A. 2005. "Welfare and the multifaceted decision to move." American Political Science Review, 99(1): 125–135.

Bane, Mary Jo, and David T. Ellwood. 1983. The dynamics of dependence: The routes to self-sufficiency. Urban Systems Research and Engineering, Incorporated.

Barber, Brad M., and Terrance Odean. 2001. "Boys will be boys: Gender, overconfidence, and common stock investment." The Quarterly Journal of Economics, 116(1): 261–292.

Becker, Tara, and Susan H. Babey. 2019. "Persistent Gap: Gender Disparities in Health Insurance and Access to Care in California." UCLA Center for Health Policy Research.

Bernasek, Alexandra, and Stephanie Shwiff. 2001. "Gender, risk, and retirement." Journal of Economic Issues, 35(2): 345–356.

Black, Bernard S., Alex Hollingsworth, Leticia Nunes, and Kosali Ilayperuma Simon. 2019. "The effect of health insurance on mortality: power analysis and what we can learn from the affordable care act coverage expansions." NBER working paper w25568.

Borjas, George J. 2003. "Welfare reform, labor supply, and health insurance in the immigrant population." Journal of Health Economics, 22(6): 933–958.

Borusyak, Kirill, and Xavier Jaravel. 2017. "Revisiting event study designs." Available at SSRN 2826228.

Boudreaux, Michel H., Ezra Golberstein, and Donna D. McAlpine. 2016. "The long-term impacts of Medicaid exposure in early childhood: Evidence from the program's origin." Journal of Health Economics, 45: 161–175.

Brown, David W., Amanda E. Kowalski, and Ithai Z. Lurie. 2020. "Long-term impacts of childhood Medicaid expansions on outcomes in adulthood." The Review of Economic Studies, 87(2): 792–821.

Bullinger, Lindsey Rose. 2021. "Child support and the Affordable Care Act's Medicaid expansions." Journal of Policy Analysis and Management, 40(1): 42–77.

Callaway, Brantly, and Pedro H.C. Sant'Anna. 2021. "Difference-in-differences with multiple time periods." Journal of Econometrics, 225(2): 200–230.

Cebula, Richard. 1979. The Determinants of Human Migration. Lexington Books.

Cebula, Richard J., and J.R. Clark. 2013. "An extension of the Tiebout hypothesis of voting with one's feet: the Medicaid magnet hypothesis." Applied Economics, 45(32): 4575–4583.

Charness, Gary, and Uri Gneezy. 2012. "Strong evidence for gender differences in risk taking." Journal of Economic Behavior & Organization, 83(1): 50–58.

Congressional Budget Office. 2020. "Who Went Without Health Insurance in 2019, and Why?" Available at ://www.cbo.gov/system/files/2020-09/56504-Health-Insurance.pdf.

Correia, Sergio. 2019. "REGHDFE: Stata module to perform linear or instrumental-variable regression absorbing any number of high-dimensional fixed effects."

Cortes, Patricia, and Jessica Pan. 2018. "Occupation and gender." The Oxford Handbook of Women and the Economy, 425–452.

Courtemanche, Charles, James Marton, Benjamin Ukert, Aaron Yelowitz, and Daniela Zapata. 2017. "Early impacts of the Affordable Care Act on health insurance coverage in Medicaid expansion and non-expansion states." Journal of Policy Analysis and Management, 36(1): 178–210.

Courtemanche, Charles, James Marton, Benjamin Ukert, Aaron Yelowitz, and Daniela Zapata. 2018. "Early effects of the Affordable Care Act on health care access, risky health behaviors, and self-assessed health." Southern Economic Journal, 84(3): 660–691.

Courtemanche, Charles J., James Marton, and Aaron Yelowitz. 2019. "Medicaid coverage across the income distribution under the Affordable Care Act." NBER Working Paper w26145.

Croson, Rachel, and Uri Gneezy. 2009. "Gender differences in preferences." Journal of Economic Literature, 47(2): 448–74.

Dague, Laura, Thomas DeLeire, and Lindsey Leininger. 2017. "The effect of public insurance coverage for childless adults on labor supply." American Economic Journal: Economic Policy, 9(2): 124–54.

Danziger, Sheldon, George Jakubson, Saul Schwartz, and Eugene Smolensky. 1982. "Work and welfare as determinants of female poverty and household headship." The Quarterly Journal of Economics, 97(3): 519–534.

De Chaisemartin, Clément, and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." American Economic Review, 110(9): 2964–96.

Fields, Gary S. 1979. "Place-to-place migration: Some new evidence." The Review of Economics and Statistics, 21–32.

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen, Katherine Baicker, and Oregon Health Study Group. 2012. "The Oregon health insurance experiment: evidence from the first year." The Quarterly Journal of Economics, 127(3): 1057–1106.

Fitzenberger, Bernd, and Astrid Kunze. 2005. "Vocational training and gender: Wages and occupational mobility among young workers." Oxford Review of Economic Policy, 21(3): 392–415.

Fiva, Jon H. 2009. "Does welfare policy affect residential choices? An empirical investigation accounting for policy endogeneity." Journal of Public Economics, 93(3-4): 529–540.

Gallaway, Lowell E., Roy F. Gilbert, and Paul E. Smith. 1967. "The economics of labor mobility: An empirical analysis." Economic Inquiry, 5(3): 211.

Garthwaite, Craig, Tal Gross, and Matthew J. Notowidigdo. 2014. "Public health insurance, labor supply, and employment lock." The Quarterly Journal of Economics, 129(2): 653–696.

Gelbach, Jonah B. 2004. "Migration, the life cycle, and state benefits: How low is the bottom?" Journal of Political Economy, 112(5): 1091–1130.

Giulietti, Corrado. 2014. "The welfare magnet hypothesis and the welfare take-up of migrants." IZA World of Labor. Available at `doi:10.15185/izawol.37`.

Goldin, Claudia. 2021. Career and Family: Women's Century-Long Journey toward Equity. Princeton University Press.

Goodman-Bacon, Andrew. 2021a. "Difference-in-differences with variation in treatment timing." Journal of Econometrics.

Goodman-Bacon, Andrew. 2021b. "The Long-Run Effects of Childhood Insurance Coverage: Medicaid Implementation, Adult Health, and Labor Market Outcomes." American Economic Review, 111(8): 2550–93.

Goodman, Lucas. 2017. "The effect of the affordable care act medicaid expansion on migration." Journal of Policy Analysis and Management, 36(1): 211–238.

Gross, Tal, and Matthew J. Notowidigdo. 2011. "Health insurance and the consumer bankruptcy decision: Evidence from expansions of Medicaid." Journal of Public Economics, 95(7-8): 767–778.

Hampton, Matt, and Otto Lenhart. 2022. "The effect of the Affordable Care Act Medicaid expansion on marriage." Economic Inquiry, 60(2): 568–591.

Hanson, Russell L., and John T. Hartman. 1994. Do welfare magnets attract? Citeseer.

Hu, Luojia, Robert Kaestner, Bhashkar Mazumder, Sarah Miller, and Ashley Wong. 2018. "The effect of the affordable care act Medicaid expansions on financial wellbeing." Journal of Public Economics, 163: 99–112.

Hutchens, Robert, George Jakubson, and Saul Schwartz. 1989. "AFDC and the Formation of Subfamilies." Journal of Human Resources, 599–628.

Jackson, Margot, Chinyere Agbai, and Emily Rauscher. 2021. "The Effects of State-Level Medicaid Coverage on Family Wealth." RSF: The Russell Sage Foundation Journal of the Social Sciences, 7(3): 216–234.

Kaestner, Robert, Bowen Garrett, Jiajia Chen, Anuj Gangopadhyaya, and Caitlyn Fleming. 2017. "Effects of ACA Medicaid expansions on health insurance coverage and labor supply." Journal of Policy Analysis and Management, 36(3): 608–642.

Kaestner, Robert, Neeraj Kaushal, and Gregg Van Ryzin. 2003. "Migration consequences of welfare reform." Journal of Urban Economics, 53(3): 357–376.

Kaiser Family Foundation. 2022. "Status of State Medicaid Expansion Decisions: Interactive Map." Available at `https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/`.

Kaplan, Greg, and Sam Schulhofer-Wohl. 2017. "Understanding the long-run decline in interstate migration." International Economic Review, 58(1): 57–94.

Keisler-Starkey, Katherine, and Lisa N. Bunch. 2021. "Health Insurance Coverage in the United States: 2020." United States Census Bureau Report P60-274. Available at `https://www.census.gov/library/publications/2021/demo/p60-274.html`.

Kim, Kosuke Imai In Song, and Erik Wang. 2019. "Matching methods for causal inference with time-series cross-sectional data."

Lee, Jun Yeong, and John V. Winters. 2021. "State medicaid expansion and the self-employed." Small Business Economics, 1–30.

Lordan, Grace, and Jörn-Steffen Pischke. 2022. "Does Rosie like riveting? Male and female occupational choices." Economica, 89(353): 110–130.

McMorrow, Stacey, Genevieve M. Kenney, Sharon K. Long, and Jason A. Gates. 2017. "U.S. Health Reform - Monitoring and Impact: The ACA Medicaid Expansion Led to Widespred Reductions in Uninsurance Among Poor, Childless Adults." Urban Institute.

McMorrow, Stacey, Sharon K. Long, Genevieve M. Kenney, and Nathaniel Anderson. 2015. "Uninsurance disparities have narrowed for black and Hispanic adults under the Affordable Care Act." Health Affairs, 34(10): 1774–1778.

Medicaid. n.d.. "Medicaid Per Capita Expenditures." Available at `https://www.medicaid.gov/state-overviews/scorecard/how-much-states-spend-per-medicaid-enrollee/index.html`,.

Miller, Sarah, and Laura R. Wherry. 2019. "The long-term effects of early life Medicaid coverage." Journal of Human Resources, 54(3): 785–824.

Moffitt, Robert. 1992. "Incentive effects of the US welfare system: A review." Journal of Economic Literature, 30(1): 1–61.

Moffitt, Robert. 2015. "The US safety net and work incentives: The Great Recession and beyond." Journal of Policy Analysis and Management, 34(2): 458–466.

Moffitt, Robert, and Barbara Wolfe. 1992. "The Effect of the Medicaid Program on Welfare Participation and Labor Supply." The Review of Economics and Statistics, 74(4): 615–626.

Musumeci, MaryBeth. 2012. "A Guide to the Supreme Court's Decision on the ACA's Medicaid Expansion." The Kaiser Commission on Medicaid and the Uninsured, The Kaiser Family Foundation.

Office for the Assistant Secretary for Planning and Evaluation. 2019. "U.S. Federal Poverty Guidelines Used to Determine Financial Eligibility for Certain Federal Programs." Available at `https://aspe.hhs.gov/topics/poverty-economic-mobility/poverty-guidelines/prior-hhs-poverty-guidelines-federal-register-references/2019-poverty-guidelines`,.

Orgera, Kendal, Robin Rudowitz, and Anthony Damico. 2021. "A Closer Look at the Remaining Uninsured Population Eligible for Medicaid and CHIP." The Kaiser Family Foundation.

Rios-Avila, Fernando, Pedro H.C. Sant'Anna, and Brantly Callaway. 2021. "CSDID: Stata module for the estimation of Difference-in-Difference models with multiple time periods."

Rudowitz, Robin, Rachel Garfield, and Elizabeth Hinton. 2019. "10 Things to Know About Medicaid: Setting the Facts Straight." The Kaiser Family Foundation.

Sacarny, Adam, Katherine Baicker, and Amy Finkelstein. 2022. "Out of the Woodwork: Enrollment Spillovers in the Oregon Health Insurance Experiment." American Economic Journal: Economic Policy, 14(3): 273–95.

Sant'Anna, Pedro H.C., and Jun Zhao. 2020. "Doubly robust difference-in-differences estimators." Journal of Econometrics, 219(1): 101–122.

Schmidt, Lucie, Lara D. Shore-Sheppard, and Tara Watson. 2020. "The impact of the ACA Medicaid expansion on disability program applications." American Journal of Health Economics, 6(4): 444–476.

Schwartz, Aaron L., and Benjamin D. Sommers. 2014. "Moving for Medicaid? Recent eligibility expansions did not induce migration from other states." Health Affairs, 33(1): 88–94.

Slusky, David J.G., and Donna K. Ginther. 2021. "Did Medicaid expansion reduce medical divorce?" Review of Economics of the Household, 19(4): 1139–1174.

Sommers, Paul M., and Daniel B. Suits. 1973. "Analysis of net interstate migration." Southern Economic Journal, 193–201.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." Journal of Econometrics, 225(2): 175–199.

Thompson, Owen. 2017. "The long-term health impacts of Medicaid and CHIP." Journal of Health Economics, 51: 26–40.

U.S. Census Bureau. n.d.. "2010-2019 American Community Survey 1-year Public Use Microdata Samples." Available at `https://www2.census.gov/programs-surveys/acs/data/pums/`.

Wherry, Laura R., and Bruce D. Meyer. 2016. "Saving teens: using a policy discontinuity to estimate the effects of Medicaid eligibility." Journal of Human Resources, 51(3): 556–588.

Wherry, Laura R., Sarah Miller, Robert Kaestner, and Bruce D. Meyer. 2018. "Childhood medicaid coverage and later-life health care utilization." Review of Economics and Statistics, 100(2): 287–302.

Winkler, Anne E. 1991. "The Incentive Effects of Medicaid on Women's Labor Supply." Journal of Human Resources, 26(2): 308–337.

Appendix

Table A1 and A2 display descriptive statistics following the three treatment-control group assignment approaches for two samples: low-income sample and the Medicaid-covered sample.

Table A1: Summary Statistics by Alternative Treatment Assignments: Low-Income Sample

	Below 138% FPL Sample					
	All States		*34 States*		*21 States*	
Variable	**(1) Non-Exp.**	**(2) Exp.**	**(3) Non-Exp.**	**(4) Exp.**	**(5) Non-Exp.**	**(6) Exp.**
Migrated Across Regions	0.017	0.014	0.016	0.017	0.015	0.016
Medicaid Coverage	0.331	0.498	0.301	0.473	0.296	0.477
Age	39.713	39.49	39.647	39.707	39.74	40.002
Male	0.429	0.447	0.427	0.443	0.425	0.443
Black	0.235	0.144	0.249	0.148	0.264	0.151
White	0.687	0.693	0.672	0.738	0.654	0.765
Hispanic	0.110	0.166	0.133	0.101	0.145	0.063
Immigrant	0.034	0.07	0.04	0.037	0.043	0.020
% FPL	70.88	69.001	70.913	69.32	70.627	70.384
Married	0.269	0.244	0.276	0.251	0.27	0.266
Family Size	2.636	2.592	2.675	2.547	2.672	2.563
Number of Children	0.758	0.757	0.756	0.750	0.744	0.758
High School Degree	0.363	0.337	0.353	0.355	0.351	0.380
Some College	0.324	0.340	0.331	0.342	0.33	0.326
Bachelor's Degree or More	0.102	0.124	0.102	0.111	0.101	0.086
Unemployment Rate	6.128	6.681	6.206	6.596	6.292	6.694
Maximum EITC Amount	0.026	0.164	0.014	0.074	0.014	0.043
Poverty Rate	14.938	13.834	15.469	13.892	15.668	15.337
Observations	1,422,329	1,440,000	1,050,375	845,498	921,630	411,901

Table A2: Summary Statistics by Alternative Treatment Assignments: Medicaid-Covered Sample

	Medicaid-Covered Sample					
	All States		***34 States***		***21 States***	
Variable	**(1) Non-Exp.**	**(2) Exp.**	**(3) Non-Exp.**	**(4) Exp.**	**(5) Non-Exp.**	**(6) Exp.**
Migrated Across Regions	0.013	0.008	0.013	0.011	0.012	0.011
With Medicaid Coverage	1	1	1	1	1	1
Age	40.838	40.024	40.931	40.294	41.062	40.619
Male	0.431	0.458	0.424	0.448	0.424	0.443
Black	0.264	0.163	0.289	0.169	0.309	0.167
White	0.662	0.665	0.638	0.717	0.616	0.752
Hispanic	0.098	0.186	0.122	0.110	0.134	0.065
Immigrant	0.027	0.080	0.032	0.039	0.035	0.018
% FPL	153.428	166.704	153.052	156.166	152.866	143.847
Married	0.287	0.280	0.294	0.285	0.286	0.287
Family Size	2.852	2.935	2.900	2.860	2.880	2.802
Number of Children	0.764	0.784	0.754	0.799	0.735	0.779
High School Degree	0.390	0.358	0.374	0.377	0.371	0.397
Some College	0.279	0.319	0.283	0.318	0.282	0.301
Bachelor's Degree or More	0.068	0.098	0.067	0.084	0.066	0.065
Unemployment Rate	5.889	6.150	6.004	6.098	6.094	6.180
Maximum EITC Amount	0.027	0.205	0.014	0.084	0.015	0.049
Poverty Rate	14.657	13.458	15.362	13.543	15.546	15.171
Observations	859,352	1,400,058	574,323	735,516	496,036	336,454

Table A3: Impact of ACA Medicaid Expansion on Migration by Year: Event Study

Dependent Variable: Net Migration into Expansion State

	Below 138% FPL			***Medicaid-Covered***		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	All States	**34 States**	**21 States**	**All States**	**34 States**	**21 States**
Treat*2010	0.0014	0.0026*	0.0021*	0.0015*	0.0020**	0.0020*
	(0.0009)	(0.0013)	(0.0012)	(0.0009)	(0.0010)	(0.0012)
Treat*2011	0.0010	0.0008	0.0016*	0.0004	0.0010	0.0015
	(0.0007)	(0.0009)	(0.0008)	(0.0010)	(0.0011)	(0.0015)
Treat*2012	0.0007	0.0010	0.0025	0.0008	0.0010	0.0014
	(0.0010)	(0.0012)	(0.0016)	(0.0009)	(0.0011)	(0.0015)
Treat*2014	0.0004	0.0015	0.0026	0.0053***	0.0049***	0.0055***
	(0.0010)	(0.0014)	(0.0018)	(0.0010)	(0.0012)	(0.0020)
Treat*2015	-0.0003	0.0020	0.0030**	0.0058***	0.0073***	0.0068***
	(0.0011)	(0.0013)	(0.0014)	(0.0011)	(0.0014)	(0.0017)
Treat*2016	0.0009	0.0030**	0.0050***	0.0058***	0.0081***	0.0085***
	(0.0012)	(0.0012)	(0.0018)	(0.0011)	(0.0014)	(0.0024)
Treat*2017	0.0019	0.0033**	0.0053***	0.0063***	0.0079***	0.0085***
	(0.0012)	(0.0015)	(0.0019)	(0.0011)	(0.0014)	(0.0018)
Treat*2018	-0.0006	0.0014	0.0040**	0.0039***	0.0066***	0.0074***
	(0.0011)	(0.0013)	(0.0016)	(0.0009)	(0.0010)	(0.0018)
Treat*2019	-0.0001	0.0020	0.0033***	0.0018**	0.0052***	0.0066***
	(0.0011)	(0.0013)	(0.0012)	(0.0009)	(0.0011)	(0.0014)
Observations	2,862,329	1,895,873	1,333,531	2,259,410	1,309,839	832,490
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: American Community Survey 1-year Public Use Microdata Sample files, 2010–2019. Each column reports OLS estimates of the impact of ACA Medicaid expansion on interstate migration using an event study framework as outlined by Equation (2). The dependent variable is an indicator taking on a value of 1 if an individual either moves from a non-expansion-to-expansion state or from an expansion-to-non-expansion state, and 0 otherwise. Columns (1)-(3) present results for a sample of individuals with family income at or below 138% of the FPL, while columns (4)-(6) present those for a sample of Medicaid-covered individuals. We use three different treatment assignment approaches: time-invariant including all states in Columns (1) and (4), dropping early and late expanders leaving 34 states in Columns (2) and (5), and only using new and never expanders leaving 21 States in Columns (3) and (6). Robust standard errors clustered at the origin-state level are shown in parentheses.