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RESEARCH ARTICLE

Labor mobility and the Affordable Care Act: Heterogeneous impacts of the preexisting conditions provision

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Abstract

The Patient Protection and Affordable Care Act (ACA) preexisting conditions provision ensures that insurance companies can no longer deny coverage, charge higher premiums, or exclude coverage due to a preexisting health condition. In this paper, we evaluate the impact of the provision on labor mobility. We use data from the Panel Study of Income Dynamics for years 2009 through 2019 and estimate difference-in-differences models to determine whether the provision improved labor mobility for individuals with chronic conditions. While females respond along the extensive margin by being less likely to work, males experience broader labor mobility improvements. Men are more likely to start a new job, become employed in a different industry, and move to a different state in the post-policy period. Labor mobility improvements are largest among males with household incomes greater than 138% of the federal poverty level, males ages 35 to 49, and males with conditions first diagnosed more than 10 years ago. Last, we show that the policy improved access to health insurance coverage and reduced the likelihood that health impacts the amount or type of work, which ultimately increased labor market flexibility. Our results highlight the heterogenous impacts of the provision on different subgroups of the population.

INTRODUCTION

The Patient Protection and Affordable Care Act (ACA), passed in 2010, changed the health insurance options available to Americans. The preexisting conditions provision, implemented on January 1, 2014 for adults, ensures that insurance companies can no longer deny coverage, charge higher premiums for coverage, or exclude coverage for specific conditions to individuals due to a preexisting health condition (Keith, 2020). Prior to the ACA, the four largest for-profit health insurance companies denied coverage to one out of every seven applicants, on average, due to preexisting conditions (Wang, 2010). This issue impacted a substantial portion of the population—nearly 27% of the adult population under age 65 had a preexisting condition in 2018 (Claxton et al., 2019).

The ACA preexisting conditions provision may impact labor mobility through several channels. As Madrian (2007) stated, “Health insurance is an important factor in almost every labor market decision made by individuals: whether to work, where to work, and how much to work” (p. 157). The ACA significantly improved access to and quality of health insurance and care, and these changes likely impact labor market decisions (Glied et al., 2017). For example, an individual may have remained in their job prior to the policy if they relied on their employer for health insurance, what is commonly referred to as job lock. The association between job lock and employer-sponsored health insurance (ESI) is well documented,[1] and it is likely particularly strong for individuals or family members of those with prior health conditions, as they were frequently denied coverage or charged higher premiums prior to the ACA. Further, an individual with preexisting health conditions may have remained in their job because it afforded them flexibility necessary to care for their condition. Improved access to and quality of health insurance may lead to alternative job opportunities for individuals with preexisting conditions if they need less time away from work to care for their condition or are more able to complete certain job tasks.

In this paper, we investigate the impact of the ACA’s preexisting conditions provision on labor mobility. We use six waves of the Panel Study of Income Dynamics (PSID) from 2009 to 2019 and a difference-in-differences (DD) research design to compare differences in labor mobility for those with a preexisting condition to those without before and after the implementation of the ACA provision in 2014. Our primary outcomes measure both occupational and geographic labor mobility and include the worker’s tenure at their current job and the likelihood of starting a new job, switching to employment in a different industry, and moving to a different state. We also complement the worker mobility outcomes with an overall labor market indicator, employment status, to determine worker responses along the extensive margin. Given the documented gender differences in expected health care costs, risk aversion, and career mobility (Depew, 2015; Fitzenberger & Kunze, 2005), our primary sample focuses on individuals with preexisting conditions parsed by sex. We also explore impacts of the ACA provision on other household and demographic characteristics, such as marital status, age, and education. Together, this allows us to better understand the heterogeneous impacts of the policy change.

The ACA is the most substantial change in health policy since the implementation of Medicare and Medicaid in the 1960s. Research on the labor market impacts of the ACA typically focuses on two provisions: (1) Medicaid eligibility expansions, which increased the income threshold to be eligible for Medicaid in some states, or (2) the dependent coverage mandate, which allowed young adults up to age 26 to remain on their parents’ insurance. We focus on the preexisting conditions mandate, an understudied yet important provision, and its impact on labor mobility among adults with health issues. Our work is similar in spirit to that of Chatterji et al. (2016), who examined how the ACA impacted the labor mobility of parents whose children have a preexisting condition. We complement this work by studying the relationship between the ACA and labor market mobility among adults with preexisting conditions. Improvements in access to health coverage and employment outcomes for this previously vulnerable group have important implications as it may reduce existing health and labor inequities.

Our results indicate that the ACA increased both occupational and geographic labor mobility for those with preexisting conditions, particularly males. While females respond strongly along the extensive margin, we find a broader response among males. Specifically, the ACA significantly reduced the likelihood of working by 5.05 percentage points, or 9.40%, for females and 2.66

[1] See Adams (2004), Bansak and Raphael (2008), Barkowski (2020), Boyle and Lahey (2010), Dague et al. (2017), Depew (2015), Garthwaite et al. (2014), Gruber and Madrian (1994), Hamersma and Kim (2009), and Madrian (1994), among others, for evidence of insurance-related job lock.

percentage points, or 3.85%, for males with preexisting conditions. Further, for males with prior health conditions, the provision also significantly decreased their job tenure (0.51 years; 5.40%) and increased their likelihood of starting a new job (5.82 percentage points; 25.21%), switching employment to a different industry (6.07 percentage points; 25.36%), and moving to a different state (2.03 percentage points; 69.28%), which all signal improvement in labor mobility. Overall, our results highlight the different labor mobility responses to the ACA for males and females, an important consideration for ongoing discussions about the policy's future.

Given that several additional ACA provisions were implemented in 2014, we further target the preexisting conditions provision by showing that many of our main results hold for: (i) individuals in states that did not expand their Medicaid programs under the ACA, and (ii) individuals in higher income households that were ineligible for Marketplace subsidies or tax credits. We complement our main analysis with additional analyses across demographic and household characteristics. We continue to observe a differential policy response among males and females. For example, increased labor mobility among males with health conditions is driven by those ages 35 to 49, while among females with health conditions is driven by those ages 18 to 34. Similarly, males' labor mobility response is strongest among those whose condition was first diagnosed more than 10 years ago, while females' response is strongest among those whose condition was first diagnosed less than 10 years ago.

Last, we explore additional outcomes and potential mechanisms to further explain the relationship between the ACA and enhanced labor mobility for individuals with preexisting conditions. After the policy, males and females with conditions are significantly less likely to self-report that their health limits the amount or type of work they can perform, fair/poor health status, and moderate mental distress. We also show that individuals with preexisting conditions have increased health insurance coverage rates after the policy. Together, this suggests that the policy change allowed individuals with prior health conditions better access to health care and insurance, which improved their mental and physical health, decreased the work limitations they faced due to their health issues, and improved flexibility in the labor market (Collins et al., 2017; Glied & Jackson, 2017; Office of the Assistant Secretary for Planning and Evaluation [ASPE], 2017). We also find evidence of reduced job lock, but only along the extensive margin; individuals with prior health conditions that had ESI in 2013 became significantly less likely work after the policy.

HEALTH INSURANCE & LABOR MOBILITY

Labor mobility & access to health insurance prior to the Affordable Care Act

The literature on health insurance and labor mobility pre-date the ACA. Madrian (1994), one of the first to quantify insurance-related job lock, estimated that alternative health insurance increased worker mobility by 25% for those with ESI. Gruber and Madrian (1994) also found that working males' job mobility increased in response to continuation of coverage mandates, which required firms to allow individuals to continue purchasing insurance coverage through their former employer for a certain amount of time after a worker's departure. Extending dependent coverage for young adults had a negative impact on their full-time employment (Depew, 2015). A chronic illness for oneself or a family member reduced men's likelihood of voluntarily leaving their job by approximately 40% if they relied on their employer for health insurance (Stroupe et al., 2001).

Another area of focus of this literature is Medicaid or other public health insurance programs. Bansak and Raphael (2008) found that near-poor working parents of children with preexisting conditions had restricted job mobility due to the need to maintain health insurance for their family. Additionally, expanding Medicaid services that enable work, such as vision benefits, positively impacted labor market activity (Boudreaux & Lipton, 2021). Several studies concluded that access to insurance not tied to one's employer reduced job lock via increased turnover (Barkowski, 2020; Hamersma & Kim, 2009), decreased transitions to jobs with ESI (Barkowski, 2020), decreased work on the intensive and extensive margins (Boyle & Lahey, 2010), and reduced employment (Dague et al., 2017). Workers also sought employment to secure health insurance when public insurance programs were no longer available (Garthwaite et al., 2014).

The Affordable Care Act

Implementation, provisions, and access to health insurance

The primary purpose of the ACA was to increase the accessibility of health insurance to Americans. Some provisions of the ACA took effect as early as 2010, with the majority following by 2014. While several policy provisions are popular with the general public, including the preexisting conditions provision (Hamel et al., 2022), the policy continues to face legal challenges and remains at the center of policy debates (National Conference of State Legislatures, 2021). This highlights the need to better understand the intended and unintended outcomes of the policy.

The policy targeted increasing both availability and uptake of health insurance through several provisions.[2] The dependent coverage mandate, implemented in September 2010, allows young adults up to age 26 to stay on parental health insurance plans. Medicaid expansion increased program eligibility to 138% of the federal poverty level in certain states beginning in January 2014.[3] The employer mandate, implemented in 2016, requires firms with at least 50 full-time employees to offer minimum value health insurance coverage to their full-time employees (or pay a fine). The ACA also created a marketplace for individual health insurance, federal tax credits for those with family incomes below 400% of the federal poverty level (FPL), and cost-sharing reductions for those with family incomes below 250% of the FPL, beginning in January 2014, to help individuals and families secure health insurance (Kamal et al., 2018).

The preexisting conditions mandate, implemented in January 2014 and the focus of this paper, forbids insurance companies from denying coverage, charging higher rates for coverage, or excluding coverage for individuals with preexisting conditions, which was common practice before the policy.[4] Prior to the ACA, a few alternative insurance options specifically targeted individuals with preexisting health conditions, but they were underutilized and often cost-prohibitive. For example, many states offered high-risk health insurance pools for those "uninsurable" due to a preexisting condition. Participation in the high-risk pools was relatively low, and costs were often prohibitively high (Pollitz, 2017). As a bridge between 2010 and 2014, the ACA also created the Preexisting Condition Insurance Plan (PCIP), a temporary, federal high-risk pool to provide health insurance to those with prior health conditions that were uninsured for at least 6 months. Similar to the high-risk pools, PCIP enrollment was low and costs were higher than anticipated (Hall & Moore, 2012). Further, Glied and Jackson (2017) found no relationship between PCIP or high-risk pool enrollment and post-2014 gains in health insurance coverage for those with prior health conditions. While alternative health insurance options existed for those with preexisting conditions prior to 2014, they were not a viable alternative for many individuals.

Overall, research indicates that the ACA increased access to health insurance for many Americans. Three important studies highlighted that the ACA preexisting conditions provision increased access to health insurance for individuals with prior health conditions (ASPE, 2017; Collins et al., 2017; Glied & Jackson, 2017). Other ACA provisions also increased access to health insurance. For example, Akosa Antwi et al. (2013) found a significant uptake of parental insurance and reduction in non-insurance for young adults aged 19 to 25 in response to the dependent coverage mandate. Medicaid expansions in the aftermath of the ACA also significantly increased insurance coverage (Kaestner et al., 2017).

[2] See French et al. (2016) for a general overview of the key provisions of the ACA.

[3] As of December 2022, 40 states have adopted the ACA's Medicaid expansion (Kaiser Family Foundation, 2022).

[4] While insurance companies can no longer vary coverage or rates based on health status, insurance claim history, or gender, they can still vary rates based on family size, tobacco use, and age.

Labor mobility and the Affordable Care Act

Researchers have also explored how the policy change affects labor market outcomes, including mobility, finding mixed results.[5] While some studies found that ACA Medicaid expansion reduced job lock for impacted individuals, including older adults (Bailey & Dave, 2019) and White men and women (Callison & Sicilian, 2018), other studies noted that Medicaid expansion had little impact on labor mobility (Gooptu et al., 2016; Kaestner et al., 2017). Further, the ACA's dependent coverage mandate had little effect on job mobility for young adults (Bailey & Chorniy, 2016; Heim et al., 2018), but increased the time young adults spent on education, searching for a new job, and leisure activities (Colman & Dave, 2018; Lenhart & Shrestha, 2017), and decreased young adults' likelihood to marry, cohabitate, or have spousal health insurance coverage (Abramowitz, 2016).[6] This suggests that the dependent coverage mandate expanded the options for young adults, which is likely linked to viable health insurance alternatives. Even and Macpherson (2019) found that the ACA employer mandate increased involuntary part-time employment, with the largest effects concentrated in low-wage occupations. This is backed up by Dillender et al.'s (2020) findings that the ACA increased low hour, involuntary part-time employment for at least 500,000 workers in retail, accommodations, and food services, which suggests that firms substituted part-time for full-time workers to avoid the additional costs of providing health insurance to all employees.

The impacts of the ACA extend beyond health insurance and health outcomes and spillover into the labor market. Our study is similar in spirit to prior work on the ACA and labor mobility, but focuses on the preexisting conditions mandate, an understudied but important provision of the ACA. We are aware of one prior study that analyzes the ACA and labor mobility for parents of children with preexisting conditions; the authors found that the ACA increased labor mobility for married fathers of children with preexisting conditions (Chatterji et al., 2016). We build upon this work by analyzing the ACA's impact on the labor mobility of the adults themselves who have a preexisting condition. We use several measures of labor mobility capturing both occupational and geographic mobility. Further, we identify the heterogeneous response to the provision across different subgroups of the population, including across sex and household characteristics, to better understand how the policy provision impacts different types of workers.

DATA

We use data from the Panel Study of Income Dynamics (PSID; University of Michigan Survey Research Center, 2020), a longitudinal survey administered by the University of Michigan's Survey Research Center. The study began in 1968 with a nationally representative sample of over 18,000 individuals living in 5,000 U.S. families. Information on the original sample and their descendants include data covering employment, income, wealth, expenditures, marriage, childbearing, education, and other topics.

The PSID includes several characteristics that are advantageous in studying health conditions and labor market outcomes. First, the PSID contains detailed information on labor market activity that we can use to measure labor market mobility, including whether an individual is working now, and whether one has started a new job, switched industries, or moved to a new state (all in the past 2 years). Second, the PSID contains rich information regarding the health status of individuals, which allows us to identify those who experience specific health conditions and are likely to be impacted by

[5] See Campbell and Shore-Sheppard (2020) for an extensive overview of the financial and labor market effects of the ACA, including a notable absence of studies on the preexisting conditions provision.

[6] ACA Medicaid expansion also reduced the likelihood of marriage (Hampton & Lenhart, 2022b) and of medical divorce among those ages 50 to 64 with a college degree (Slusky & Ginther, 2021).

the ACA policy.[7] Third, the longitudinal nature of the survey has several advantages. It allows us to control for unobserved heterogeneity at the individual level. Given the dynamic nature of both one's health production and labor market outcomes, the ability to account for individual-level confounders is a particularly advantageous feature of the PSID. It also allows us to track individual changes in labor market activity and health status across time. The detailed information in the PSID on labor mobility and health status and the longitudinal nature of the data are particularly important for the context of our study.

We use biannual PSID data from 2009 to 2019, which includes three survey waves prior to (2009, 2011, and 2013) and three waves after (2015, 2017, and 2019) the policy. We follow Hampton and Lenhart (2019) and define a preexisting condition by identifying whether a doctor has ever diagnosed a respondent with any of the following health conditions: stroke, heart attack, heart disease, lung disease, diabetes, cancer, and other serious chronic conditions including seizures, kidney disease, autoimmune disorder, Parkinson's disease, coronary problems, and bone disorder.

Prior to the ACA, individual insurance companies typically screened applicants for prior health conditions and maintained a list of "declinable medical conditions." As Claxton et al. (2016) noted, "people with a current or past diagnosis of one or more listed conditions were automatically denied [insurance coverage]" (para. 10). While we cannot directly identify whether an individual has been denied coverage or charged higher premiums due to their health condition, all but one of our selected health conditions overlap with the most common declinable conditions (Claxton et al., 2016; Fehr et al., 2018). Many of the selected conditions also led to automatic eligibility for high-risk enrollment pools before the ACA (Centers for Medicare & Medicaid Services, n.d.).[8] Our definition of a preexisting condition is not exhaustive, but it includes many of the more serious health conditions that were categorized as declinable conditions prior to the ACA.

We define the main treatment group as individuals who report having at least one of the aforementioned preexisting conditions in all three pre-policy survey waves. We limit the sample to working-aged adults (ages 18 to 64) and to individuals whose health and labor information are available in each survey wave. Further, we exclude individuals who report a preexisting condition for the first time in one of the post-policy survey waves. The final sample yields treatment groups of 1,187 males (7,120 observations) and 1,222 females (7,333 observations) and control groups of 8,211 males (49,267 observations) and 9,748 females (58,486 observations).

Our primary outcomes of interest capture labor mobility. We include measures of an individual's ability to make changes in the labor market across jobs (occupational mobility) and an individual's ability to physically move to a new location (geographic mobility). We include three measures of occupational mobility: (i) the tenure of their current, or most recent, job, (ii) whether they started a new job (in the last 2 years), and (iii) whether they switched to employment in a different industry (in the last 2 years).[9] We include one measure of geographic mobility, whether the respondent moved to a different state (in the last 2 years).[10] Last, we analyze the respondent's employment status to determine whether individuals adjusted their labor market behavior along the extensive margin.

[7] Many alternative datasets include disability status or self-reported health status but do not include information on individual health conditions. For example, the American Community Survey (ACS) and the Current Population Survey (CPS) ask about six disabilities: hearing difficulty, vision difficulty, cognitive difficulty, ambulatory difficulty, self-care difficulty, and independent living difficulty. Most preexisting conditions do not fall under these disability options, which limits the use of alternative datasets to target individuals with prior health conditions.

[8] Bone disorder is not included in the list of declinable conditions, although "many additional, less common" declinable conditions were omitted from the tables (Claxton et al., 2016; Fehr et al., 2018). Seizures and bone disorder are not included in the list of conditions that qualified for automatic eligibility in high-risk pools (Centers for Medicare & Medicaid Services, n.d.).

[9] Industry codes include 19 Census industry codes and are listed in Appendix Table A1. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[10] Given the biannual structure of the PSID, whether an individual started a new job, switched to employment in a different industry, or moved to a different state are all measured over the last 2 years. For 2015, this means that the 2-year period overlaps with the pre-policy period for these variables. For this reason, we confirm that our results are robust to dropping the 2015 wave from the analysis, which ensures zero overlap between the pre- and post-policy periods. See the "Robustness Checks" section for more details.

TABLE 1 Descriptive statistics.

	Males		Females	
	Treatment group	**Control group**	**Treatment group**	**Control group**
Age	45.4594	39.0330	45.6660	39.1527
	(10.8201)	(10.0215)	(10.5822)	(10.1911)
Married	0.7567	0.7456	0.6547	0.6476
	(0.4291)	(0.4355)	(0.4755)	(0.4777)
# children in HH	1.1242	1.5028	1.1950	1.6121
	(1.2942)	(1.4116)	(1.4597)	(1.4251)
White	0.6447	0.6257	0.5383	0.5343
	(0.4786)	(0.4839)	(0.4986)	(0.4988)
Black	0.2751	0.3053	0.3945	0.4059
	(0.4466)	(0.4605)	(0.4888)	(0.4911)
At most high school degree	0.1513	0.1450	0.4683	0.4101
	(0.3584)	(0.3521)	(0.4990)	(0.4919)
Some college	0.3124	0.2762	0.2879	0.2656
	(0.4635)	(0.4471)	(0.4528)	(0.4417)
College degree	0.5363	0.5788	0.2438	0.3131
	(0.4987)	(0.4938)	(0.4294)	(0.4638)
Stroke (pre)	0.0643	-	0.0455	-
	(0.2453)		(0.2085)	
Heart attack (pre)	0.1159	-	0.0643	-
	(0.3201)		(0.2003)	
Heart disease (pre)	0.1107	-	0.0739	-
	(0.3138)		(0.2616)	
Lung disease (pre)	0.1126	-	0.1271	-
	(0.3162)		(0.3331)	
Diabetes (pre)	0.4022	-	0.4121	-
	(0.4904)		(0.4219)	
Cancer (pre)	0.1197	-	0.1224	-
	(0.3246)		(0.3278)	
Other chronic condition (pre)	0.3756	-	0.2850	
	(0.4843)		(0.4515)	
N	7,120	49,267	7,333	58,486

Notes: Summary statistics from the PSID, waves 2009 to 2019. Treatment group refers to individuals with a preexisting condition in waves 2009, 2011, and 2013. Control group refers to individuals that did not have a preexisting condition in the pre- or post-policy period.

Table 1 provides summary statistics for males and females in the treatment and control groups. Individuals in the treatment group are slightly older on average than those in the control group. Additionally, treated individuals are less likely than those in the control group to have children or a college degree. The lower half of Table 1 shows the proportion of the males and females in the treatment group with various preexisting health conditions. Diabetes is the most common health condition, affecting over 40% of the treated sample, followed by other serious chronic conditions (37.6% for males; 28.5%

TABLE 2 Descriptive statistics - outcome variables.

	Males		Females	
	Treatment group	**Control group**	**Treatment group**	**Control group**
Working now				
Pre	0.6915	0.8569	0.5375	0.6963
	(0.4619)	(0.3502)	(0.4987)	(0.4599)
Post	0.7155	0.8851	0.5403	0.7362
	(0.4512)	(0.3189)	(0.4984)	(0.4407)
Job tenure (in years)				
Pre	9.4604	6.8952	7.1076	5.7571
	(9.2497)	(7.4255)	(7.8089)	(6.3171)
Post	8.7069	7.5658	7.0114	6.0275
	(9.8439)	(7.9012)	(8.3784)	(6.8331)
Started a new job in last 2 years				
Pre	0.2309	0.3544	0.2775	0.3427
	(0.4215)	(0.4783)	(0.4478)	(0.4746)
Post	0.3011	0.3262	0.2715	0.3574
	(0.4588)	(0.4688)	(0.4448)	(0.4792)
Switched to different industry in last 2 years				
Pre	0.2394	0.3044	0.2747	0.3220
	(0.4269)	(0.4602)	(0.4465)	(0.4672)
Post	0.2688	0.2296	0.3772	0.4018
	(0.4434)	(0.4206)	(0.4848)	(0.4903)
Moved to a different state in last 2 years				
Pre	0.0293	0.0639	0.0308	0.0604
	(0.1565)	(0.2447)	(0.1727)	(0.2382)
Post	0.0530	0.0543	0.0282	0.0559
	(0.2241)	(0.2265)	(0.1655)	(0.2298)
N	7,120	49,267	7,333	58,486
	56,387		65,819	

Notes: Summary statistics calculated from PSID. Pre includes waves 2009, 2011, and 2013; post includes waves 2015, 2017, and 2019. Treatment group refers to individuals with pre-existing conditions in all three pre waves; the control group refers to those without a prior health condition in the pre-policy period.

for females), and lung disease and cancer (~12% each).[11] One noticeable difference across males and females with prior health conditions is the higher likelihood of males to experience heart disease or heart attacks.

Table 2 displays sample means of the primary labor mobility outcome variables for males and females in the treatment and control groups, before and after the policy change. Across all outcome variables, the average for treated males in the post-policy period signals labor mobility improvements

[11] Individuals in the treatment group may experience more than one preexisting condition. Therefore, the total across each health condition subcategory sums to more than 100. In alternative specifications, we exclude individuals who only report to experience "other serious chronic conditions" from the treatment group. The results, which are available upon request, are very similar to our main estimates both in magnitude and statistical significance. This suggests that our findings are not driven by the inclusion of "other serious chronic conditions" in the treatment group.

relative to the pre-policy period. In contrast, most average changes for males in the control group reflect decreases in labor mobility. Many of the average changes for females are smaller in magnitude or close to zero for both the treatment and control groups. Although, females are more likely to switch industries of employment after the policy. Overall, sample means in Table 2 reflect that the 2014 ACA preexisting conditions provision improved labor mobility for those experiencing chronic health conditions, particularly males.

METHODS

Our primary strategy relies on a difference-in-differences (DD) methodology to test the impact of the ACA preexisting conditions provision on labor mobility outcomes. In the main analysis, we compare changes in labor market mobility among individuals with preexisting health conditions (first difference) before and after the policy implementation in 2014 (second difference).[12] We present estimates for males and females separately. The identifying variation in our study, which is the same exploited by Hampton and Lenhart (2019, 2022a), is differences in the presence of preexisting health conditions across individuals.

The baseline empirical model that tests the impact of the preexisting conditions provision on labor mobility is given by:

$$\mathrm{Y_{ist}} = \beta_0 + \delta_{\mathrm{DD}}\mathrm{Post}^{*}_{\mathrm{ist}}\mathrm{Condition_i} + \beta_1\mathrm{X_{ist}} + \beta_2\mathrm{Z_{st}} + \lambda_1\mathrm{Year_t} + \alpha_\mathrm{i} + \varepsilon_{\mathrm{ist}}, \tag{1}$$

where Y_{ist} is the dependent variable, which is an indicator for whether individual i, living in state s, in time period t is employed, and 0 otherwise. In other models, the dependent variable is job tenure (number of years at current job), and indicators for whether an individual has recently started a new job, switched industries, or moved to a different state, all in the last 2 years. $Post_{ist}$ is an indicator taking on the value of 1 in the post policy years, 2015, 2017, or 2019, and 0 otherwise. $Condition_i$, captures whether an individual falls into the treatment group, i.e., has a preexisting condition in each of the three pre-policy survey waves. The parameter of interest is δ_{DD}, which captures the effect of the ACA preexisting conditions provision on labor market outcomes.[13]

Each model controls for observable characteristics denoted by X_{ist}, which include household size, education level, and age. The vector Z_{st} accounts for five additional state-level policies that could impact health insurance coverage and labor market decisions for those with preexisting conditions. These policies include Medicaid expansion, Community First Choice Medicaid options (which allow states to provide community-based support for individuals with disabilities), Home and Community-Based Services (which give states additional options for providing home and community services through Medicaid state plans to individuals with mental health distress), whether states allow the sale of “grandfathered” insurance plans that existed prior to the ACA, and state-level dependent coverage mandate laws. Additionally, to mitigate concerns of unobserved confounders varying across time or at the individual level, the model includes year fixed effects, $Year_t$, and individual fixed effects, α_i.[14]

We estimate all models via unweighted linear probability models.[15] Since the policy change was implemented nationally, we only have two groups (treatment and control). Thus, we follow the literature and include small-cluster corrections in our analysis. Specifically, we use a wild bootstrap resampling method with 1,000 replications to calculate our p-values, which works well with a small

[12] There is an emerging literature on modeling difference-in-differences with differential treatment timing (Callaway & Sant’Anna, 2021; Goodman-Bacon, 2021; Sun & Abraham, 2021). The ACA preexisting conditions provision was implemented at a single point in time for all adults, so the standard DD model is appropriate for our study.

[13] The $Post_{ist}$ and $Condition_i$ independent variables are absorbed in the year and individual fixed effects, respectively.

[14] Results from regressions including state fixed effects rather than individual fixed effects are shown in Appendix Table A2.

[15] Weighted results are shown in Appendix Table A3.

number of clusters (Cameron et al., 2008). We also use the 6-point distribution bootstrap weight, which works better than the Rademacher distribution with a small number of clusters (MacKinnon & Webb, 2017; Webb, 2023).

To investigate the parallel trends assumption and to test for year-by-year effects of the policy change, we augment equation (1) to reflect an event study of the form:

$$Y_{ist} = \beta_0 + \sum_{(t=2009)}^{2019} \delta_t Year_t * Condition_i + \beta_1 X_{ist} + \beta_2 Z_{st} + \lambda_1 Year_t + \alpha_i + \varepsilon_{ist}, \qquad (2)$$

where δ_t estimates heterogeneous effects of the policy across the years 2009 to 2019 (in this analysis, the year 2013 is excluded as the reference category). Not only does the event study specification in equation (2) allow the effect of the policy to vary across time (which distinguishes between contemporaneous and lagged effects), it also allows for testing of the DD parallel trends assumption. If δ_t is estimated to be statistically indistinguishable from zero in the years prior to 2014, then this implies that there were no statistical differences between labor market activity of the treatment and control groups prior to the ACA, which supports the validity of the DD approach.

Last, as a robustness check, we estimate models that combine propensity score matching with difference-in-differences. This allows us to compare the distribution of outcomes for treated individuals with that of matched individuals in the control group, without making any functional form assumptions. As noted by García-Gómez and López-Nicolás (2006), the use of longitudinal data eliminates potential concerns of bias related to propensity score matching. The panel nature of the PSID allows us to first difference the outcomes of the treated and control groups to eliminate any unobservable fixed effects that influence selection into the groups as well as the outcomes of interest. Our estimated treatment effects are weighted averages of the differences in differences between each of the treated individuals and their matched control. To match individuals, we use estimated propensity scores, which represent the probability of treatment given a vector of observable characteristics.[16] Standard errors are obtained following Abadie and Imbens (2016), who established a method that accounts for estimated propensity scores in the first stage. The authors showed that ignoring this fact when estimating treatment effects on the treated in the second stage may lead to confidence intervals that are either too large or too small.[17] In the empirical analysis, we use three alternative methods when matching treated individuals to those in the control group: (a) 1 to 1 nearest neighbor matching, (b) 2 to 1 nearest neighbor matching, and (c) radius matching with a caliper of 0.1.

RESULTS

Main results

Table 3 presents our main estimates—the effects of the ACA preexisting conditions provision on labor mobility for all individuals (Panel A) and only those who are working (Panel B), presented separately for males and females. When examining the extensive margin of employment (Panel A), our estimates show that the policy reduced the likelihood of working by 2.66 percentage points (pp) for males with prior health conditions ($p < 0.01$), or a decline of 3.85% from the sample mean. When evaluating whether the policy change impacted the length of stay at the current or most recent job, we find a reduction in male job tenure by 0.51 years ($p < 0.05$), or a decline of 5.4%. Additionally, we show that the provision increased males' likelihood of both starting a new job and switching to a different

[16] We estimate the propensity scores using probit models based on pre-treatment variables. We include the following observable characteristics to obtain the propensity scores: age, education, race, the number of children in the household, industry, and occupation.

[17] By showing that the propensity score matching estimators have approximately normal distributions, Abadie and Imbens (2016) provided evidence that matching on estimated propensity scores is more efficient than matching on the true propensity score in large samples.

TABLE 3 The effects on employment outcomes – males and females with preexisting conditions.

	Working now	Job tenure (current or most recent job)	Started a new job in last 2 years	Switched industry in last 2 years	Moved to a different state in last 2 years	*N*
Panel A: Main results						
Males	−0.0266***	−0.5140**	0.0582***	0.0607***	0.0203***	56,387
	[0.0060]	[0.0310]	[0.0000]	[0.0000]	[0.0000]	
Sample mean	0.6915	9.4604	0.2309	0.2394	0.0293	
Females	−0.0505***	−0.1306	−0.0327***	0.0445***	0.0017	65,819
	[0.0000]	[0.4885]	[0.0040]	[0.0060]	[0.7297]	
Sample mean	0.5375	7.1076	0.2775	0.2747	0.0308	
Difference male/female estimate	**	**	***	**	***	
Panel B: Workers only						
Males	-	−0.4339*	0.0688***	0.0559***	0.0110*	47,928
		[0.0601]	[0.0000]	[0.0000]	[0.0591]	
Sample mean		10.0438	0.2545	0.2202	0.0259	
Females	-	−0.1129	−0.0289*	0.0311*	−0.0049	45,405
		[0.6316]	[0.0991]	[0.0521]	[0.4194]	
Sample mean		7.9325	0.3464	0.2368	0.0238	
Difference male/female estimate		**	***	**	***	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on labor market outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

industry since the previous wave by 5.82 and 6.07 pp (both $p < 0.01$), respectively. In comparison with the pre-policy period, these two estimates correspond to increases of approximately 25%. Finally, we also find that males with preexisting health conditions are 2.03 pp ($p < 0.01$) more likely to have moved to a different state since the previous wave in the post-treatment period, a 69.3% increase. Both the statistical significance and magnitude of these effects suggest that labor flexibility increased substantially among males with prior health issues following the policy. While the magnitude of some of the effects is smaller when only examining males who are currently working, we also find consistent results for this sample (Panel B).

For females, we find smaller effects on most labor mobility outcomes overall, except along the extensive margin. Females with prior health conditions are 5.50 pp ($p < 0.01$) less likely to be working after the policy, which reflects a 9.4% decline relative to the pre-policy period. The estimates for females' job tenure and state migration are much smaller than the corresponding effects for males and statistically insignificant. However, we find a 3.27 pp reduction ($p < 0.01$) in the likelihood of females starting a new job since the previous wave (which reflects a decrease in labor mobility) and a 4.45 pp increase ($p < 0.01$) in the likelihood of females switching to a different industry in the last 2 years. When narrowing the sample to females who are currently working, we find smaller and more imprecise estimates for all four measures of labor mobility. As shown in Table 3, treatment effects for all five outcome variables are statistically different between males and females in both panels (at least $p < 0.05$).

Table 3 indicates that males and females with prior health issues both experienced a decline in labor supply along the extensive margin. A decline in labor supply can be considered an improvement in labor mobility if individuals actively chose to leave their job. For example, if alternative insurance options reduced reliance on an employer for health insurance or expanded alternative employment options, the policy may have enabled some individuals to voluntarily leave their position. However, we do not have reliable data on the reason a specific individual is no longer working, so it is also possible that this reflects involuntary unemployment, which does not align with enhanced labor mobility. It is also possible that the decline in labor supply for males and females in the treated group partially reflects individuals with chronic health conditions taking time off to focus on their health.

Table 3 also indicates that males with prior health issues experienced more broad increases in labor mobility following the ACA preexisting conditions provision in comparison to females. We believe there are two possible explanations for the different labor responses for males versus females, a proxy for gender. First, systematic different attitudes toward risk for men and women are well established (Barber & Odean, 2001; Bernasek & Shwiff, 2001; Charness & Gneezy, 2012; Croson & Gneezy, 2009). Making a change in the labor market or moving to a new state all involve uncertainty and risk. Women are more risk averse than men, which could explain why we find more labor mobility improvements among males (Cortes & Pan, 2018). Second, research finds differences with respect to social and job preferences for men and women. While men place a higher value on money, women report higher levels of job satisfaction and are less likely to leave people-oriented occupations (Lordan & Pischke, 2016). Women are also more likely to take on caregiving obligations or unpaid work (Goldin, 2021) and are less likely to make occupational changes (Fitzenberger & Kunze, 2005). Thus, our results may also reflect different social and job preferences across males and females or different constraints that males and females face when making labor mobility decisions.

Event study

Our main results from the standard DD framework do not allow impacts of the ACA provision to vary across post-policy years. Therefore, we use an event study framework, outlined in equation (2), to determine how the impacts of the policy change vary across years. Figures 1 and 2 present our event study estimates. Figure 1 shows results for the five measures of labor mobility among males, while Figure 2 shows those for females. Figure 1 clearly illustrates the impact of the preexisting

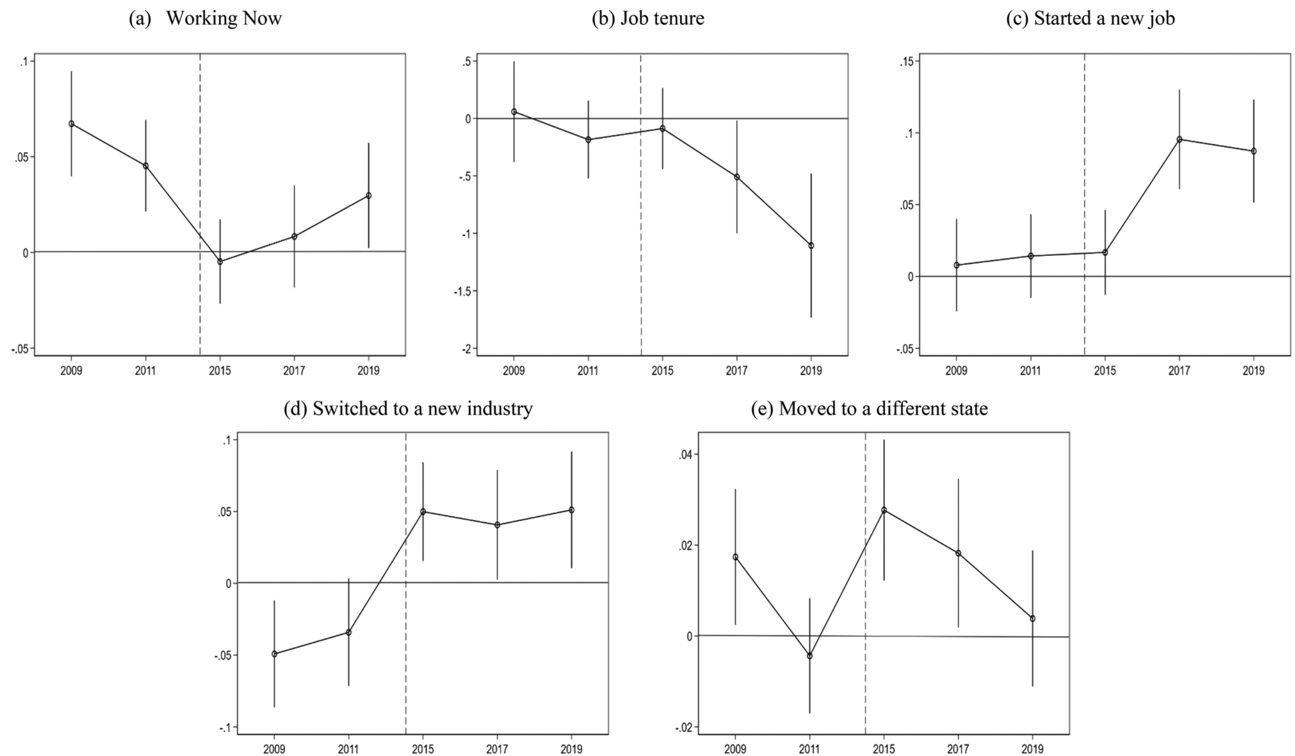

FIGURE 1 Event study effects of ACA preexisting conditions provision, males.

Notes: Sample includes all males, ages 18 to 64. Figures display estimated coefficients (black dots) from the event study model outlined in equation (2). Labor mobility dependent variables are indicated above each sub-figure. The vertical line at 2014 represents the year the ACA preexisting conditions provision was implemented for adults. All coefficients are relative to the 2013 baseline year.
Source: University of Michigan Survey Research Center, 2020.

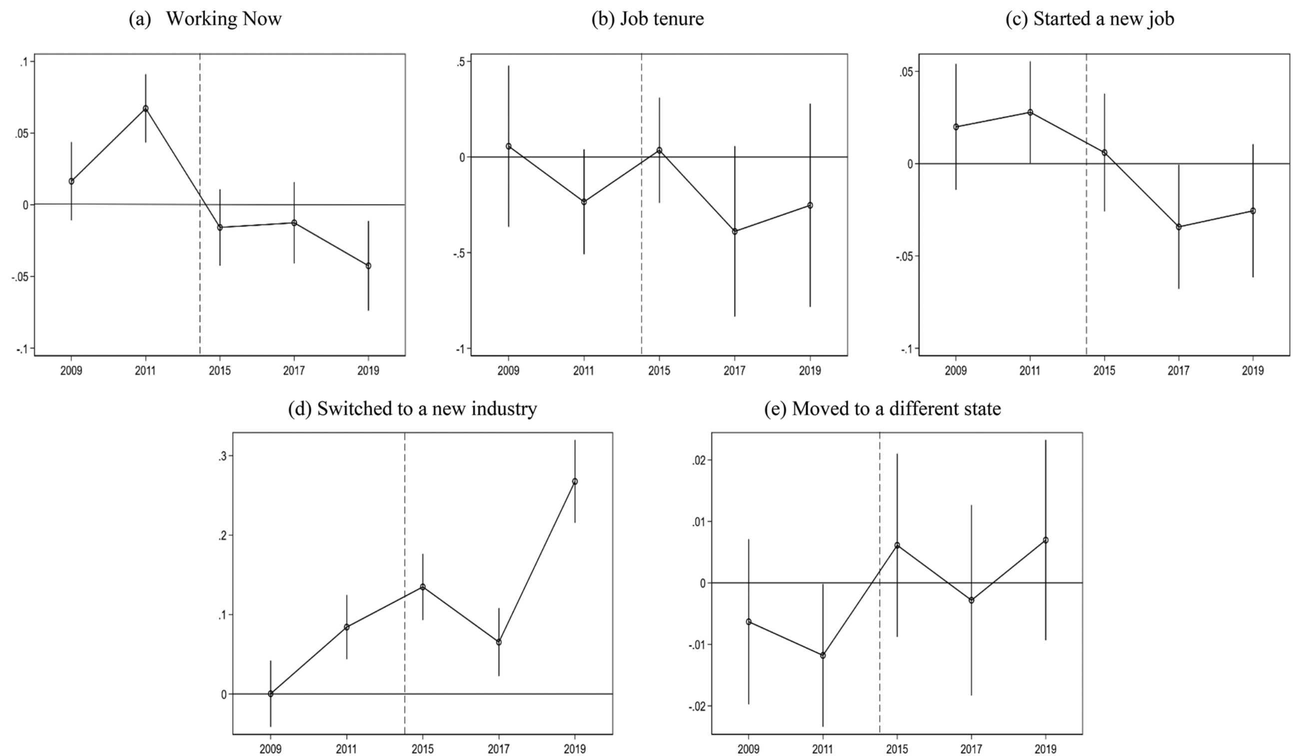

FIGURE 2 Event study effects of ACA preexisting conditions provision, females.

Notes: Sample includes all females, ages 18 to 64. Figures display estimated coefficients (black dots) from the event study model outlined in equation (2). Labor mobility dependent variables are indicated above each sub-figure. The vertical line at 2014 represents the year the ACA preexisting conditions provision was implemented for adults. All coefficients are relative to the 2013 baseline year.
Source: University of Michigan Survey Research Center, 2020.

conditions provision on labor mobility for males with prior health issues. For the working now, job tenure, and starting a new job outcomes, changes are observable with a slight delay from 2017 onward, while immediate effects are noticeable for switching industries and interstate migration. Furthermore, Figures 1(b) and 1(c) provide evidence for the presence of parallel trends in three pre-treatment waves for job tenure and starting a new job respectively. Although, pre-trends are noisier for the other outcome variables, working now (1a), switching industries (1d), and moving to a different state (1e).

Figure 2 shows the corresponding event study effects for females with prior health conditions. While trends for the first four measures of job mobility (working now, job tenure, new job, switch industry) are negative following the ACA provision, the change in trends from the pre-2014 wave is substantially smaller compared to that of males. This is consistent with our main findings in Table 3. With the exception of working now (2a) and switching to a new industry (2d), the event study graphs for the other three outcomes (2b, 2c, and 2e) all provide evidence for the presence of parallel trends during the three survey waves prior to the policy. In the "Robustness Checks" section, we further explore the validity of the parallel trends assumption and the robustness of our results.

Targeting the preexisting conditions provision

As discussed in Section 2, several other ACA provisions were also implemented in 2014, such as Medicaid expansion, marketplace tax credits, and marketplace cost-sharing subsidies. Given our DD model, it is possible that our primary results are also picking up effects from other ACA provisions beyond the preexisting conditions mandate. In this section, we extend our primary analysis to further target the preexisting conditions provision by exploring changes in labor mobility across state Medicaid expansion status, household income, and state high risk pools prior to the ACA.

Table 4 presents the labor mobility results across ACA Medicaid expansion status for males and females. Panel A shows that improvements in labor mobility for males with preexisting conditions is driven by those in non-expansion states. For example, males with conditions in non-expansion states are less likely to be working (-6.5 pp or 9.4%; $p < 0.01$) and more likely to start a new job (8.86 pp or 38.1%; $p < 0.01$), switch to employment in a different industry (12.37 pp or 56.5%; $p < 0.01$), or move to a different state (5.07 pp or 179.2%; $p < 0.01$). Most of the analogous estimates for males living in expansion states are either statistically insignificant, or the coefficient sign aligns with declines in labor mobility, with the exception of moving to a different state. Females' response along the extensive margin, the likelihood to work less, is also concentrated among those in non-expansion states (-5.73 pp or 12.6%; $p < 0.01$). Although, we also observe an increase in the likelihood that females with conditions living in expansion states started a new job or switched to employment in a different industry. Overall, Table 4 indicates that Medicaid expansion is not the primary driver of our main results.

Next, we explore changes in labor mobility for those with preexisting conditions across household income levels (Table 5). Families with household income above 250% of the FPL are not eligible for cost-sharing subsidies and those with household income above 400% of the FPL are not eligible for marketplace tax credits. The results in Table 5 show some improvements in labor mobility for those with household income less than 400% of the FPL. However, many of our primary results hold for the sample of individuals with income above 400% of the FPL, i.e., those ineligible for subsidies or tax credits. After the policy change, males in high-income households with prior health conditions are 3.94 pp less likely to be working ($p < 0.01$, 4.5%), 3.34 pp more likely to switch employment to a different industry ($p < 0.10$, 8.8%), and 3.08 pp more likely to move to a different state ($p < 0.01$, 280%). Females with conditions in high-income households are 3.51 pp less likely to be working ($p < 0.05$, 4.9%), 5.91 pp more likely to switch employment to a different industry ($p < 0.01$, 32.7%), and 2.38 pp more likely to move to a different state ($p < 0.05$, 50.5%) after the 2014 policy.

TABLE 4 The effects on employment outcomes - males and females with preexisting conditions by ACA Medicaid expansion status.

	Working now	Job tenure (current or most recent job)	Started a new job in last 2 years	Switched industry in last 2 years	Moved to a different state in last 2 years	*N*
Panel A: Males						
Expansion states	0.0110	0.9615**	0.0064	−0.1084***	0.0354***	18,522
	[0.6837]	[0.0490]	[0.8368]	[0.0010]	[0.0010]	
Non-expansion states	−0.0650***	−0.8616***	0.0886***	0.1237***	0.0507***	37,865
	[0.0000]	[0.0030]	[0.0000]	[0.0000]	[0.0000]	
Panel B: Females						
Expansion states	−0.0243	1.2713***	0.0680**	0.2041***	−0.0016	20,785
	[0.4695]	[0.0030]	[0.0390]	[0.0000]	[0.8949]	
Non-expansion states	−0.0573***	−0.4017	−0.0497***	0.0255	0.0102	45,034
	[0.0000]	[0.1712]	[0.0040]	[0.2963]	[0.1942]	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on labor market outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap p-values are shown in brackets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 5 The effects on employment outcomes - males and females with preexisting conditions by income groups.

	Working now	Job tenure (current or most recent job)	Started a new job in last 2 years	Switched industry in last 2 years	Moved to a different state in last 2 years	*N*
Panel A: Males						
<138% FPL	−0.0485	1.9666*	0.0679*	−0.2842**	0.0300*	5,041
	[0.2232]	[0.0641]	[0.0911]	[0.0300]	[0.0691]	
138 to 400% FPL	−0.0213	−1.3031***	0.1361***	0.1243***	0.0142	18,466
	[0.2803]	[0.0020]	[0.0000]	[0.0010]	[0.1071]	
>400% FPL	−0.0394***	−0.2740	0.0131	0.0334*	0.0308***	32,880
	[0.0000]	[0.3624]	[0.4154]	[0.0591]	[0.0000]	
Panel B: Females						
<138% FPL	−0.0957***	0.3924	−0.0862***	0.1379**	−0.0141	12,738
	[0.0010]	[0.5175]	[0.0010]	[0.0110]	[0.1782]	
138 to 400% FPL	−0.0238	−0.3351	0.0012	0.0600**	0.0083	21,867
	[0.2693]	[0.5155]	[0.7037]	[0.0150]	[0.1141]	
>400% FPL	−0.0351**	−0.9177**	0.0179	0.0591***	0.0238**	10,381
	[0.0180]	[0.0340]	[0.6086]	[0.0060]	[0.0381]	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on labor market outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap p-values are shown in brackets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Last, we analyze changes in labor mobility for individuals living in states with and without high-risk insurance pools prior to the nationwide ACA preexisting condition provision (Table 6). The results suggest that males with preexisting conditions living in states with high-risk insurance pools prior to the ACA experienced larger post-policy increases in labor mobility relative to those living in states without high-risk pools. We see a similar story for females; the estimates for females with prior health issues living in states with high-risk pools are larger in comparison to those in states without high-risk pools for both the likelihood to be working now and to switch to a different industry. While these results suggest there may be forces beyond the preexisting condition provision behind our primary results, uptake rates for high-risk insurance pools were low, approximately 2%, prior to the ACA due to the high costs of insurance through the program (Pollitz, 2017). We are likely observing labor mobility improvements for those with conditions living in states with high-risk pools since the high-risk insurance pools were not a viable option for many individuals with preexisting conditions.[18] Together, Tables 4, 5, and 6 show that other ACA provisions—specifically Medicaid expansion, marketplace cost-sharing subsidies, and marketplace tax credits—are not the primary driver behind our main results.

Heterogeneous effects

Now that we have better targeted the connection between our main results and the preexisting conditions provision, we further examine how individual responses to changes in health policy vary across household and demographic characteristics. For this analysis, we still focus on comparing individuals with prior health conditions to those without conditions, but further split the sample across: children in the household, marital status, age, educational attainment, and time elapsed since diagnosis. In other words, we compare changes for those with prior health conditions to those without health conditions for a given demographic or household characteristic.

Table 7 shows separate estimates for the impact of the ACA policy change for males and females with and without children in the household. The results indicate that male labor mobility changes for those with versus without prior health conditions are more likely to vary based on whether they have children in the household. For example, males with prior health conditions without children in the household are less likely to work and more likely to switch industries in comparison to those without conditions (and without children). In contrast, males with prior health conditions with children in the household are more likely to start a new job or move to a different state in comparison to those without prior health conditions (and with children in the household). While it is reasonable to assume that it is more difficult in general for individuals with children to move, our results suggest that the ACA increased the likelihood that males with preexisting conditions with children moved in comparison to men without preexisting conditions with children. In contrast, regardless of whether children are in the household, females with preexisting health conditions are less likely to be working and more likely to switch industries after the policy change.

We also explore labor mobility changes in response to the policy by marital status (Table 8). The results are somewhat similar to those by children in the household: labor mobility responses for males varies some across marital status for those with versus without prior health conditions, while the response for females is more consistent. Married males with prior health conditions are less likely to be working (-4.85 pp or 6.7%; $p < 0.01$) and more likely to move to a different state (2.12 pp or 135%; $p < 0.01$) in comparison to married males without prior health conditions, while unmarried males with prior health conditions are more likely to start a new job or switch to employment in a

[18] The individual mandate was also implemented in 2014 and required all individuals to have health insurance. In the absence of the preexisting conditions provision, insurance companies would still be able to deny coverage, charge higher premiums, or exclude certain conditions from coverage for individuals with prior health conditions, even with the individual mandate. Thus, the individual mandate alone would not significantly improve health insurance options for individuals with preexisting conditions.

TABLE 6 The effects on employment outcomes - males and females with preexisting conditions by pre-2014 risk pools.

	Working now	Job tenure (current or most recent job)	Started a new job in last 2 years	Switched industry in last 2 years	Moved to a different state in last 2 years	*N*
Panel A: Males						
States with high-risk pools	−0.0377***	−0.7534***	0.0551***	0.0412**	0.0342***	39,794
	[0.0020]	[0.0090]	[0.0010]	[0.0346]	[0.0000]	
States w/o high-risk pools	0.0006	0.6107*	0.0415*	0.0596**	0.0100	16,206
	[0.9742]	[0.0870]	[0.0521]	[0.0072]	[0.2680]	
Panel B: Females						
States with high-risk pools	−0.0689***	−0.3430	−0.0266*	0.0605***	0.0095	45,791
	[0.0010]	[0.1273]	[0.0890]	[0.0030]	[0.1128]	
States w/o high-risk pools	−0.0243	0.0545	−0.0413*	0.0274	0.0051	19,689
	[0.2245]	[0.8420]	[0.0890]	[0.3214]	[0.6722]	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on labor market outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap p-values are shown in brackets. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 7 The effects on employment outcomes - males and females with preexisting conditions by household type.

	Working now	Job tenure (current or most recent job)	Started a new job in last 2 years	Switched industry in last 2 years	Moved to a different state in last 2 years	*N*
Panel A: Males						
No children in HH	−0.0817***	0.6195	−0.0012	0.0597***	0.0036	19,042
	[0.0000]	[0.1922]	[0.9550]	[0.0070]	[0.7317]	
Children in HH	0.0193*	−0.5955**	0.0979***	0.0260	0.0367***	37,345
	[0.0911]	[0.0180]	[0.0000]	[0.2302]	[0.0000]	
Panel B: Females						
No children in HH	−0.0473**	−0.0641	−0.0133	0.0859***	−0.0145	19,195
	[0.0210]	[0.8789]	[0.4635]	[0.0040]	[0.1201]	
Children in HH	−0.0646***	−0.0136	−0.0857***	0.0477**	0.0028	46,624
	[0.0000]	[0.9540]	[0.0000]	[0.0160]	[0.6797]	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on labor market outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap p-values are shown in brackets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 8 The effects on employment outcomes - males and females with preexisting conditions by marital status.

	Working now	Job tenure (current or most recent job)	Started a new job in last 2 years	Switched industry in last 2 years	Moved to a different state in last 2 years	*N*
Panel A: Males						
Married	−0.0485***	−0.0613	0.0295**	0.0190	0.0212***	42,123
	[0.0000]	[0.7320]	[0.0216]	[0.2842]	[0.0010]	
Sample Mean	0.7277	10.4367	0.2160	0.1949	0.0244	
Unmarried	−0.0387	−0.4798	0.1351***	0.1401***	0.0047	14,264
	[0.2139]	[0.4965]	[0.0020]	[0.0050]	[0.8568]	
Sample Mean	0.6288	4.6768	0.4232	0.4688	0.0944	
Panel B: Females						
Married	−0.0582***	−0.4060*	−0.0152	0.0180	0.0145**	42,039
	[0.0020]	[0.0915]	[0.3650]	[0.4624]	[0.0264]	
Sample Mean	0.5881	7.6955	0.2555	0.2458	0.0292	
Unmarried	−0.0444**	−0.2144	−0.0466**	0.0377	0.0076	21,652
	[0.0179]	[0.6244]	[0.0246]	[0.2845]	[0.5318]	
Sample Mean	0.4994	5.4443	0.3519	0.3818	0.0388	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on labor market outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 9 The effects on employment outcomes - males and females with preexisting conditions by age groups.

	Working now	Job tenure (current or most recent job)	Started a new job in last 2 years	Switched industry in last 2 years	Moved to a different state in last 2 years	N
Panel A: Males						
18–34	0.0222	−0.2612	−0.0758*	−0.0106	0.0293	19,966
	[0.4865]	[0.3403]	[0.0811]	[0.7928]	[0.2142]	
35–49	0.0156	−0.7211***	0.0705***	0.0521	0.0174*	24,438
	[0.3403]	[0.0050]	[0.0050]	[0.1001]	[0.0881]	
50–64	−0.0399**	0.7984*	−0.0128	−0.0139	0.0012	11,983
	[0.0100]	[0.0851]	[0.4915]	[0.4995]	[0.8559]	
Panel B: Females						
18–34	−0.1031***	0.5188**	−0.1107***	0.0158	−0.0444**	23,134
	[0.0030]	[0.0310]	[0.0040]	[0.7688]	[0.0280]	
35–49	0.0198	−0.5733**	−0.0271	0.0360	0.0097	28,490
	[0.3514]	[0.0270]	[0.2422]	[0.2082]	[0.4004]	
50–64	−0.0085	−0.6936*	0.0020	0.0004	−0.0046	14,195
	[0.6386]	[0.0841]	[0.9019]	[0.9800]	[0.4705]	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on labor market outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap p-values are shown in brackets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

different industry (~14 pp or 41%; $p < 0.01$ for both) in comparison to unmarried males without preexisting health conditions. Regardless of marital status, females with prior health conditions are less likely to be working after the policy change, showing a reduction of approximately 9% from the sample mean; while only married females with preexisting health conditions are more likely to move to a different state (1.45 pp or 49.7%; $p < 0.05$). Taken together, these results suggest that individuals with prior health conditions are more likely to move to a new state after the policy if they are married in comparison to those without prior health issues. At the same time, the results continue to reveal heterogeneous responses for males and females: females with preexisting health conditions respond more consistently than males across both children in the household and marital status.

Table 9 presents estimates for three different age groups: 18 to 34, 35 to 49, and 50 to 64. Among males with prior health conditions, we find that the oldest age group (50 to 64) drives the decline in overall likelihood of working (-3.99 pp or 6.4%; $p < 0.05$), while the middle age group (35 to 49) drives the increase in other labor mobility measures (job tenure, new job, new state). We continue to find that females respond differently to the policy change. Among females with prior health conditions, the youngest age group (18 to 34) solely drives the reduction in the likelihood of working (-10.31 pp or 19.1%; $p < 0.01$). The other labor mobility estimates for younger females indicate reductions in labor mobility, whereas no effects are significant for females with conditions in the other two age categories, except for a reduction in job tenure.

In our analysis across education groups (Table 10), we find that males with conditions are less likely to be working after the policy change across all three education categories, although the largest decline is for males with a college degree or more (-6.13 pp or 7%; $p < 0.01$). For those with prior health conditions, males with a college degree or more are also more likely to move to a different state (4.79 pp or 184.9%; $p < 0.01$), while those with a high school degree or less are more likely to start a new job (10.14 pp or 53.1%; $p < 0.01$) and switch to a new industry (9.11 pp or 34.1%; $p < 0.01$) in comparison to those without health conditions. The results for females are somewhat similar but are more concentrated among those with a college degree or more. Females with conditions that have a

TABLE 10 The effects on employment outcomes - males and females with preexisting conditions by education groups.

	Working now	Job tenure (current or most recent job)	Started a new job in last 2 years	Switched industry in last 2 years	Moved to a different state in last 2 years	*N*
Panel A: Males						
At most HS degree	−0.0431***	−0.4756	0.1014***	0.0911***	0.0082	23,741
	[0.0064]	[0.1726]	[0.0000]	[0.0035]	[0.3428]	
Some college	−0.0365**	−0.1917	−0.0123	−0.0205	0.0157*	14,164
	[0.0486]	[0.6326]	[0.6730]	[0.4259]	[0.0587]	
College degree	−0.0613***	0.0257	0.0207	0.0539**	0.0479***	18,482
	[0.0020]	[0.9524]	[0.3258]	[0.0243]	[0.0010]	
Panel B: Females						
At most HS degree	−0.0940***	−0.0281	−0.0096	0.1070***	0.0003	27,419
	[0.0000]	[0.9457]	[0.5668]	[0.0045]	[0.9672]	
Some college	0.0160	0.5599*	−0.0567**	−0.0587*	−0.0210**	18,298
	[0.4631]	[0.0916]	[0.0281]	[0.0680]	[0.0478]	
College degree	−0.1182***	−0.8126**	−0.0211	0.0380	0.0396***	20,102
	[0.0010]	[0.0214]	[0.3744]	[0.2317]	[0.0115]	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on labor market outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap p-values are shown in brackets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

college degree or more are less likely to be working (-11.82 pp or 17.2%; $p < 0.01$), have a shorter job tenure (-0.81 years or 14.6%; $p < 0.05$), and more likely to move to a different state (3.96 pp 49.6%; $p < 0.01$) compared to females without prior health issues.[19] At the same time, females with conditions that have a high school degree or less are also less likely to be working (-9.40 pp 27.9%; $p < 0.01$) and more likely to switch industries (10.70 pp or 37.7%; $p < 0.01$) after the policy change.

Finally, as shown in Table 11, we also find that increases in male labor mobility are entirely driven by those with longstanding prior health issues (initial diagnosis more than 10 years ago). Males with more time elapsed since initial diagnoses are more likely to start a new job (8.07 pp or 34.6%; $p < 0.01$), switch industries (9.74 pp 42.4%; $p < 0.01$), and move to a different state (2.11 pp or 69.6%; $p < 0.01$). While males with more recent diagnoses are less likely to work (-8.15 pp or 11.9%; $p < 0.01$), we find decreases in labor mobility for this group across the other outcome variables. In contrast, the decline in the likelihood of working for females with conditions is entirely driven by those with more recent diagnoses (initial diagnosis within last 10 years). These results suggest that individuals with more recent diagnoses are more likely to respond along the extensive margin by no longer working, while those with longer term diagnoses are more likely to adjust within the labor market. Overall, the additional results continue to support the idea that males and females respond differently to the change in health policy.

Robustness checks

In this section, we present a variety of robustness checks to further explore the validity of our primary results in Table 3. First, we repeat the main analysis using two alternative treatment group definitions. Second, we estimate DD models using three types of propensity score matching to account for differences between the treatment and control groups. Third, we estimate two different placebo tests using data prior to 2014 and artificial policy dates to see if our results are spurious in nature. Fourth, we estimate our primary results using alternative sample years: including additional pre-treatment years in the analysis and excluding year 2015 from the analysis. Last, we explore the sensitivity of our results to the parallel trends assumption. We discuss each robustness check in greater detail below; for the sake of space, all corresponding tables are presented in the appendix.[20]

Alternative treatment groups

Our main results define the treatment group as individuals who report a prior health condition in all three of the pre-policy waves (2009, 2011, and 2013). Next, we present labor mobility estimates obtained by using two alternative treatment group definitions in Appendix Table A8. In Panel A, we loosen our initial sample restrictions and include all individuals with a preexisting health condition in 2013 (the wave before the policy change) in the treatment group. Our results are consistent with the main findings shown in Table 3. We again find increases in labor mobility among males with prior health issues across all outcome variables following the provision and a strong decline in the likelihood

[19] The fact that highly educated individuals are more likely to migrate to a new geographic location is consistent with general labor market findings (Basker, 2018; Hernández-Murillo et al., 2011; Malamud & Wozniak, 2012; Rosenbloom & Sundstrom, 2004). This is partially linked to the need for financial resources to make a geographic move, along with other indirect effects of higher education networks. These include increased awareness of employment opportunities in other places, reduced psychic cost of moving due to improved openness to new experiences, a more geographically integrated market for highly educated people, and other non-economic characteristics (such as marriage) that could impact the likelihood of migration (Malamud & Wozniak, 2012).

[20] We also show that our main results are robust to the inclusion of state fixed effects (Appendix Table A2), longitudinal sample weights (Appendix Table A3), industry fixed effects (Appendix Table A4), state unemployment rates (Appendix Table A5) and the exclusion of the five state-level policy controls captured by Z_{st} in equations 1 and 2 (Appendix Table A6, Panel A) as well as the exclusion of all time-variant controls (Appendix Table A6, Panel B). Further, Appendix Table A7 shows the effects of the policy change on each of these five state-level controls.

TABLE 11 The effects on employment outcomes - males and females with preexisting conditions by length of health condition.

	Working now	Job tenure (current or most recent job)	Started a new job in last 2 years	Switched industry in last 2 years	Moved to a different state in last 2 years	*N*
Panel A: Males						
Condition >10 years ago	0.0012	−0.7376***	0.0807***	0.0974***	0.0211***	53,692
	[0.8949]	[0.0084]	[0.0000]	[0.0000]	[0.0052]	
Condition ≤ 10 years ago	−0.0815***	0.8254***	0.0085	−0.0487***	0.0097	51,962
	[0.0000]	[0.0078]	[0.6321]	[0.0082]	[0.3651]	
Panel B: Females						
Condition >10 years ago	0.0006	−0.9078***	0.0291**	0.0013	0.0035	44,861
	[0.9942]	[0.0020]	[0.0314]	[0.9939]	[0.6315]	
Condition ≤ 10 years ago	−0.0726***	0.5241	0.0314*	−0.0068	0.0128	40,596
	[0.0062]	[0.1034]	[0.0991]	[0.8406]	[0.3103]	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on labor market outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap p-values are shown in brackets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

of currently working for females with prior health conditions. For the analysis in Panel B, both partners in the household must have a preexisting condition to be in the treatment group. Using this narrower sample restriction, our estimates continue to provide evidence for increases in labor mobility. The results in Appendix Table A8 show that our main estimates are robust to using alternative treatment indicators.

DD matching results

Next, we test whether our main DD results are robust to estimating propensity score matching DD models. Appendix Table A9 presents treatment effects obtained using three alternative matching techniques. Consistent with our main analysis, we find evidence that the preexisting conditions provision significantly increased labor mobility among individuals with prior health issues. These effects are observable for all three matching techniques for both males and females. Thus, it should be noted that our DD matching analysis also provides some statistically significant increases in labor mobility among females, most notably for job tenure and the likelihood of switching to a different industry. Overall, the findings in Appendix Table A9 provide evidence that the observed increases in labor mobility among individuals with preexisting conditions following the policy change are not driven by inherent differences across the treatment and control groups.

Placebo tests

Next, we estimate two different placebo tests using data prior to 2014 and artificial policy dates (Appendix Table A10). Panel A uses data from 2003 to 2009 (artificial policy change in 2007), while Panel B examines the period 2007 to 2013 (artificial policy change in 2011). With the exception of one estimate, out of ten, being statistically significant for each time period, we find no evidence for differential impacts on labor mobility across individuals in the treatment and control groups following the artificial policy changes for both males and females. In addition to further illustrating that our main results are tied to the 2014 change in policy, the results in Appendix Table A10 also provide additional evidence for the presence of parallel trends during the pre-treatment period.

Alternative sample years

Our preferred specifications use data from years 2009 to 2019, which includes three pre-policy waves and three post-policy waves. Appendix Table A11 presents estimates obtained using additional pre-treatment years in the analysis. Panel A adds the 2007 survey and Panel B adds both the 2005 and 2007 surveys to the analysis. The estimates for males are very consistent with the corresponding main results in Table 3, suggesting that the impact on male labor mobility is robust to alternative sample lengths. For females, we find more evidence of increased labor mobility using this longer sample period compared to our main analysis. In particular, we find a significant change in job tenure and geographic mobility, for which we initially found no effects among females in Table 3. Appendix Figures A1 and A2 show event study estimates for the period 2007 to 2019 for males and females, respectively. While the added pre-policy wave adds more noise to some outcomes (job tenure for males, starting a new job for females), the results are overall consistent with the main event study results shown in Figures 1 and 2.[21]

[21] The 2009 to 2019 period remains our preferred sample for two reasons. First, it avoids including the onset of the Great Recession in 2008. This is important in our context since individuals with chronic health conditions were adversely affected by the recession (Reeves et al., 2014). Second, given that we follow the same individuals over time, sample attrition rates become larger the longer we go back in time.

Last, since the PSID waves are available biannually and three of our outcome variables (new job, industry switch, and moving to a new state) are based on 2-year comparisons between the current and previous wave, there is an overlap in the pre- and post-policy period for these outcomes in 2015. In other words, these outcomes in 2015 (post-policy) are relative to 2013 (pre-policy). Therefore, Appendix Table A12 shows the primary results when data for year 2015 is excluded from the analysis. The effects remain consistent when excluding 2015 from the analysis, which removes potential concerns that this overlap is driving our findings.

Parallel trends sensitivity

The event study graphs that use the longer sample period (2007 to 2019, Appendix Figures A1 and A2) provide suggestive evidence for possible violations of the parallel trends assumption. Therefore, we follow Rambachan and Roth (2023) and conduct a sensitivity analysis of our main DD estimates to empirically assess possible parallel trends violations. While our main DD analysis requires that parallel trends hold exactly, the authors introduce a robustness check that imposes restrictions on how different the post-treatment violations of parallel trends can be from the pre-treatment differences in trends. Thus, this sensitivity check allows us to evaluate the validity of our estimates based on the observed worst-case violation in the pre-treatment period. Appendix Figures A3 and A4 show the results from this robustness test for our main analyses for males and females, respectively. The results show that the "breakdown value" (Rambachan & Roth, 2023) for significant effects is between 1 and 1.5. This suggests that the significant estimates are robust to possible violations of parallel trends between 1 to 1.5 times the maximum violation in the pre-treatment period.

Mechanisms

Last, now that we have established the significant improvements in labor mobility for individuals with preexisting health conditions, particularly males, after the policy, we examine additional outcomes and potential mechanisms to explain these results. We look at both the role of physical and mental well-being, health insurance coverage, and job lock as potential connections between the ACA preexisting conditions provision and changes in labor mobility.

Physical and mental well-being

The results for physical and mental well-being are presented in Table 12.[22] Our preferred measure of physical health is an indicator that equals one if respondents are limited in the amount and/or type of work they can do due to health problems (column 1), as this variable offers the most direct linkage between an individual's health and their labor abilities. For both males and females, we find that the policy change reduced the likelihood of individuals with preexisting health conditions reporting that their health issues impact the amount or type of work they can perform. The effects are statistically significant ($p < 0.01$) and correspond to declines of 11% and 7.7% for males and females, respectively, compared to the baseline mean. We also find that treated individuals are less likely to report fair or poor health status (column 2) and moderate mental distress (column 3).[23] While physical health effects are larger for males, mental effects are larger for females.[24]

[22] Summary statistics for measures of physical and mental well-being are included in Appendix Table A13.

[23] Mental distress is captured by the Kessler Psychological Distress Scale (K6).

[24] This is consistent with findings by Hampton and Lenhart (2022a).

TABLE 12 The effects on physical and mental health outcomes - males and females with preexisting conditions.

	Amount/type of work limited by health	Fair/poor health status	Moderate mental distress	*N*
Males	−0.0323***	−0.0667***	−0.0230**	56,387
	[0.0010]	[0.0000]	[0.0320]	
Sample Mean	0.2934	0.3318	0.2679	
Females	−0.0303***	−0.0404***	−0.0318***	65,819
	[0.0040]	[0.0020]	[0.0030]	
Sample Mean	0.3927	0.3917	0.3884	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on physical and mental health outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap p-values are shown in brackets. $^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Overall, the findings in Table 12 provide evidence that the ACA preexisting condition provision improved both the physical and mental well-being of individuals targeted by the policy change. While these health improvements can be considered additional outcomes of the policy, they could to some extent explain the increases in labor mobility found in our main analysis, particularly when coupled with treated individuals being less likely to report that their health impacts the amount or type of work they can perform. For example, it is plausible that the policy change allowed individuals with preexisting conditions better access to health care and insurance, which improved their mental and physical well-being. These health improvements likely increased their productivity and ability to perform various work duties, reducing the likelihood that their health impacts the amount or type of work. With fewer work duty limitations because of their health, individuals with prior health conditions may be better able to make changes in their labor market behavior, such as taking a new job or moving to a new state.

Health insurance coverage

A natural extension of Table 12 is to examine the potential effects of the policy on health insurance coverage. For this purpose, we use data from the IPUMS CPS, which provides more detailed information on health insurance coverage in comparison to the PSID.[25] Given that the data does not have the same information on health conditions as the PSID, our treatment indicator for this analysis is whether individuals report fair or poor health.[26] Table 13 shows DD estimates for the effects of the policy change on the likelihood of having any insurance coverage as well as on several types of insurance coverage. We find an increase in the likelihood of having insurance of 3.58 and 3.65 pp (both 4.2%; both $p < 0.01$) for males and females with fair or poor health, respectively. The estimates for the other insurance outcomes indicate that the policy decreased the likelihood of treated individuals being the policyholder of an ESI plan, while increasing coverage through public insurance plans. These results suggest that the ACA did in fact increase access to health care for people with prior health

[25] The health insurance data in the IPUMS CPS has been used by health policy researchers for several decades (Davern et al., 2009) and is a critical data source for federal and state policy making and health policy research (Blewett et al., 2004). While the CPS has better information on health insurance, it does not include the level of detail on individual health status. See footnotes 7 and 27 for more details.

[26] While fair or poor health status is only a proxy for being affected by the policy change, our PSID sample provides validity to the use of this proxy. In our main PSID sample, 37.0% of the those belonging to the treatment group (with preexisting condition) report either fair or poor health compared to only 6.6% of those in the control group (without preexisting condition).

TABLE 13 The effects on health insurance source - males and females with preexisting conditions (CPS).

	Any insurance	Policyholder of ESI	Private coverage (policyholder)	Medicaid	Any public coverage	*N*
Males	0.0358***	−0.0239***	0.0064	0.0247***	0.0432***	1,167,594
	[0.0000]	[0.0000]	[0.1712]	[0.0000]	[0.0000]	
Sample Mean	0.8577	0.2298	0.3503	0.5301	0.5279	
Females	0.0365***	−0.0262***	0.0074	0.0235***	0.0451***	1,197,710
	[0.0000]	[0.0000]	[0.1358]	[0.0000]	[0.0000]	
Sample Mean	0.8718	0.1895	0.5978	0.3945	0.5395	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on health insurance outcomes using the IPUMS CPS data. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap p-values are shown in brackets. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

issues, which is consistent with previous work on the provision (ASPE, 2017; Collins et al., 2017; Glied & Jackson, 2017).[27]

Job lock

Last, given the reduction in ESI coverage after the policy change, we analyze whether improvements in labor mobility for individuals with prior health conditions also translate to reductions in job lock. As Section 2 discussed, there was a notable lack of financially feasible private insurance options for individuals with preexisting conditions prior to the ACA. Therefore, it is possible that individuals with prior health conditions were even more vulnerable to job lock before the ACA if a labor market change meant they risked losing their ESI. For this analysis, we estimate a difference-in-difference-in-differences (DDD) model using ESI coverage in 2013 as the third difference. In other words, the DDD estimate identifies a change in labor market behavior after the policy change for individuals with prior health conditions who had ESI in 2013.

Table 14 shows the estimates for the DDD model using ESI coverage in 2013 as an additional comparison group for males and females. Both males and females with preexisting conditions who had ESI in 2013 are significantly less likely to work after the policy, a 4.57 pp decline for males ($p < 0.05$, 6.6%) and a 6.75 pp decline for females ($p < 0.01$, 12.6%). This suggests that with viable non-ESI insurance options (policies that are affordable, cannot exclude coverage for a specific health condition, and are not tied to employment), individuals with preexisting conditions are less likely to be working now. In other words, this supports the idea that the policy change also reduced job lock along the extensive margin. The remaining results for other labor mobility changes are either insignificant or indicate declining labor mobility. Thus, we only find evidence that the policy reduced job lock for individuals with preexisting conditions along the extensive margin. For those who remained employed, our results do not suggest significant declines in ESI-related job lock.

[27] In Appendix Table A14, we show results for changes in health insurance coverage using our main data set, the PSID, which contains less detailed health insurance information than the CPS. Similar to the IPUMS CPS analysis, we find a reduction in ESI coverage for both males and females and an increase in public coverage for males following the policy change. We also find an increase in the likelihood of having any coverage among males, but the estimate is not statistically significant. For females, the effects for having any coverage or public coverage are small and imprecisely estimated.

TABLE 14 The effects on employment outcomes - DDD analysis (additional comparison group - ESI in 2013).

	Working now	Job tenure (current or most recent job)	Started a new job in last 2 years	Switched industry in last 2 years	Moved to a different state in last 2 years	*N*
Males	−0.0457**	0.6968	−0.0653***	−0.0883***	−0.0004	56,387
	[0.0120]	[0.1081]	[0.0060]	[0.0030]	[0.9670]	
Females	−0.0675***	0.1883	−0.0078	0.0083	0.0069	65,819
	[0.0020]	[0.6316]	[0.7598]	[0.7968]	[0.4354]	

Notes: The results provide DD treatment effects obtained from estimating the effects of the preexisting conditions provision on labor market outcomes. All specifications control for age, years of education, the number of children living in the household, other ACA provisions as well as year and individual fixed effects. All specifications use the wild cluster bootstrap procedure with 1,000 replications to estimate *p*-values, as proposed by Cameron et al. (2008). Wild cluster bootstrap *p*-values are shown in brackets. $^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

CONCLUSION

The ACA is the most significant health policy change this century. The policy includes several important provisions intended to increase accessibility to health insurance. For example, the preexisting conditions provision ensures that insurance companies can no longer deny coverage, charge higher premiums, or exclude coverage for certain conditions to individuals with prior health conditions. We focus on this important, but understudied, provision of the ACA to determine whether individuals with preexisting conditions experienced enhanced labor mobility after the policy's implementation.

Our results provide strong evidence that the ACA preexisting conditions provision significantly improved both occupational and geographic labor mobility for males with prior health issues. In comparison to the pre-policy period, males with prior health issues are 4% less likely to be working, 25% more likely to have started a new job or switched to employment in a different industry (in the last 2 years), and almost 70% more likely to have moved to a different state (in the last 2 years). In contrast, the policy primarily impacted females along the extensive margin. Females with prior health issues are 9% less likely to be working after the policy change. Thus, we observe different labor market responses to the policy change across males and females.

We supplement our primary analysis by further targeting the ACA provision and exploring the heterogeneous impacts of the policy change across household and demographic characteristics. We show that individuals with conditions living in states that did not expand Medicaid programs under the ACA and those with family incomes above 400% of the FPL who are not eligible for marketplace subsidies or tax-credits still experience labor mobility improvements after the policy. Therefore, Medicaid expansion, Marketplace subsidies, and Marketplace tax-credits, three ACA provisions that were also implemented in 2014, are not the primary driver behind our main results.

Across demographic and household characteristics, we continue to see that males and females respond differently to the policy change. For example, labor mobility changes for males with conditions are driven by those age 35 to 64, while those for females with conditions are driven by those ages 18 to 34. Further, females are less likely to be working regardless of marital status or presence of children in the household, while only married males and those without children in the household are less likely to be working after the policy. The results by education suggest that lower educated males (high school degree at most) experience the largest occupational mobility changes - starting a new job and switching to a different industry. The education results also reveal a few similarities for males and females: those with at least a college degree are most likely to no longer be working after the policy change and to move to a different state.

Last, we analyze additional outcomes and potential mechanisms through which the policy impacted labor mobility. After the policy change, individuals with preexisting conditions self-reported better mental and physical well-being. These are likely additional outcomes of the policy, as individuals had better access to health care and quality insurance. We use a supplemental data source to see whether the policy did in fact increase health insurance coverage rates for treated individuals. For both men and women with conditions, we find an increase in the likelihood of having any insurance coverage of 4.2%. Individuals with prior health conditions were also less likely to self-report that their health impacted the amount or type of work they can perform after the policy, which provides a direct connection between the individual's health and labor abilities. Thus, given the mental and physical well-being improvements and increased access to insurance after the policy, it is likely that this expanded the ability for individuals with chronic health issues to complete more work tasks, increasing their options in the labor market.

While one might consider the health insurance results a first-stage effect to the second stage effects on labor mobility (which were much larger), there are a few reasons this should be done with caution. First, our health insurance analysis uses a different data set and different health indicators for selection into the treatment group. Second, the data only accounts for whether an individual has health insurance, so we cannot identify changes in the quality of that insurance coverage. The quality of insurance coverage is important in our context since it was common practice before the ACA provision for insurance companies to not only deny coverage, but also to charge higher premiums for coverage or exclude specific conditions from coverage. Some individuals with prior health issues likely had health insurance before the ACA but were able to obtain higher quality insurance after the policy change, which we cannot identify in the data. These reasons likely explain why the health insurance results (4.2% increase) are much smaller in comparison to the labor mobility results (e.g., 25% increase for males with conditions starting a new job or switching industries).

The insurance results also suggest a decreased reliance on ESI, so we further explore whether our results translate to a reduction in job lock. Individuals with prior health conditions that had ESI in 2013 are less likely to be working after the policy change. Although this supports the notion of reduced job lock along the extensive margin, we do not find any evidence of changes in job lock across the other labor mobility measures. Despite the decreased reliance on ESI and broad labor mobility improvements for individuals with prior health issues, particularly males, we do not find overwhelming evidence of reduced job lock.

Prior work by Chatterji et al. (2016) found that the ACA increased voluntary separation among married fathers of children with preexisting conditions. We contribute to the literature on the labor market impacts of the ACA by studying the labor mobility among adults themselves with prior health conditions. Interestingly, our results are similar to those of Chatterji et al. (2016) as we find broader labor mobility improvements for males with conditions. Specifically, Chatterji et al. (2016) found a 35% increase in the likelihood that married fathers voluntarily leave an employer, while we find a 25% increase in starting a new job or switching industries among males. While our results measure all job changes and Chatterji et al.'s (2016) results are specific to voluntary job changes, it is reassuring that our main findings are comparable in magnitude to earlier work. It is important to note that due to the inability to directly identify whether individuals have been denied, charged a higher premium for, or had a condition excluded from insurance coverage prior to the ACA, both our results and those of Chatterji et al. (2016) are intent-to-treat (ITT) effects. We would expect any treatment of treated (ATT) effects to be larger in magnitude. It would be helpful for future research to collect data that allows for the examination of the labor market response among those individuals with preexisting conditions that were denied coverage prior to the ACA policy to better evaluate ATT effects.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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