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Medicaid Benefit Generosity and Labor Market Outcomes: Evidence from Medicaid Adult Vision Benefits*

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Abstract

Previous work suggests that Medicaid eligibility expansions may lead to declines in labor market activity. This paper explores the related, but novel question of whether variation in Medicaid benefit generosity alters employment outcomes. We consider adult vision benefits as a case study. Our findings suggest that vision benefits have a net positive effect on intensive margin measures including hours worked and occupational skill requirements, but no significant effect on the likelihood of being employed. These results indicate that Medicaid's effect on labor market activity is sensitive to the set of covered services.

Keywords: Health insurance, Medicaid, Employment, Vision care. **JEL codes:** I13, I18, J22, H75

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1. Introduction

The number of non-elderly adults enrolled in Medicaid has increased substantially over the last few decades, reaching 27 million in 2017 (Sommers & Grabowski 2017). As the number of working-age adults has increased, the effects the program has on labor market activity have grown in importance. Standard economic theory suggests that means-tested benefits will discourage employment by reducing the returns to work and imposing an implicit tax on earnings. On balance, previous research suggests small-to-moderate negative effects of program eligibility on any employment, hours worked, and earnings (a review of recent studies is available in Garrett and Kaestner (2014)).

In this paper, we examine a related, but novel question concerning Medicaid's effect on employment. We consider whether the benefit package a state offers Medicaid enrollees influences labor market activity, using adult vision benefits as a case study. Vision screening and corrective lenses are meaningful services to consider given that half of all adults have a clinically important refractive error (Vitale et al. 2008). Although all states must offer vision screening and eyeglasses to children, states have the option of covering these services for adults (Kaiser Family Foundation 2014a). Not all states cover vision benefits and individual states have added and dropped these benefits over time. Vision benefits are likely to be valuable to beneficiaries given that the out-of-pocket cost for an optometrist visit and corrective lenses averages $382 for an uninsured person, approximately 37% of monthly income for a single adult living at the federal poverty line (Medical Expenditure Panel Survey, 2017). Previous work has found that Medicaid adult vision coverage increases the use of vision services and improves the rate of appropriately corrected distance vision by up to 10 percentage points (Lipton & Decker 2015; Lipton & Decker 2016). Using data from the Current Population Survey (CPS), we build on that work by examining economic outcomes that could plausibly respond to increased access to vision services.

The effect of vision coverage on employment outcomes among adult Medicaid enrollees is theoretically ambiguous. Access to vision services could improve labor market prospects all else equal, both on the *extensive* employment margin and on the *intensive* margin (e.g., hours worked and occupation type). For example, correcting a refractive error could increase the number and type of jobs a beneficiary is qualified for, it could reduce barriers to transportation that limit the amount or type of work, or it could reduce the disutility of work by relieving the discomfort and strain that often accompanies uncorrected visual impairment. While there is little research on the causal effects of vision correction on human capital and economic outcomes, correlational studies have found that vision difficulty is associated with significant functional impairments that could disrupt employment (Swanson & McGwin 2004; Varma et al. 2006). Further, nearly 90% of visual impairments can be eliminated with corrective lenses (Vitale et al. 2006).

On the contrary, Medicaid adult vision benefits could discourage work activity by increasing the value of the program and its associated work disincentives. The addition of vision coverage could reduce reliance on an employer for vision benefits. Further, reduced out-of-pocket costs for vision services could, in theory, have an income effect.

Our preferred empirical estimates of the effect of Medicaid adult vision coverage on employment outcomes come from a triple difference model. Our approach compares Medicaid enrollees to a control group of low-income adults who are not enrolled (first difference), in states with and without Medicaid adult vision coverage (second difference), and before and after changes in vision coverage policy (third difference). Since the control group should not be directly affected by Medicaid benefit generosity, the triple difference approach purges our estimates of unobserved time-varying state-level omitted variables that affect Medicaid enrollees and the control group similarly. An important assumption of this strategy is that vision benefits themselves do not induce enrollment in Medicaid. Otherwise, our results could be biased by compositional effects. We test that assumption directly and find that offering vision coverage has no effect on Medicaid participation. This finding increases our confidence in the empirical design.

Our results suggest that vision benefits have a net positive effect on labor market activity. While we do not find evidence of a significant effect on the extensive employment margin (employment in at least one week of the calendar year), we do find that Medicaid adult vision coverage is associated with a 3.6 percentage point increase in the likelihood of working full time compared to working part time or not working, for Medicaid enrollees relative to the control group. Among the employed, vision coverage is associated with a 6.1 percent increase in usual hours worked per week (or about two additional weekly hours), a 5.6 percentage point increase in the likelihood of working full time compared to part time, and a shift toward occupations that require higher levels of skill. All of these results are completely concentrated among Medicaid enrollees. The associations between Medicaid adult vision coverage and employment outcomes among the control group are in general small, non-significant, and often the opposite sign. We also examined whether the employment effects of vision benefits vary by subgroup. Our findings suggest that effects tend to be concentrated among women, but estimates do not vary substantially by age (under/over 35) or marital status.

Our results are robust to a number of sensitivity tests. For example, our conclusions are robust to direct controls for other important sources of Medicaid benefit generosity that could be correlated with vision benefits, namely per-person spending and adult dental benefits. Further, we conduct placebo checks, explore alternative control groups, conduct intent-to-treat analyses, estimate difference-in-differences analyses with no within-state control group, relax our preferred sample inclusion requirements, and compare weighted and unweighted models. The outcome of these tests suggests that our main results are unlikely to be explained by competing hypotheses.

This paper contributes to several different strands of literature. First, we produce some of the first plausibly causal evidence on the effect of vision benefits (regardless of source) on labor market activity. Second, our results suggest that Medicaid's effect on employment is sensitive to the set of services that the program covers. Finally, we complement a growing set of papers that suggest that Medicaid acts as an investment in health and economic well-being (Boudreaux, Golberstein, & McAlpine 2016; Brown, Kowalski, & Lurie, 2015; Cohodes et al. 2015; Goodman-Bacon 2016; Lipton et al. 2016; Miller & Wherry 2015; Wherry et al. 2015). Previous papers have shown that Medicaid coverage in childhood can improve outcomes over the long term. In this paper, we show that Medicaid coverage for adults can have shorter run economic payoffs. In this regard, our paper complements other studies, such as those on child care subsidies and the Earned Income Tax Credit, that show that public transfer programs can increase labor market activity under the right conditions (Herbst 2009; Grogger 2003). Such findings may have important implications for designing means-tested benefit programs in ways that enable fuller labor force activity.

The outline for the paper is as follows. The rest of Section 1 provides additional background on Medicaid and the literatures to which we contribute. Section 2 describes our data and methods. Section 3 presents results, and Section 4 concludes.

1.1. Background

Medicaid is a state-federal partnership that provides means-tested health insurance coverage to income eligible recipients in the U.S. Historically, the program was restricted to single-parent families receiving cash-welfare under the Aid to Families with Dependent Children Program (AFDC), the low-income elderly, and low-income people with a disability. Beginning in the 1980's, the program was expanded to new categories of beneficiaries including low-income parents of dependent children and ultimately to childless non-elderly adults as part of the Affordable Care Act (ACA) (Buchmueller, Ham,

& Shore-Sheppard 2015). While states must extend Medicaid eligibility to parents and children who would have been eligible under the AFDC requirements of July 1996 (i.e., the final year of the AFDC program), covering parents above these thresholds and childless adults at any income level remains optional. Prior to implementation of the ACA's Medicaid expansion, many states opted to cover parents at income levels above those required by law, but childless adults were not eligible for Medicaid regardless of their income in many states. By 2005 (approximately the mid-point of our study period), the median income eligibility limit for parents was 67% of poverty with substantial heterogeneity across states (Kaiser Family Foundation 2014b).

While states are required to cover a set of essential services for all adult beneficiaries, other services are covered at the states' option. These optional services constitute approximately 30% of program spending (Kaiser Commission on Medicaid and the Uninsured 2005). While some optional services, such as prescription drugs, are covered by all states, other services such as dental and vision are only covered by a subset of states.

In work using similar methods to ours and based on data from the National Health Interview Survey, Lipton and Decker (2015) found that Medicaid coverage for vision screening and corrective eyeglasses increased visits to the eye doctor by 17.5%. This estimate is smaller than the effect implied by the Rand Health Insurance Experiment, which found that free care relative to cost-sharing increased the likelihood of visiting an eye doctor by 32% for poor adults (Lurie et al., 1989; Manning et al. 1987). Lipton and Decker (2015) also found significant reductions in self-reported vision impairment and vision-related functional limitations. A subsequent paper found that providing Medicaid adult vision benefits led to improvements in auto-refractor measured distance visual acuity using data from the National Health Examination and Nutrition Survey (Lipton & Decker 2016). The authors estimated an improvement of up to 10 percentage points in appropriately corrected distance vision, providing strong evidence of a first stage effect.

The finding that Medicaid adult vision benefits improve self-reported vision-related function and measured distance visual acuity raises the possibility that vision benefits might reduce work limitations that constrain labor supply. This effect could be particularly salient on the intensive margin given that Medicaid enrollees who do not work at all often have substantial disabilities or have familial responsibilities that completely prohibit labor force participation (Kaiser Family Foundation, 2017a). Unfortunately, there is little previous evidence on the direct role that refractive error (and its correction) plays in economic outcomes. A small randomized trial conducted by Daum et al. (2004) found that experimentally manipulated astigmatic refractive error delayed time to completion on a set of standard computer tasks. Glewwe, West, and Lee (2014) used a randomized trial in Title I elementary schools in Florida to study the effect of providing free eye exams and eyeglasses. They find that providing both services improves 5th grade reading and math scores. This evidence is complementary to results from a large randomized control trial in China, though the results of this latter study suggested particularly large returns in the form of higher test scores equivalent to up to 0.9 additional years of schooling (Glewwe et al. 2016). Ours is one of the first studies, to our knowledge, to contribute plausibly causal evidence on the effect of vision coverage on labor supply.

The majority of the literature examining Medicaid's effects on the employment of non-disabled adults has focused on the role of eligibility rules. In theory, income-based eligibility rules create a disincentive for workers to increase hours and for non-workers to join the labor force because earnings above the threshold cause a loss of Medicaid benefits, whose cash-value can be substantial (Garrett & Kaestner 2014). The empirical literature on this topic has come to mixed conclusions. Early work found that those estimated to place a high value on Medicaid were less likely to leave the program and become employed (Moffitt & Wolfe, 1992). Yelowitz (1995) investigated the de-linking of cash-welfare and Medicaid for children that occurred in the early 1990's on the labor supply of single-mothers with dependent children and found a small, but significant decline in employment. Later work by Ham and

Shore-Sheppard (2005) and Meyer and Rosenbaum (2001) which used a slightly different parameterization failed to find any effect when studying the same expansions. Decker and Selck (2012) and Strumpf (2011) found no effect of the introduction of Medicaid in the late 1960's on the labor supply decisions of single-mothers while Dave et al. (2015) found relatively substantial reductions in employment as the result of expansions to pregnant women that occurred in the mid-1980's.

Papers that have studied recent expansions to non-elderly and non-disabled adults are perhaps the most applicable to our work. The Oregon Health Insurance Experiment found no significant change in employment as the result of randomly assigning Medicaid eligibility to a group of low-income childless adults (Baicker, Finkelstein, & Taubman 2014). By contrast, analysis of quasi-experimental data from Wisconsin (Dague, DeLeire, & Leninger 2016) and Tennessee (Garthwaite, Gross, & Notowidigdo 2014) suggest that changes to Medicaid eligibility can have relatively substantial employment effects among adults. Dague et al. (2016), using comprehensive administrative data, found that Wisconsin's expansion to childless adults was associated with a two to ten percentage point decline in employment, depending on the model used. Garthwaite et al.'s (2014) CPS-based study of a large Medicaid disenrollment event in Tennessee suggested substantial employment effects (25%) that are somewhat unique in the literature. Other work has shown that the employment effects of recent eligibility expansions differ by subgroup. For example, Hamersma and Kim (2009) found that parental eligibility expansions reduced job-lock for unmarried women, but not for married women or for men.

On balance, the existing literature suggests small-to-moderate negative effects of historical Medicaid eligibility expansions on employment outcomes, with results varying across time period and population. Evaluations of the most recent expansions under the Affordable Care Act (ACA) have consistently failed to find evidence that the ACA Medicaid expansion has decreased labor market activity (Duggan, Goda, & Jackson 2017; Gooptu et al. 2016; Kaestner et al. 2017; Leung & Mas 2016; Moriya, Selden, & Simon 2016). The current study has important implications for the literature on

Medicaid and labor market outcomes. Rather than focusing on the effects of changes to eligibility rules, we examine whether there are non-eligibility dimensions of public health insurance that enable or depress labor activity.

2. Data and Methods

2.1. The Current Population Survey

The Current Population Survey is a monthly household survey that serves as the main data source for U.S. labor force statistics. We used the Annual Social and Economic Supplement (ASEC) to the survey, which is conducted in the spring of each year and contains expanded labor force information in addition to questions about family income and insurance status. Our analysis used the 2002-2013 survey years. We did not include 2014 and 2015 because the survey underwent a major redesign in 2014 that affected how insurance coverage and income were reported (Medalia et al. 2014).

Outcomes of interest included full-year employment status (employment in one or more weeks versus no employment in any week)[1], full-time status (i.e., at least 35 hours per week), part-time status (i.e., fewer than 35 hours per week), usual hours worked, and hourly wages. We also examine changes in occupation type using an index of occupational skill from Autor (2013) that is defined as the mean log occupational wage for non-farming three-digit occupation categories. We consider the joint probability of being employed and working full time (respectively part time) for the full sample as well as the likelihood of working full time (vs. part time) among those who worked at least one week in the past year. Usual hours worked, hourly wages, and occupational skill are analyzed only for employed individuals. We constructed hourly wages by dividing total annual earned income, which was deflated using the consumer price index, by the product of usual hours worked and number of weeks worked in

[1] Respondents were instructed to count weeks in which they worked for even a few hours.

the previous year. Observations where the nominal hourly wage was below the federal minimum for tipped employees ($2.13 during our entire study period) were excluded from our analysis of wages given previous literature suggesting a high degree of measurement error for incomes at the bottom of the distribution (Meyer & Sullivan 2003).[2]

The reference year for the income and health insurance questions as well as for all of the outcomes used in our analysis is the previous calendar year (i.e., 2001-2012).

2.2. State Coverage Policies

As described in Lipton and Decker (2015) and Lipton and Decker (2016), we used annual Kaiser Family Foundation (KFF) reports based on a 50-state survey combined with vision coverage information available on the KFF website to determine Medicaid adult vision coverage policies for each state and year (Kaiser Family Foundation 2014a). We used coverage policies applicable to non-elderly adult enrollees who were not pregnant or disabled. While benefit coverage policies are often consistent across eligibility categories, benefits can differ for adults eligible due to pregnancy (typically benefits are more generous) or disability. Further, states may provide a different benefit package to adults eligible through an 1115 waiver program. In instances where most low-income adults were included in the waiver population, we used coverage policies applicable to that group. Except for states with no Medicaid fee-for-service (FFS) component (e.g., Tennessee), our vision coverage policies represent those applicable to FFS enrollees.[3] We used exact dates of policy changes whenever possible, and

[2] We include these low wage workers in outcomes whose measurement is not dependent on earnings in order to maximize sample size. However, excluding them has no effect on the results of other outcomes.

[3] Managed care plans may choose to provide benefits that fee-for-service enrollees do not receive such as eye exams and eyeglasses. However, we chose to use FFS policies in all states to be consistent. When

otherwise assumed that the change occurred at the beginning or mid-point of the appropriate state fiscal year, depending on when the change was reported. To supplement the information available from KFF, we searched state Medicaid websites and news articles and contacted state health departments to resolve discrepancies.

We classified state coverage policies as coverage of a preventive eye exam and eyeglasses for correction of refractive error compared to coverage of an exam only or no coverage for either service because eyeglasses constitute the majority of the costs of refraction (Vitale et al. 2006). Most states that provide coverage of exams also cover eyeglasses, with only a small number of states covering an exam only and no states covering eyeglasses, but not exams during our period of analysis. We defined a binary coverage variable equal to one for respondents residing in states that offered coverage of both an exam and eyeglasses for at least six months of the reference calendar year and zero otherwise. Because we expected that gaining or losing vision coverage would first affect use of eye care with any potential impacts on labor market decisions occurring with a lag, our main analysis used a version of this coverage variable lagged by one year. (For results using concurrent coverage, Appendix Table 3.)

This coverage indicator provides an estimate of the effects of Medicaid adult vision coverage, averaged across programs with different features. For example, states that cover exams and eyeglasses may differ in how often enrollees can receive new eyeglasses, whether a minimum diopter correction is required, and whether coverage is first dollar or there is a copayment or dispensing fee, among other aspects of coverage generosity (Kaiser Family Foundation 2014a). Though information is not available in all years, data collected by KFF suggest that the majority of states with an adult vision benefit cover exams and eyeglasses replacement every one or two years, with a handful of states covering eyeglasses

comparing FFS vision coverage policies to those for the main managed care provider in each state in 2012, we found that coverage was consistent in all but two cases.

replacement every three to five years.[4] Most states required a minimum diopter correction to cover new eyeglasses, and many states charged a small copayment or dispensing fee, typically between $1 and $3, for exams and eyeglasses.

While states both added and dropped vision coverage over our study period, more states dropped than added coverage. In particular, 34 states provided coverage according to our definition (coverage of both an exam and glasses) in 2001 compared to 26 states in 2012. Between 2001 and 2012, 14 states changed vision coverage policy. Figure 1 provides a detailed timeline of these changes. Because of our definition of coverage, which requires that a state cover exams and eyeglasses for at least six months of the year, and the fact that we used lagged vision coverage policies, 10 states contributed to identification of the effects of vision coverage in our main analysis (i.e., California, Florida, Massachusetts, Michigan, Missouri, Nevada, New Mexico, Oregon, Texas, and Utah). These 10 states represented 45% of adult Medicaid beneficiaries in 2014 (Kaiser Family Foundation 2017b).

Figure 2 shows the percentage of Medicaid enrollees with vision coverage in each year of our study period, and demonstrates that coverage declined over time, though not monotonically. About 76 percent of enrollees had coverage in 2001, according to our definition. This figure declined by about ten percentage points between 2001 and 2005, increased between 2005 and 2008, and then declined dramatically after 2009. By 2012, only about 50 percent of enrollees had vision coverage. While many states changed their vision coverage policies prior to 2008, including some large states, the most substantial change in the percentage of enrollees with vision coverage coincided with the Great Recession. This graph demonstrates the likely sensitivity of optional Medicaid benefits to macro-

[4] Maine covered only one pair of eyeglasses per lifetime, which we considered as not providing coverage.

economic conditions, an issue we address in a few ways, including (but not limited to) directly controlling for local economic conditions in our regression models.

2.3. Empirical Approach

We first conduct an exploratory analysis of whether a state's decision to offer vision coverage has a direct impact on enrollment in Medicaid among low-income adults. This parameter is of interest in isolation, however, finding an effect would have cast doubt on the analytical strategy we use to answer our main research question. As described in more detail below, our main research question is addressed using a triple difference (DDD) approach that relies on Medicaid status to identify the treated sample. Our results could be biased if enrollment in Medicaid is systematically correlated with state vision coverage policies. We might observe a correlation for a few reasons. More generous coverage could induce higher participation in Medicaid among eligible adults. On the contrary, vision benefits could decrease Medicaid participation if they enable increased earnings or switches to jobs with coverage benefits. Finally, it is also possible that enrollment could change at the same time as changes to vision coverage policies for other reasons (i.e., if eligibility changes occur around the same time as vision coverage policy changes). The main concern in terms of estimate bias is that the marginal person that enrolls due to a change in vision coverage policy could have a different propensity to be employed or to work full time compared to the average enrollee.

While separating the effects of vision coverage from compositional changes would be difficult, we conduct the more direct test of whether vision coverage policies are correlated with the likelihood that a low-income adult participates in Medicaid using a difference-in-differences design. Our approach accounts for time invariant state-level characteristics that could be correlated with both vision coverage policies and Medicaid enrollment and national trends in enrollment. [5] We estimate models with and without controls for a set of important time varying state-level characteristics and state-specific linear time trends. The most comprehensive regression takes the following form:

(1) $\text{Medicaid}_{ist} = \beta_1 \text{Vision}_{s,t-1} + \beta_2 \text{X}_{ist} + \beta_3 Z_{s,t-1} + \tau_t + \gamma_s + t \times \gamma_s + \varepsilon_{ist}$

where Medicaid_{ist} is a binary variable indicating that individual *i* residing in state *s* during year *t* is enrolled in Medicaid at some time during the calendar year, $\text{Vision}_{s,t-1}$ is equal to one if state *s* covered eye exams and glasses for at least six months of year *t-1*, X_{ist} is a vector of demographic characteristics including age, race/ethnicity, marital status, sex, education, and citizenship status, τ_t is a set of year fixed effects, γ_s is a set of state fixed effects, and $t \times \gamma_s$ represents linear state-specific trends. Finally, $Z_{s,t-1}$ is a set of state-year variables including the poverty rate, unemployment rate, the number of primary care physicians per 10,000 population, the Medicaid managed care penetration rate, the Medicaid eligibility threshold for working parents, and an indicator for whether a state had an earnings disregard for parental eligibility. These variables incorporate a one year lag from the reference calendar year, similar to the Medicaid adult vision coverage indicator, since the main purpose of including them is to account for changes to state-level factors that could be coincident with changes to vision coverage policies. The subscript *t* refers to the reference calendar year (rather than the survey year). All estimates are weighted to produce nationally representative estimates using survey weights available from the Census, and errors are clustered at the state level to account for serial correlation in the policy variable

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[5] Significant changes to the composition of the Medicaid sample that are concurrent with changes to vision benefits would be a potential concern regardless of the source, and our analysis should capture such changes. However, it should be noted that while this is perhaps the most appropriate test as it relates to the validity of our main analysis, it is more exploratory in assessing the relationship between vision benefits and participation in Medicaid.

(Bertrand et al. 2004). Given the clusters are moderate in number (51), this approach is unlikely to over-reject the null (Cameron & Miller 2015).

After investigating whether state vision coverage policies are correlated with enrollment in Medicaid, we proceed with our analysis of the effect of vision benefits on employment outcomes. Our main results come from a triple difference (DDD) model that estimates effects for a treatment group of adults enrolled in Medicaid at some time during the reference year relative to a low-income control group of adults who were not enrolled in Medicaid at any time during the year and who are not expected to receive any direct benefit from Medicaid vision coverage. Intuitively, the DDD estimate nets out any confounding state-specific time-varying factor that is common for Medicaid enrollees and their control group counterparts. Our preferred specification is of the following form:

(2) $$\mathrm{Y}_{ist} = \beta_1 \mathrm{Medicaid}_{it} + \beta_2 \mathrm{Vision}_{s,t-1} \times \mathrm{Medicaid}_{it} + \beta_3 \mathrm{X}_{ist} + \tau_t + \gamma_s + \tau_t \times \mathrm{Medicaid}_{it} + \gamma_s \times \mathrm{Medicaid}_{it} + \tau_t \times \gamma_s + \varepsilon_{ist}$$

Where $\mathrm{Medicaid}_{it}$ is a binary variable equal to one if individual *i* is enrolled in Medicaid at any time during reference calendar year *t* and the vector of demographic variables are as defined above. In addition to state and year fixed effects, our preferred DDD model also includes a full set of interactions between year and Medicaid status, state and Medicaid status, and state and year. These terms provide flexible control for differences in trends over time and across states, respectively, for Medicaid enrollees and the control group, as well as for time-varying state-level factors that do not vary systematically with Medicaid status. The main coefficient of interest, $\widehat{\beta_2}$, represents the effect of vision coverage (i.e., exams and eyeglasses compared to exams only or neither) on employment outcome, Y_{ist}, for Medicaid enrollees relative to the control group (i.e., the DDD estimate). As before, all estimates are weighted to be nationally representative and errors are clustered at the state level.[6]

Identification under the DDD framework requires less restrictive assumptions than a typical difference-in-differences approach—namely the DDD is not biased by omitted variables that affect both the propensity to provide vision benefits and labor market outcomes, as long as those variables affect the Medicaid and non-Medicaid populations similarly. For example, the approach will subtract out any general effect of a macro-economic shock.

We also present results for alternative models that omit the full set of state-by-year terms and instead include the set of time-varying state-level variables as described above and/or state-specific linear time trends. When omitting state-by-year effects, we include both the Medicaid adult vision coverage indicator as well as the interaction of vision coverage with Medicaid status. This allows us to estimate an effect for the control group based on the coefficient estimate on the vision coverage indicator, providing a check on our estimates for Medicaid enrollees.[7] Significant control group effects are not automatically cause for concern. However, estimated control group effects that are statistically and/or economically significant would place substantial onus on the control group to absorb

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[6] All analyses use the Census provided weights. However, we also estimate models using alternative weights that adjust for imputation biases and a non-linearity in the sum of the Census weights that is induced by a switch to new Decennial Census population totals (Ziegenfuss & Davern, 2011). We also repeat analyses without survey weights. Results are consistent regardless of which (or if any) weights are used. See Appendix Table 4.

[7] We also estimate separate models for the control group and our findings are very similar. Results are available upon request.

confounding factors that are correlated with both Medicaid adult vision coverage policies and labor market outcomes, whereas small and non-significant effects would suggest that this is less of a concern.[8]

We conduct several checks to examine the robustness of our results. First, perhaps the largest threat to our design is if a state makes other changes to its Medicaid program at the same time as it changes its vision coverage policy. For example, a state might cut adult vision benefits at the same time as it cuts other important optional benefits like dental coverage, which might also effect employment. Though we cannot definitively rule out this possibility, we estimate models that control for two measures of Medicaid program generosity: Medicaid spending per person and state-by-year indicators of dental coverage. In both cases these variables are interacted with Medicaid status so that we can preserve the full set of two-way interactions shown in Equation 2.

Second, we examine how sensitive our results are to the use of alternative control groups, including all higher income adults, privately insured low-income adults, and uninsured low-income adults. Because the labor-market activity of these various groups is likely influenced by a different set of state-year factors, finding consistent results across control groups would increase our confidence in the main model. We also estimate a difference-in-differences model with no control group to test the sensitivity of our results to the use of any control group.

Third, we examine economic conditions as a potential source of bias by assigning the vision coverage histories of those states that changed their vision coverage policy to a geographic neighbor that did not change its policy during our study period, but was likely subject to similar economic shocks. This placebo test is similar to one used by Buchmueller, Miller, and Vujicic (2016) in their study of

[8] Non-significant control group effects, of course, do not completely rule out the possibility of confounding factors as a source of bias.

Medicaid adult dental coverage policies. In the event that shocks common to geographic neighbors were driving our results, we would expect this test to show significant associations between placebo vision coverage policies and employment outcomes of the same sign and similar magnitude to our main estimates. As a further check, we examine results using data from only prior to the Great Recession and the imposition of the ACA's maintenance of eligibility rules in 2010 (results are available in Appendix Table 5).

Fourth, our preferred analysis restricts the sample to adults with incomes of less than 200% of poverty. We examine if relaxing or removing this restriction alters our findings. In particular, we want to ensure that restricting by income does not lead to sample changes coincident with changes to vision coverage policies, since it is plausible that adding vision benefits could increase income above the threshold for sample inclusion.

Finally, we estimate an intent-to-treat difference-in-differences model where we use adults with less than a high school education, or alternatively, those with family incomes less than 400 percent FPL, as our analysis sample (Appendix Table 7). These models control for the demographic characteristics included in our main models as well as state and year fixed effects. While we expect these results to be smaller in magnitude and less precisely estimated than our main results since the vast majority of these samples would not be affected by Medicaid adult vision benefit policies, results that are qualitatively similar would provide further reassurance that our findings are not driven by compositional changes coincident with changes to vision coverage policies.

2.4. Final Sample

Our main Medicaid sample included survey respondents ages 22-64 with family income less than two times the federal poverty level who reported that they had Medicaid coverage at some time during the reference calendar year. Similar to previous analyses of the effects of Medicaid adult vision coverage, we selected this age range since Medicaid enrollees up to age 21 are eligible for vision coverage through the Early and Periodic Screening, Diagnostic, and Treatment (EPSDT) benefit, and therefore are not subject to Medicaid adult vision coverage policies. We excluded people who were age 65 and over since these individuals were likely eligible for Medicare and retirement benefits, which could affect health and employment outcomes. Those under age 65 who reported Medicare coverage and those receiving any supplemental security income were also excluded since these individuals were likely eligible for Medicaid due to disability.[9] According to previous calculations, the majority of non-elderly adults (about 81 percent) eligible for Medicaid and not Medicare are not eligible due to a disability (Lipton & Decker 2015). We limited our Medicaid sample to individuals with family income below two times the federal poverty level because most state income eligibility limits for adults were far below this level during our period of study (Kaiser Family Foundation 2014b). Finally, we excluded individuals who reported Medicaid and a second form of insurance coverage since these individuals may have had an alternative source of vision coverage.

We imposed similar restrictions on the control group sample to improve comparability. The main control group for our DDD analysis consisted of adults ages 22-64 with family incomes below two times the federal poverty level who did not report Medicaid or Medicare coverage and did not report receiving any supplemental security income during the reference calendar year. Given these exclusions, our main analysis sample included 48,020 Medicaid enrollees and 267,734 low-income adults not enrolled in Medicaid interviewed during 2002-2013.

[9] Adults eligible for Medicaid due to disability are in many instances, though not always, subject to the same vision coverage policies as non-disabled adults. However, employment outcomes among these individuals likely respond differently to changes in coverage generosity. For these reasons, we exclude those who appear to be on Medicaid due to disability from our sample.

Table 1 provides the means of the demographic characteristics included as control variables in our model for the sample of Medicaid enrollees, low-income individuals not enrolled in Medicaid, and the combined sample.[10] Among the combined sample, the average age is about 39 years, 49 percent are non-Hispanic white, 45 percent are male, and 25 percent have less than a high school diploma. On average during 2001-2012, 65 percent resided in a state that provided Medicaid adult vision coverage according to our definition. Comparing the Medicaid and control group samples, Medicaid enrollees are significantly less likely to be non-Hispanic White, married, male, or to have some college or more education and more likely to be non-Hispanic black, have less than a high school degree, and to be a U.S. citizen.

Significant differences in average characteristics for Medicaid enrollees and the control group sample are not an issue for our empirical strategy in isolation. However, compositional differences in the Medicaid sample relative to the control group sample that are correlated with changes to vision coverage policies could bias our estimates if our model is misspecified. We test for compositional differences in observable characteristics using the following regression:

$$(3)\quad X_{ist} = \beta_1 Medicaid_{it} + \beta_2 Vision_{s,t-1} \times Medicaid_{it} + \tau_t + \gamma_{0s} + \tau_t \times Medicaid_{it} + \gamma_{0s} \times Medicaid_{it} + \gamma_{0s} \times \tau_t + \varepsilon_{ist}$$

[10] In Appendix Table 1, we provided a detailed descriptive table of the outcome means. In this table, we compare the outcomes of Medicaid enrollees with and without vision coverage and control group individuals in states with and without Medicaid vision coverage. While the descriptive differences between these groups cannot be interpreted as the causal effect of vision coverage, they are nonetheless qualitatively similar to our main empirical results.

Where X_{ist} represents the set of covariates and all other variables are as defined before. A significant coefficient estimate, $\widehat{\beta_2}$, would indicate a difference in the covariate for Medicaid enrollees relative to the control group in states with relative to without vision coverage. Table 2 presents the results of this exercise, as well as an analogous investigation for the Medicaid sample only. As shown in the third column of Table 2, estimates for most covariates are not significant at conventional levels. The exception is race/ethnicity. In particular, it appears that Medicaid enrollees residing in states with compared to without vision coverage are more likely to be non-Hispanic white and Asian, and less likely to be Hispanic relative to the control group. (Results are similar for the Medicaid sample only, except that the coefficient estimate for non-Hispanic white is smaller and not statistically significant.) Controlling for race/ethnicity in our regression models may reduce or eliminate potential bias if the model is properly specified. Further, combining these estimates with computed outcome means by race/ethnicity to assess the potential magnitude of any bias suggests it is unlikely that compositional effects could explain our findings. For example, we estimated that vision benefits are associated with a 3.6 percentage point increase in the likelihood of working full time compared to part time or not working. Our calculations based on the results shown in Table 2 imply that about 0.18 percentage points, or 5%, of this increase could be explained by compositional differences.

2.5. Outcome Trends

While the main assumption underlying our DDD model is fundamentally untestable, we assess whether outcome trends differed between states that eventually changed their vision coverage policies relative to those that did not for Medicaid beneficiaries relative the control group. To capture the largest number of states that ultimately changed their vision coverage policies before any change, we restricted our analysis period to 2001-2007 (CPS years 2002-2008). Eight states changed their coverage policies for the first time during or after 2008, including: California, Idaho, Michigan, Nevada, New Mexico, North Carolina, Oregon, and Washington.[11] States that changed their coverage policies prior to 2008 were excluded from the sample for this analysis. We estimated the following regression:

(4) $\mathrm{Y}_{ist} = \beta_1 \mathrm{Changer}_s \times \mathrm{Medicaid}_{it} \times \mathrm{year}_t + \beta_2 \mathrm{X}_{ist} + \tau_t + \gamma_s + \tau_t \times \mathrm{Medicaid}_{it} + \gamma_s \times \mathrm{Medicaid}_{it} + \tau_t \times \gamma_s + \varepsilon_{ist}$

Where $\mathrm{Changer}_s$ is an indicator equal to one for the eight states that eventually changed their vision coverage policies during our study period and zero otherwise, year_t is a linear yearly trend, and all other variables are as defined above. The coefficient estimate on the interaction between being a changer state, Medicaid status, and the linear yearly trend is of interest. We also estimated analogous models with no within-state control group (i.e., Medicaid beneficiaries only).

Table 3 presents the results of this analysis, both for the Medicaid sample only (Model 1) and including the within-state control group (Model 2). We did not detect a significant difference in trends for most of the outcomes we studied, with the exception of the log hourly wage for which trends differed at the five percent level regardless of whether we included the within-state control group. We also found a borderline significant difference in trends in part-time work when we included the within-state control group (p=0.06), but not when we analyzed the Medicaid sample only (p=0.21). Taken together, we do not find strong evidence that our identifying assumption is violated. Further, we present results with various alternative within-state control groups as well as without a control group, and our results are

[11] Three of these states changed their policies in 2011, and therefore do not contribute to identification in our DDD analysis that uses lagged vision coverage policies. We repeated the same analysis excluding these three states (ID, NC, and WA) with very similar results. We chose to include all eight states in the analysis that appears in the paper since the larger sample size may increase the chance of detecting significant differences in outcome trends.

very consistent across these specifications. Our results are also generally robust to the inclusion of Medicaid-specific linear state trends. However, our analysis of outcome trends suggests caution when interpreting the log hourly wage results, in particular.

3. Results

3.1. Vision Benefits and Enrollment in Medicaid

We find no evidence of an association between Medicaid adult vision coverage and enrollment in Medicaid among low-income adults. Coefficient estimates for the vision coverage indicator shown in Table 4 are relatively small in magnitude and not statistically significant regardless of the model specification considered. The estimated association ranges from 0.04 to 0.32 percentage points, depending on model controls. The 95 percent confidence intervals for these estimates suggest that we can rule out large effects. For example, the 95 percent confidence interval for the Model 4 estimate ranges from -0.7 percentage points to 1.4 percentage points. Coefficient estimates for the other explanatory variables are of the expected signs (not shown). Racial and ethnic minorities, females, those with less education, and U.S. citizens are all significantly more likely to report Medicaid coverage. These findings improve our confidence that the results that follow are not a function of compositional changes in our sample.

3.2. Difference-in-Difference-in-Difference Results

Table 5 presents the results of our preferred, fully saturated DDD model (Model 5), as well as several alternative models that do not include the full set of state-by-year interaction terms (Models 1-4).[12] The controls included in each column of Table 5 become progressively more flexible moving from left to right. In particular, Model 1 does not include any explicit controls for time-varying state-level

[12] Coefficient estimates for key explanatory variables are available in Appendix Table 2.

factors, Model 2 incorporates specific time-varying state-level variables, Model 3 includes linear state-specific trends, Model 4 includes both state-specific variables and trends, and finally Model 5 includes fully flexible state-by-year interactions. Our results are largely consistent across models and suggest that Medicaid adult vision coverage is associated with a significant increase in the likelihood of working full-time compared to part-time or not working, and among the employed, increases in usual hours worked, full-time vs. part-time work, and the mean log occupation wage.

Focusing on the results of Model 5, we find that vision coverage is associated with an increase in the likelihood of working full time compared to part time or not working of 3.6 percentage points, representing an increase of about 13 percent relative to the mean in states without vision coverage (28.3 percent). We also find a borderline significant 2.2 percentage point reduction in the likelihood of working part-time (11 percent reduction relative to the mean). While the magnitude of this latter estimate is fairly consistent across models, it is not statistically significant in some specifications (i.e., Models 2-4). Regardless of the model, vision coverage does not appear to be significantly associated with a change in the likelihood of being employed for at least one week. Our preferred estimate suggests a 1.4 percentage point increase, but this estimate is not statistically significant at conventional levels.[13]

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[13] Our measure of employment indicates whether a respondent reported working at all during the reference calendar year, a very inclusive measure. We also considered alternative measures based on the number of weeks worked (e.g., worked at least 26 weeks compared to fewer). Estimates using these alternative measures were generally similar in magnitude to those shown in the paper, though were sometimes borderline significant. For example, we estimated that vision coverage was associated with a 1.9 percentage point increase in having worked 26 or more weeks compared to fewer, and this estimate was significant at the 10 percent level. Nonetheless, these analyses did not produce strong evidence of a significant positive effect on extensive margin employment measures.

To further investigate potential intensive margin effects, we examined hours worked and other outcomes among the subsample of Medicaid enrollees who were employed for at least one week during the year. Because we do not find large changes in the likelihood of being employed as a result of changes to vision coverage policies, sub-setting to the employed is unlikely to introduce substantial bias. Again focusing on model 5, we estimate that vision coverage is associated with an increase in usual hours worked of 5.9 log points, or 6.1 percent (i.e., about 2.0 additional hours during a typical week). We also find an increase of 5.6 percentage points in the likelihood of working full time compared to part time, representing an increase of about 10 percent relative to the mean in states without vision coverage (58.9 percent). In addition to changes in hours worked, we also find evidence that vision coverage may facilitate switching to higher skilled occupations. Similar to Autor (2013), we use the mean log occupation wage for non-farming occupations to measure the degree of skill required for a given occupation. Our findings imply that vision coverage is associated with a significant increase in this measure.[14] The results of Models 1-4 are remarkably similar to those from Model 5, as shown in Table 5.

We do not, however, find evidence of a significant association between vision coverage and the implied hourly wage. In fact, the point estimates for this outcome are negative. Because we estimated significant differences in trends for the log hourly wage in states that changed their vision coverage policies relative to those that did not, we are less confident in the estimates for this outcome. However, there are a few potential explanations for the apparent disconnect between the mean log occupation wage and log hourly wage results. First, if an individual remains in the same job, then wages would likely adjust more slowly to improvements in productive capability than hours worked. Further, there

[14] Results (not shown) were generally similar when we included Medicaid-specific state linear time trends, both in terms of magnitude and significance.

may be restrictions on how much compensation an employer can provide for a given position. Second, if an individual switches to a new occupation with higher earning potential, he may not realize these wage gains until he accrues some experience in the new position. Finally, occupation may be reported more accurately than earnings, which we used to compute the hourly wage.

Our intent-to-treat difference-in-differences estimates using a sample of adults with less than a high school education and alternatively, with family income less than 400 percent FPL provide additional support for our main findings (see Appendix Table 7). These results are expectedly weaker and smaller in magnitude compared to our main results, but we find evidence of a significant increase in intensive margin measures. For example, when considering adults with less than a high school education, we estimate an increase of 0.8 log points in usual hours worked ($p<0.05$) and a 0.9 percentage point increase in the likelihood of working full time compared to part time ($p<0.10$). Since about 13.5% of this sample was enrolled in Medicaid during the reference calendar year, the magnitude of these estimates are roughly in line with what we would expect. In particular, scaling these intent-to-treat estimates by the proportion of treated individuals would suggest an increase of 5.8 log points in usual hours worked and a 6.7 percentage point increase in the likelihood of working full time compared to part time. By comparison, our main results suggested increases of 5.9 and 5.6 in these measures.

Because Models 1-4 do not include state-by-year terms, they include the Medicaid adult vision coverage indicator as well as its interaction with Medicaid status. The coefficient estimate for the vision coverage indicator provides an estimate of the association between vision coverage policies and outcomes for the control group. Table 6 provides additional estimates from Model 1 for the control group and Medicaid enrollees in addition to the DDD estimates shown in Model 5 of Table 5. Estimates for the control group, shown in the second column of Table 6, are generally small in magnitude and none are statistically significant. While the primary purpose of the control group is to absorb time-varying state-level confounders that are associated with vision coverage policies and also affect employment outcomes, a significant association could be concerning to the extent that these confounders are not fully captured by the use of a control group or by the model controls. While the absence of a significant association does not completely eliminate this concern, it is reassuring.[15]

3.3. Subgroup Analysis

We use our preferred, fully saturated DDD model to investigate whether Medicaid adult vision coverage policies have different effects by sex, marital status, and age. Results may differ across these strata if vision benefits have differential effects on the use of vision services or improvements to vision by subgroup, or if certain subgroups are more likely to work in occupations where resolving vision-related difficulties has a larger effect on employment-related outcomes. Further, access to vision coverage could interact with underlying differences by subgroup that are not captured by model controls, such as discriminatory practices or differences in alternatives to work. The results by sex are shown in Table 7. Results by marital status and age are available in Appendix Table 6.

Our results indicate that the effects of vision coverage on employment outcomes may be more pronounced among females than males. Vision coverage is associated with a significant 5.4 percentage point increase in the likelihood of working full time compared to part time or not working among females compared to a point estimate of 1.3 percentage points that is not statistically significant among males, with the difference being significant at the ten percent level. Vision coverage is not significantly associated with the likelihood of being employed for males or females, though the point estimate for females is larger in magnitude (i.e., 2.2 percentage points compared to 0.9 percentage points). Among the employed, we find that vision coverage is associated with a significant 8.6 log points, or 9.0%, increase in usual hours worked for females compared to a point estimate of 2.9 log points, or 3.0%, that is not statistically significant among males, though this difference is not statistically significant

[15] Results are very similar when a difference-in-differences analysis is run for the control group alone.

(p=0.11). Vision coverage is, however, associated with a significantly greater increase in the likelihood of working full time compared to part time among females compared to males (i.e., 9.1 percentage points vs. 0.7 percentage points, with the difference being significant at the ten percent level).

Results for married compared to unmarried individuals are similar in many instances (see Appendix Table 6), though there appears to be more evidence that effects are mostly on the intensive margin for married individuals whereas this attribution is less clear among unmarried individuals. Further, the association between vision coverage and the mean log occupation wage is larger in magnitude for married individuals than the corresponding estimate for unmarried individuals (which is also not statistically significant), though the difference between these estimates is not significant at conventional levels. When considering results for individuals under age 35 compared to at least age 35, results are very similar in magnitude in most instances, and none of the differences for these age groups are statistically significant (see Appendix Table 6).

3.4. Robustness Checks

We conduct several tests of the robustness of our main results. First, we explore whether our results are sensitive to inclusion of other measures of Medicaid program generosity. Table 8 presents results from our preferred DDD model that also includes Medicaid expenditures per person as a measure of general program generosity (Model 1), and alternatively, Medicaid adult dental benefits as a measure plausibly related to adult vision benefits (Model 2). These measures are each interacted with Medicaid status, and the results shown are the DDD estimates for Medicaid adult vision coverage after including these controls. Overall, our estimates are very similar to our main results. While the coefficient estimate for having worked at least one week in the last year increases in magnitude in both Models 1 and 2, it is only borderline significant in Model 1 and remains insignificant in Model 2.

Second, we examine the robustness of our results to the use of alternative control groups to ascertain how stable our results are across different counterfactuals (Table 9). Our main control group (i.e. Tables 5 and 6) consisted of all low-income adults who did not report enrollment in Medicaid at any time during the past year, regardless of what other coverage they may have had. In Table 9, we report results from models that use control groups composed of (1) low-income adults who were privately insured at some point during the past year; (2) low-income adults who were uninsured all year; and (3) higher income adults with family incomes between 300 and 400 percent FPL. In addition to providing an indication of the stability of our results across different control group populations, survey participants may be more likely to confuse different sources of insurance coverage than to misreport their insured status. Therefore, those that said they were uninsured for the full year may be less likely to have had Medicaid coverage at some point (and therefore less likely to be inaccurately assigned to the control group). Reassuringly, our results are similar regardless of the control group used.

Table 9 also shows the results of a difference-in-differences analysis with no within state control group (first column). Again, results are very similar to our preferred DDD model.

Third, we explore the potential for bias due to policy endogeneity. In addition to controlling for the annual state unemployment rate (Table 5), and showing that our results are robust to inclusion of other measures of Medicaid program generosity (Table 8), we employ a placebo test that assigns vision coverage policy changes to neighboring states that did not actually experience a change (similar to one used by Buchmueller et al. (2016)). The idea is that geographic neighbors were likely subject to similar economic shocks, so that if economic conditions were driving our results rather than changes to vision coverage policies, we would estimate significant placebo effects of a similar magnitude to our main results. Our sample for this analysis included all states that did not change coverage policies during our study period and excluded those states that did experience a policy change. We were able to match eight of the ten states that changed coverage policies during our study period (and contributed to identification in our main model) to a geographic neighbor. The results of this analysis are shown in Table 10, with and without controlling for state-year variables, linear state-specific time trends, and the full set of state-by-year interactions. Of 35 estimates (seven outcomes across five different models), only one estimate is significant at the ten percent level and it is wrong-signed. The estimated association between vision coverage and being employed last year is similar in magnitude to our main results, though this association is not significant in our placebo or main analysis. We estimate a placebo association between vision coverage and working full time compared to part time or not working that is about half the size of our main estimate, and a placebo estimate for part time status that is wrong-signed and less than one-quarter the size of our main estimate. When considering the employed sample, our placebo estimate of the association between vision coverage and usual hours worked is less than ten percent of the size of our main estimate, and the placebo estimate for the mean log occupation wage is wrong-signed. Overall, these results provide additional evidence that economic conditions are unlikely to be driving the relationship we observe between vision coverage policies and intensive margin employment measures such as hours worked and occupational skill requirements.

We also test whether the effects of changes to vision benefits could be conflated with the Great Recession or the maintenance of eligibility rules implemented in 2010 as part of the ACA by restricting our analysis period to calendar years 2001-2007. While this restriction eliminates some of our identifying variation, our main findings are of the expected sign and maintain statistical significance in almost all instances (these results are shown in Appendix Table 5). Since this analysis covers a different timeframe and only a subset of the states that changed their coverage policies are used to identify the effects of vision benefits, some differences from our main results are not unexpected. However, one surprising and interesting departure is that the estimate for the effect of vision benefits on the hourly wage becomes positive and statistically significant at the five percent level. Overall, the fact that the results are, in general, qualitatively similar to results using the full analysis period suggests that neither the Great Recession nor maintenance of eligibility rules is driving our findings.

Finally, we examine whether our results are sensitive to the income restriction we place on our sample, since increases in earnings associated with vision coverage could be obscured by this exclusion. Most individuals meeting all requirements for our Medicaid sample *except* for the income restriction have incomes below this level (about 80 percent), and would need to in order to be eligible for Medicaid at some point during the year. Nonetheless, we explore this potential source of bias by comparing results that restrict the sample to those with family incomes up to 200 percent FPL to results that use a sample restriction of income up to 400 percent FPL, and also to results that do not impose any income restriction on the sample (Table 11). In general, results that were significant in our preferred specification maintain significance when the income restriction is relaxed, but the estimated intensive margin effects are smaller in magnitude in some instances when considering the higher income samples. The indicator for working part time is no longer statistically significant once the sample income restriction is relaxed, though the estimated effect of vision coverage on this outcome is only significant at the 10 percent level in our main specification.

4. Conclusions

The provision of Medicaid adult vision benefits substantially increases eye doctor visits, decreases self-reported visual impairment, and improves the likelihood of having appropriately corrected distance vision by up to 10 percentage points (Lipton & Decker 2015; Lipton & Decker 2016). Given evidence that poor vision can have adverse impacts on a range of activities of daily living, it is plausible that improvements to vision could have positive effects on work productivity. Our findings suggest that Medicaid coverage of adult vision services does indeed increase hours worked, the likelihood of working full time compared to part time, and that it facilitates transitions to occupations with higher earning potential. These intensive margin effects could have been facilitated by increasing worker qualifications for different types of jobs, decreasing transportation constraints that allow working more hours at the same job, working more jobs, working different shifts (i.e. evening and night shifts) that require night driving, or relieving discomfort that limits the amount or type of work a beneficiary pursues.

Because corrective lenses are durable goods that only need to be replaced in the event of loss, damage, or further vision deterioration, the effects we observed might persist after a worker leaves Medicaid or if a state withdraws vision benefits. This also suggests we may underestimate the effects of dropping vision coverage as they may not materialize in the near term.

Our estimates of the effect of vision coverage on extensive margin employment were positive, but small and non-significant. While we excluded individuals most likely to be eligible for Medicaid due to a disability, there is evidence that a substantial share of adult enrollees who are not receiving supplemental security income have a work-limiting health problem. According to research from the Kaiser Family Foundation (2017a), more than one-third of non-disabled adult enrollees who are not working cite illness or disability as the reason. An additional 28% report that they cannot work because they are taking care of home or family, and 26% report that they are going to school or retired. Only 11% of non-disabled adult enrollees who are not working report the reason as not being able to find work, or other. This analysis indicates that the majority of Medicaid enrollees who are not working have low labor force attachment and may not be able to, or desire to, enter into employment regardless of the incentive or a marginal change in functional ability. The lack of a significant effect on extensive margin employment may also be less surprising given that our employment variable was full-year—non-workers did not work at all. Further, it is possible that people with at least some work experience are more likely to be aware of vision coverage when it exists and more able to navigate the health system to utilize those benefits. Regardless, our estimates suggest that vision benefits improve the labor activity of those who are already supplying some labor in a given year.

Eye exams and corrective lenses represent substantial financial burdens to a typical low-income adult without vision coverage. However, the costs faced by Medicaid can be relatively small. For example, the 2017 fee schedule in New York stipulated a $78 fee for evaluation and management of a new non-facility optometry patient (code 92004), $6 for frames (code V2020), and $6-$17 for lenses (codes V2100 – V2114), depending on correction strength (New York State Department of Health, 2017). Our results suggest that there might be a significant return to a state's relatively minor investment in vision coverage.

Though we did not find evidence of an increase in the hourly wage, our main estimates implied that vision coverage increased typical weekly hours worked by 6.1 percent, or about 2.0 hours per week. Since, on average, Medicaid enrollees earned about $12.50 per hour in 2017 dollars, this increase translates to an additional $24.50 per week worked. Given that employed Medicaid enrollees reported working about 37 weeks of the year on average, a back-of-the envelope calculation implies a $907 increase in annual earnings. This estimate may represent a lower bound for a beneficiary with a correctable vision deficiency, assuming that they are the only people that benefit from vision services. Given that 37% of Medicaid beneficiaries in states without vision coverage have any under-correction of distance vision (i.e., presenting visual acuity of 20/30 or worse that can be corrected to 20/25 or better) (Lipton & Decker 2016), extending vision benefits in states that currently do not cover them could increase annual earnings for those most likely to gain from access to vision correction by as much as $2,451 ($907/0.37).

Comparing Medicaid's cost, based on the New York fee schedule, and the potential for additional earnings based on our estimates suggests that an enrollee would have to work for about four weeks of the year to compensate for the states' costs of providing an eye exam and glasses. Put another way, an investment in vision coverage could result in an $809 per person surplus ($24.50*33 weeks) by the end of the year among employed beneficiaries. Even only accounting for the monetary benefits of vision coverage to the employed and assuming every beneficiary who was not employed incurred the cost of an exam and glasses (at the New York fee schedule), our calculation implies that the benefits of vision coverage easily outweigh the costs given that about half of the adults in our sample were employed. New York generally pays lower rates to providers than other states and it is likely that other states face higher costs to provide exams and glasses. However, providing vision coverage would only have an unfavorable cost to benefit comparison if the cost of an exam and glasses were nearly five times as much as the New York cost.

While this back-of-the-envelope calculation (subject to the usual caveats) could under- or overstate the true returns to gaining vision coverage, it does suggest a large return relative to the cost from the individual perspective. We estimated that uninsured people pay an average of $382 in out-of-pocket costs for a vision exam and glasses, which is substantially smaller than the estimated $907 increase in annual earnings. This raises the question of why low-income people without vision benefits do not finance vision exams and eyeglasses themselves. There are several possible reasons. First, the cost of vision correction must be paid up front, while the benefits accrue slowly over time. Second, and relatedly, we estimated the average out-of-pocket cost to obtain vision correction without insurance to be about 37% of a low-income person's monthly income. Individuals living below the poverty level may be unable or unwilling to finance that cost at the expense of other necessities. Third, financing the costs of vision correction in the near term because of expected increased future earnings assumes accurate foresight and rationality. Our findings suggest that vision benefits are associated with about two additional hours worked per week. Some individuals may not anticipate this relatively minor change to their work schedules as a result of improved vision. Further, a large literature in behavioral economics demonstrates significant departures from rationality in a variety of settings. For example, present bias suggests that people may delay immediate costs even if they are associated with substantial long-run gain (O'Donoghue & Rabin, 1999). Finally, people may underestimate the severity of their vision problems, and therefore also underestimate the benefit to gaining vision correction.

Our results are subject to a number of caveats. For example, Medicaid status is known to be reported with error in the CPS. Given that this error usually results in misclassification of coverage type rather than coverage status we were encouraged by the fact our results remained consistent when restricting the control group to uninsured individuals. It is also possible that some unaccounted for factor correlated with a state's vision coverage decision was also correlated with the outcomes of interest. However, our triple-difference design substantially limits the number of potential factors to those that affected the Medicaid population, but not any of the alternative control groups we considered. Furthermore, our results remained consistent when controlling for state-specific trends or explicitly controlling for changes in macro-economic conditions, other Medicaid policy features, and general health care supply.

In this paper, we provide some of the first evidence to suggest that a relatively low cost intervention financed by Medicaid can have important positive effects on the short-run economic activity of adults. Our results have the potential to inform the trade-off that state and federal policy makers must make between the benefits of Medicaid generosity and program cost, as well as ongoing policy debates over establishing work requirements in Medicaid (Price & Verma 2017). In particular, our findings suggest that, in some cases, Medicaid enrollees are not restricting their labor only because of work disincentives predicted by standard economic theory, but because they lack resources that could enable fuller participation in the labor market. This suggests that a worthwhile avenue for those interested in encouraging labor force participation among Medicaid enrollees is the provision of services that alleviate work-limiting impairments.

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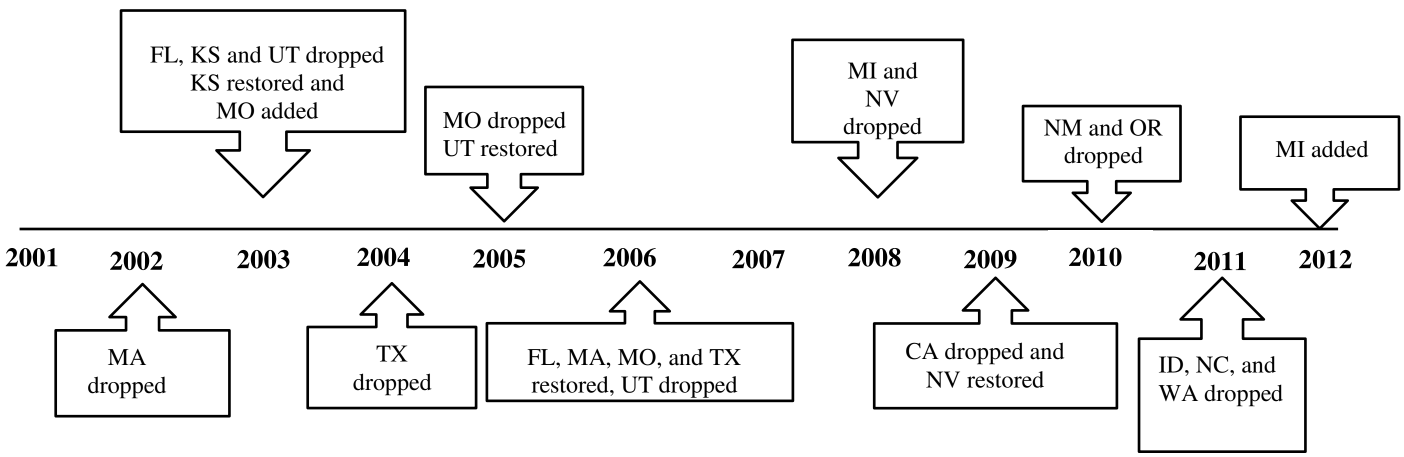
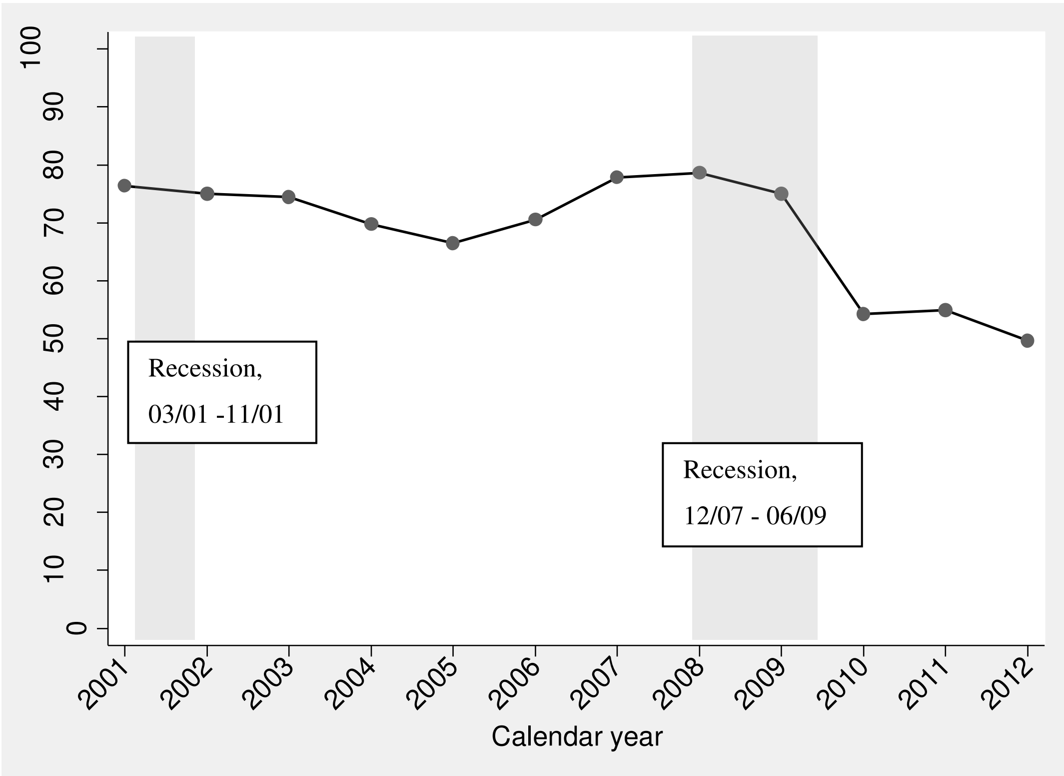
Figures

Figure 1: Timeline of changes to Medicaid adult vision coverage



Source: Authors' analysis of Medicaid adult vision coverage policies (various sources).

Figure 2: Percentage of Medicaid enrollees with vision coverage for at least six months of the calendar year, with US recession bars, CPS 2002-2013



Source: Authors' analysis of the Current Population Survey, 2002-2013.

Tables

Table 1: Weighted sample characteristics, CPS 2002-2013

	Mean/Percent (SE)		
	All	**Medicaid**	**Control group**
Age	38.92	37.48	39.17***
	(0.14)	(0.24)	(0.17)
White, non-Hispanic	48.90	44.00	49.73**
	(4.41)	(4.77)	(4.44)
Black, non-Hispanic	16.96	21.81	16.14***
	(2.13)	(2.74)	(2.07)
Hispanic	27.02	26.31	27.14
	(5.45)	(6.31)	(5.42)
Asian/other	7.12	7.87	6.99
	(0.90)	(0.94)	(0.90)
Married	48.16	46.53	48.43
	(1.27)	(2.35)	(1.21)
Male	45.01	32.35	47.14***
	(0.40)	(0.81)	(0.46)
Less than high school degree	25.38	32.01	24.26***
	(2.01)	(2.55)	(2.12)
High school degree	36.49	37.64	36.30**
	(1.58)	(1.84)	(1.55)
Some college or more education	38.13	30.35	39.44***
	(0.93)	(0.99)	(1.03)
US citizen	79.76	82.65	79.28*
	(3.38)	(4.50)	(3.24)
Medicaid enrollee	14.39	100.00	0.00
	(1.37)		
Resides in state with Medicaid adult vision coverage	65.48	67.10	65.21
	(6.37)	(6.78)	(6.43)

Source: 2002-2013 Current Population Survey-Annual Social and Economic Supplement. The sample includes 48,020 adults who were on Medicaid at some point during the past calendar year and 267,734 low-income adults who were not on Medicaid in the past year. All estimates are expressed as percentages, except for age which is expressed in years. Sampling weights are used to produce nationally-representative estimates. Standard errors are in parentheses and are clustered by state. T-tests were used to test the difference in mean characteristics between Medicaid beneficiaries and the control group. Significance stars indicate a significant difference compared with Medicaid beneficiaries. * p<0.10, **p<0.05, ***p<0.01.

Table 2: Covariate balance test, CPS 2002-2013

Explanatory variables	**Coefficient (SE)**	
	Model 1	Model 2
Age	0.05	0.18
	(0.41)	(0.49)
White, non-Hispanic	0.82	2.72**
	(1.18)	(1.34)
Black, non-Hispanic	-1.13	-1.18
	(1.02)	(1.08)
Hispanic	-2.12**	-3.49**
	(0.85)	(1.42)
Asian/other	2.43***	1.95**
	(0.74)	(0.96)
Married	1.92	0.96
	(1.98)	(1.68)
Male	0.77	1.41
	(0.68)	(1.28)
Less than high school degree	1.17	-0.39
	(0.95)	(1.03)
High school degree	-0.92	-0.70
	(1.25)	(0.82)
Some college or more education	-0.25	1.09
	(1.42)	(1.39)
US citizen	-3.19*	-0.77
	(1.86)	(0.70)
Control group?	No	Yes

Source: 2002-2013 Current Population Survey-Annual Social and Economic Supplement. The sample includes 48,020 adults who were on Medicaid at some point during the past year and 267,734 low-income adults not on Medicaid in the past year. Model 1 is a linear probability model in which each explanatory variable is regressed on vision coverage status and state and year fixed effects for the sample of Medicaid enrollees only (each coefficient comes from a separate model). Model 2 includes the low-income control group and is as described in the text. Survey weights were used to produce nationally representative estimates and errors were clustered at the state level. All coefficients were multiplied by 100, except for age. The coefficients for age are in terms of years, and the coefficients for all other variables are in terms of percentage points. Standard errors are shown below estimates in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 3: Outcome trends in treatment and control states before changes to vision coverage policy, CPS 2002-2008[a]

	P-value for Coefficient on Interaction Term	
	Model 1	Model 2
Full sample		
Worked at least one week last year	0.16	0.18
Usually worked full time last year (vs. part time or no work)	0.59	0.99
Usually worked part time last year (vs. full time or no work)	0.21	0.06
Employed last year		
Usual hours worked last year (log)	0.96	0.59
Usually worked full time last year (vs. part time)	0.71	0.35
Hourly wage last year (log)	0.03	0.01
Mean log occupation wage	0.56	0.47
Control group?	No	Yes

Source: 2002-2008 Current Population Survey, Annual Social and Economic Supplement. The sample includes eight states that changed their vision coverage policies for the first time during or after 2008, including: CA, ID, MI, NV, NM, NC, OR, and WA, as well as all states with consistent coverage during our full study period. The results under Model 1 report the p-values for the interaction between changer state status and a linear yearly trend for a sample of Medicaid enrollees only. The results under Model 2 report the p-values for the three-way interaction between changer state status, Medicaid status, and a linear yearly trend for a sample of Medicaid enrollees and the low-income adult control group. Further details are provided in the text.

Table 4. Regression estimates of the association between vision coverage and participation in Medicaid, CPS 2002-2013

	Coefficients (SE) Percentage Point Change (Scaled by 100)			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Vision benefits	0.04 (0.69)	0.29 (0.62)	0.07 (0.81)	0.32 (0.53)
State and year FE	Yes	Yes	Yes	Yes
State-specific trends	No	Yes	No	Yes
State-year variables	No	No	Yes	Yes

Source: 2002-2013 Current Population Survey-Annual Social and Economic Supplement. The sample includes 315,754 low-income adults (from the main analysis sample). All regression results were estimated using linear probability models that controlled for state and year fixed effects in addition to demographic variables. Survey weights were used to produce nationally representative estimates and errors were clustered at the state level. Standard errors are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 5. Triple Difference Estimates of the Effect of Medicaid Adult Vision Benefits on Employment Outcomes, CPS 2002-2013

	Coefficients (SE) Scaled by 100				
	Model 1	**Model 2**[‡‡]	**Model 3**	**Model 4**[‡‡]	**Model 5**
Full sample					
Worked at least one week last year	1.77	2.02	1.71	1.98	1.44
	(1.78)	(1.55)	(1.74)	(1.51)	(1.76)
Usually worked full time last year (vs. part time or no work)	4.02***	3.87***	3.56***	3.70***	3.60***
	(0.83)	(0.77)	(0.76)	(0.74)	(0.80)
Usually worked part time last year (vs. full time or no work)	-2.25*	-1.85	-1.85	-1.72	-2.16*
	(1.28)	(1.27)	(1.28)	(1.30)	(1.29)
Employed last year					
Usual hours worked last year (log)	6.21***	5.49***	5.68***	5.20***	5.90***
	(1.41)	(1.53)	(1.39)	(1.47)	(1.37)
Usually worked full time last year (vs. part time)	6.03***	5.50***	5.32***	5.21***	5.63***
	(0.99)	(1.11)	(1.03)	(1.20)	(1.07)
Hourly wage last year (log)	-1.48	-1.13	-1.52	-1.19	-1.06
	(1.73)	(1.78)	(1.79)	(1.86)	(1.95)
Mean log occupation wage[‡]	2.55***	2.84***	2.35***	2.68***	2.27***
	(0.65)	(0.62)	(0.57)	(0.56)	(0.59)
State-year variables	No	Yes	No	Yes	No
State-specific linear trends	No	No	Yes	Yes	No
Full state-year interactions	No	No	No	No	Yes

Source: 2002-2013 Current Population Survey-Annual Social and Economic Supplement. The sample includes 48,020 adults who were on Medicaid at some point during the past year and 267,734 low-income adults not on Medicaid in the past year. All regression results were estimated using linear probability models that controlled for demographic characteristics, state and year fixed effects, and interactions between Medicaid status and state and Medicaid status and year. Survey weights were used to produce nationally representative estimates and errors were clustered at the state level. The reported coefficient estimates are for the interaction between the vision coverage indicator and Medicaid status. Standard errors are shown in parentheses. Estimates for binary variables represent percentage point effects. Estimates for logged variables are in terms log points. * p<0.10, ** p<0.05, *** p<0.01.

[‡]Mean log occupation wage is the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from the IPUMS-CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations.

[‡‡]Models 2 and 4 include the percentage of the population in poverty, the unemployment rate, the number of primary care physicians per 10,000 population, the Medicaid managed care penetration rate, the Medicaid eligibility threshold for working parents, and an indicator for whether a state had an earnings disregard for parental eligibility. Information on the earnings disregard was missing for CPS years 2002 and 2004, and these years were therefore excluded from Models 2 and 4.

Table 6. The effect of Medicaid adult vision benefits on employment outcomes, by Medicaid status, CPS 2002-2013

	Coefficients (SE) Scaled by 100		
	Medicaid	**Control group**	**DDD**
Full sample			
Worked at least one week last year	1.53	-0.23	1.77
	(1.91)	(0.46)	(1.78)
Usually worked full time last year (vs. part time or no work)	3.95***	-0.06	4.02***
	(0.75)	(0.57)	(0.83)
Usually worked part time last year (vs. full time or no work)	-2.42*	-0.17	-2.25*
	(1.30)	(0.21)	(1.28)
Employed last year			
Usual hours worked last year (log)	6.34***	0.13	6.21***
	(1.60)	(0.37)	(1.41)
Usually worked full time last year (vs. part time)	6.36***	0.33	6.03***
	(0.91)	(0.39)	(0.99)
Hourly wage last year (log)	-1.86	-0.38	-1.48
	(1.94)	(0.58)	(1.73)
Mean log occupation wage	2.24***	-0.31	2.55***
	(0.62)	(0.28)	(0.65)

Source: 2002-2013 Current Population Survey-Annual Social and Economic Supplement. The sample includes 48,020 adults who were on Medicaid at some point during the past year and 267,734 low-income adults not on Medicaid in the past year. All regression results were estimated using linear probability models that control for demographic characteristics, state and year fixed effects, and interactions between Medicaid status and state and Medicaid status and year. Survey weights were used to produce nationally representative estimates and errors were clustered at the state level. The estimates in the first column report the sum of the coefficient estimates for the vision coverage indicator and the interaction between vision coverage and Medicaid status, those in the second column report the coefficient on the vision coverage indicator, and those in the third column report the coefficient on the interaction term between the vision coverage indicator and Medicaid status. Standard errors are in parentheses. Estimates for binary variables represent percentage point effects. Estimates for logged variables are in terms of log points. Mean log occupation wage represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from the IPUMS-CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 7. Triple difference estimates of the effect of Medicaid adult vision benefits on employment outcomes, by gender, CPS 2002-2013

	Coefficients (SE) Scaled by 100	
	Male	**Female**
Full sample		
Worked at least one week last year	0.92	2.17
	(2.26)	(1.55)
Usually worked full time last year (vs. part time or no work)	1.27	5.35*** c
	(1.84)	(0.87)
Usually worked part time last year (vs. full time or no work)	-0.35	-3.19**
	(2.32)	(1.22)
Employed last year		
Usual hours worked last year (log)	2.91	8.59***
	(2.91)	(1.61)
Usually worked full time last year (vs. part time)	0.73	9.11*** c
	(3.02)	(1.83)
Hourly wage last year (log)	1.27	-2.19
	(2.84)	(2.54)
Mean log occupation wage	1.51	3.01***
	(1.15)	(0.90)

Source: 2002-2013 Current Population Survey-Annual Social and Economic Supplement. The results shown above are from our preferred DDD model including the full set of state by year interactions, except that the sample is stratified by gender. Standard errors are shown in parentheses. Estimates for binary variables represent percentage point effects. Estimates for logged variables are in terms of log points. Mean log occupation wage represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from the IPUMS-CPS variable occ1990), excluding farming/fishing occupations and any categories with fewer than 100 observations. * p<0.10, ** p<0.05, *** p<0.01.

Table 8. Robustness to controls for other sources of Medicaid benefit generosity, 2002-2013 CPS

	Coefficient (SE) Scaled by 100	
	Model 1	**Model 2**
Full sample		
Worked at least one week last year	2.56*	2.70
	(1.49)	(2.35)
Usually worked full time last year (vs. part time or no work)	4.10***	4.26***
	(0.69)	(1.16)
Usually worked part time last year (vs. full time or no work)	-1.55	-1.55
	(1.35)	(1.62)
Employed last year		
Usual hours worked last year (log)	5.17***	4.34**
	(1.57)	(1.82)
Usually worked full time last year (vs. part time)	5.30***	5.30***
	(1.30)	(1.46)
Hourly wage last year (log)	-0.87	0.51
	(2.20)	(2.57)
Mean log occupation wage	2.46***	2.05***
	(0.58)	(0.62)
Medicaid expenditures per person	Yes	No
Medicaid adult dental coverage	No	Yes

Source: 2002-2013 Current Population Survey-Annual Social and Economic Supplement. Model 1 includes a control for per person Medicaid expenditures in addition to all other controls included in our preferred DDD specification. These data are only available for CPS years 2005-2013. Model 2 removes these controls (so we can use the full set of sample years), and adds state by year indicators of Medicaid adult dental benefit coverage. Standard errors are in parentheses. Estimates for binary variables represent percentage point effects. Estimates for logged variables are in terms of log points. Mean log occupation wage represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from the IPUMS-CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 9. Triple difference estimates of the effect of Medicaid adult vision benefits on employment outcomes, by control group definition, 2002-2013 CPS

	Coefficients (SE) Scaled by 100				
	No control group	**All low income adults**	**Higher income adults**	**Privately insured low income adults**	**Uninsured low income adults**
Full sample					
Worked at least one week last year	1.19	1.44	1.13	0.08	2.17
	(2.09)	(1.76)	(1.93)	(1.80)	(2.03)
Usually worked full time last year (vs. part time or no work)	3.61***	3.60***	3.22***	3.07***	4.04***
	(0.88)	(0.80)	(0.91)	(0.82)	(0.90)
Usually worked part time last year (vs. full time or no work)	-2.43*	-2.16*	-2.09*	-2.99**	-1.87
	(1.32)	(1.29)	(1.13)	(1.44)	(1.37)
Employed last year					
Usual hours worked last year (log)	6.21***	5.90***	5.43***	6.57***	5.48***
	(1.53)	(1.37)	(1.39)	(1.15)	(1.72)
Usually worked full time last year (vs. part time)	6.22***	5.63***	5.83***	6.14***	5.75***
	(0.83)	(1.07)	(0.74)	(1.31)	(1.04)
Hourly wage last year (log)	-1.94	-1.06	-2.44	-1.89	0.07
	(1.85)	(1.95)	(2.38)	(1.87)	(2.26)
Mean log occupation wage	2.24***	2.27***	2.25**	2.23**	2.32***
	(0.65)	(0.59)	(0.86)	(0.85)	(0.69)

Source: 2002-2013 Current Population Survey-Annual Social and Economic Supplement. The first column ("No control group") is a difference-in-differences specification based only on the Medicaid sample. All remaining columns have the same form as our preferred DDD model including the full set of state by year terms. Estimates for binary variables represent percentage point effects. Estimates for logged variables are in terms of log points. Mean log occupation wage represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from the IPUMS-CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 10. Geographic neighbor placebo test, CPS 2002-2013

	Coefficients (SE) Scaled by 100				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Full sample					
Worked at least one week last year	1.15	1.53	1.02	1.69	1.83
	(1.73)	(1.59)	(1.70)	(1.59)	(2.04)
Usually worked full time last year (vs. part time or no work)	1.66	1.97	1.36	1.77	2.08
	(1.30)	(1.22)	(1.28)	(1.24)	(1.62)
Usually worked part time last year (vs. full time or no work)	-0.51	-0.43	-0.35	-0.08	-0.25
	(1.10)	(1.16)	(1.10)	(1.08)	(1.19)
Employed last year					
Usual hours worked last year (log)	0.46	0.64	0.42	0.28	0.38
	(2.18)	(2.75)	(2.25)	(2.72)	(2.29)
Usually worked full time last year (vs. part time)	1.86	2.16	1.55	1.57	1.85
	(1.57)	(1.77)	(1.61)	(1.71)	(1.75)
Hourly wage last year (log)	2.27	2.09	2.31	2.20	2.08
	(2.76)	(2.67)	(2.79)	(2.63)	(2.87)
Mean log occupation wage	-0.90	-0.70	-1.12	-0.96	-1.88*
	(0.85)	(0.82)	(0.96)	(0.92)	(1.01)
State-year variables‡	No	Yes	No	Yes	No
State-specific linear trends	No	No	Yes	Yes	No
Full state-year interactions	No	No	No	No	Yes

Source: 2002-2013 Current Population Survey-Annual Social and Economic Supplement. Estimates are from DDD models with controls as indicated in the table, and are for the interaction between a placebo vision coverage indicator and Medicaid status. The placebo vision coverage indicator was assigned to a treatment state's neighbor which did not actually change their policies during our study period. States that had a true change in policy were excluded from the sample. In particular, CA was matched with AZ, MA was matched with CT, MI was matched with WI, FL was matched with GA, MO was matched with IA, NM was matched with CO, UT was matched with WY, and TX was matched with OK. There were no suitable matches for Nevada or Oregon. Standard errors are shown in parentheses.

Estimates for binary variables represent percentage point effects. Estimates for logged variables are in terms of log points. Mean log occupation wage represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from the IPUMS-CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. * p<0.10, ** p<0.05, *** p<0.01.

[ǂ]State-year variables include the percentage of the population in poverty, the unemployment rate, the number of primary care physicians per 10,000 population, the Medicaid managed care penetration rate, the Medicaid eligibility threshold for working parents, and an indicator for whether a state had an earnings disregard for parental eligibility. Information on the earnings disregard was missing for CPS years 2002 and 2004, and these years were therefore excluded from Models 2 and 4. * p<0.10, ** p<0.05, *** p<0.01.

Table 11. Triple difference estimates of the effect of Medicaid adult vision benefits on employment outcomes, by sample income restrictions, 2002-2013 CPS

	Coefficient (SE) Scaled by 100		
	≤ 200% FPL	≤ 400% FPL	None
Full sample			
Worked at least one week last year	1.44	1.49	0.64
	(1.76)	(1.57)	(1.62)
Usually worked full time last year (vs. part time or no work)	3.60***	2.75***	1.47*
	(0.80)	(0.84)	(0.83)
Usually worked part time last year (vs. full time or no work)	-2.16*	-1.26	-0.83
	(1.29)	(1.15)	(1.30)
Employed last year			
Usual hours worked last year (log)	5.90***	4.49***	3.88**
	(1.37)	(1.52)	(1.80)
Usually worked full time last year (vs. part time)	5.63***	4.28***	3.10**
	(1.07)	(1.11)	(1.49)
Hourly wage last year (log)	-1.06	-1.16	-2.04
	(1.95)	(2.23)	(1.67)
Mean log occupation wage	2.27***	1.54***	1.68**
	(0.59)	(0.49)	(0.74)

Source: 2002-2013 Current Population Survey-Annual Social and Economic Supplement. Estimates are from our preferred DDD model that includes the full set of state by year interactions. The first column replicates our results using our main analysis sample of adults with incomes of no more than 200% FPL. The second column includes observations up to 400% of FPL and the final column puts no income restriction on the sample. Standard errors are in parentheses. Estimates for binary variables represent percentage point effects. Estimates for logged variables are in terms of log points. Mean log occupation wage represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from the IPUMS-CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. * p<0.10, ** p<0.05, *** p<0.01.

SUPPLEMENTARY APPENIDX

Medicaid Benefit Generosity and Labor Market Outcomes: Evidence from Medicaid Adult Vision Benefits

Michel Boudreaux and Brandy Lipton

This appendix provides supplementary content not featured in the main paper. Our data and methods mirrors those in the main paper, except when noted.

List of Tables

This appendix extends the analysis shown in the main paper in several ways. Table 1 provides the mean of each outcome considered in the paper by Medicaid and vision coverage status. These results enable calculation of regression estimated effects relative to the mean of interest, and also allow for comparison of regression-adjusted effects with unadjusted results. The final column of Appendix Table 1, "Unadjusted Difference-in-Difference," computes the difference between each outcome for Medicaid enrollees with and without vision coverage relative to control group individuals with and without vision coverage. The results can be compared with the regression-based difference-in-difference and triple difference estimates provided in the main paper. While they do not have a causal interpretation, these unadjusted results are qualitatively similar to the findings from our regression analysis.

Appendix Table 2 provides coefficient estimates for key explanatory variables included in our regression analysis. These results correspond with the triple difference analysis shown in Table 5 in the main paper. These estimates suggest that younger age, Hispanic ethnicity, unmarried status, male sex, higher educational attainment, and US citizenship are associated with a higher likelihood of employment. Among the employed, younger age, Hispanic ethnicity, married status, male sex, and having less than a high school diploma are associated with greater hours worked. Older age, married status, male sex, higher educational attainment, and US citizenship are associated with higher hourly wages and a higher mean log occupation wage.

Appendix Table 3 compares our main triple difference estimates that use the one year lag of vision coverage policies to results where concurrent vision coverage policies are used instead. The estimates shown in the main paper use the one year lag of vision coverage policies in regression analyses since we hypothesized that changes to vision coverage would first affect the likelihood of an eye doctor visit and receipt of a new prescription for eyeglasses before having an effect on employment outcomes. In line with our expectations, results are generally smaller in magnitude when concurrent vision coverage policies are used, though estimates are of the expected sign and key results maintain statistical significance in most instances. One exception is the mean log occupation wage, which is no longer statistically significant. The fact that switching occupations may take more time than increasing hours at a current job could, in part, explain this finding.

Results in the main paper are based on the Census provided ASEC sample weight. Appendix Table 4 describes how sensitive our main results are to the use of these weights. This robustness test examines several potential problems with the Census provided weights.

The ASEC weights are targeted to Census Population Estimates which are derived from counts obtained from the previous Decennial Census and are updated over time for migration, births, and deaths. When a new Decennial Census becomes available, the Population Estimates are re-calibrated to the new Census counts. As a result, the sum of the ASEC weights are not smooth over time, but shift abruptly when the re-calibrated Population Estimates are incorporated into the weighting routine. Additionally, because the ASEC is a voluntary supplement to the main monthly CPS, a number of eligible monthly CPS interviews refuse the supplement. The Census Bureau fully imputes the supplement data for these missing ASEC interviews and includes them in the public use file. However, due to previously described misspecifications in the imputation routine the inclusion of these fully imputed cases causes biases in estimates of health insurance and income. A fuller description of these issues is available in Ziengenfuss and Davern (2011) and Gouskova (2015).

In Appendix Table 4, we describe how our results vary across three alternative weights. Model 1 repeats results from the main paper using the Census provided ASEC weight. Model 2 uses an alternative weight that is applied only to the sample that has not been fully imputed. The weight, produced by the State Health Access Data Assistance Center, has been inflated so that the restricted sample is representative of the full population and it has been smoothed over time to account for the re-calibration of the control totals. Model 3 presents unweighted results. While there are some minor differences, these results are fairly consistent and do not call into question our substantive conclusions.

To test whether our main findings might be driven by the Great Recession, Appendix Table 5 compares our main results to estimates using a sample period that ends in calendar year 2007. As described in more detail in the paper, the results of this analysis are fairly consistent with our main findings and suggest that changes to the US economy during the recession and recovery period are unlikely to explain our results.

Appendix Table 6 provides results by age and marital status and extends the subgroup analysis shown in Table 7 in the main paper. There are two significant findings. Compared to married individuals, unmarried individuals experience a significantly larger effect to employment (yes/no). However, the effect of vision coverage for unmarried individuals is not statistically different from zero. Unmarried individuals, compared to their married counterparts, receive substantially less effect on part-time work (vs. full time or no work). There are no significant differences across the two age bands we consider (less than 35 versus 35 or older).

Finally, Appendix Table 7 estimates "intent-to-treat" effects for two samples more likely to be eligible for Medicaid: adults with less than a high school degree, and adults with family incomes up to 400 percent FPL. The results for these two samples are expectedly weaker and smaller in magnitude than our main results, as only about 10-13 percent of these individuals reported enrollment in Medicaid during the reference calendar year. However, we find evidence of significant impacts of vision benefits on intensive margin measures including usual hours worked, full-time status, and the mean log occupation wage. As expected, these results are completely concentrated among individuals who reported enrollment in Medicaid.

References

Gouskova, E., 2015. Public health insurance, labor suppy, and employment lock: Effects or data artifacts? Social Science Research Network Working Paper. From: http://dx.doi.org/10.2139/ssrn.2688582.

Ziegenfuss, J.Y., Davern, M.E., 2011. Twenty years of coverage: an enhanced current population survey – 1989-2008. Health Services Research 46(1), 199-209.

Appendix Table 1. Outcome Means for Medicaid Enrollees and Control Group Individuals, with and without Medicaid Adult Vision Coverage[a]

	Medicaid Enrollees			Control Group			
	With vision coverage	**Without vision coverage**	**Difference**	**With vision coverage**	**Without vision coverage**	**Difference**	**Unadjusted Difference-in-Difference[b]**
Full sample							
Worked at least one week last year	50.63	48.09	2.55*	67.79	66.65	1.14	1.41
	(1.15)	(0.94)	(1.50)	(0.61)	(0.56)	(0.76)	(1.36)
Usually worked full time last year (vs. part time or no work)	31.32	28.30	3.01***	50.61	50.43	0.17	2.84**
	(0.70)	(0.84)	(1.07)	(0.58)	(0.71)	(0.67)	(1.13)
Usually worked part time last year (vs. full time or no work)	19.31	19.78	-0.47	17.19	16.22	0.97	-1.43
	(1.09)	(0.60)	(1.25)	(0.51)	(0.53)	(0.64)	(0.89)
Employed last year							
Usual hours worked last year	34.00	33.36	0.64	36.86	37.11	-0.25	0.89**
	(0.28)	(0.30)	(0.44)	(0.17)	(0.18)	(0.18)	(0.38)
Usually worked full time last year (vs. part time)	61.85	58.86	2.99	74.64	75.66	-1.02	4.01***
	(1.54)	(1.11)	(1.88)	(0.68)	(0.79)	(0.83)	(1.48)
Hourly wage last year (1999 dollars)	8.61	8.41	0.20	9.36	8.82	0.54**	-0.34
	(0.24)	(0.28)	(0.36)	(0.18)	(0.11)	(0.22)	(0.38)

[a] All estimates represent mean values. Estimates use sampling weights and errors are clustered by state. Standard errors are in parentheses below estimates. The sample includes 48,020 adults who were on Medicaid at some point during the past year and 267,734 low-income adults not on Medicaid in the past year. * p<0.10, ** p <0.05, *** p<0.01.

[b] Estimates represent the difference between the third and sixth column.

Appendix Table 2. Coefficient Estimates for Key Explanatory Variables, Triple Difference Specification[a]

	Outcomes						
	Full sample			Employed last year			
	Worked at least one week last year	Usually worked full time last year	Usually worked part time last year	Usual hours worked last year (log)	Usually worked full time	Hourly wage last year (log)	Mean log occupation wage
Explanatory variable							
Medicaid x vision benefits	1.44	3.60***	-2.16*	5.90***	5.63***	-1.06	2.27***
	(1.76)	(0.80)	(1.29)	(1.36)	(1.07)	(1.95)	(0.59)
Age	-0.51***	-0.37***	-0.14***	-0.05***	-0.00	0.16***	0.08***
	(0.39)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Black, non-Hispanic	0.84	3.82***	-2.99***	4.01***	5.55***	0.05	-6.95***
	(0.88)	(0.67)	(0.39)	(0.35)	(0.44)	(0.59)	(0.37)
Hispanic	5.65***	8.88***	-3.22***	4.76***	7.03***	-0.36	-5.98***
	(0.56)	(0.74)	(0.42)	(0.54)	(0.80)	(0.88)	(0.51)
Other race, non-Hispanic	-3.76***	-1.20*	-2.56***	2.51***	2.30***	-0.60	-3.25***
	(0.64)	(0.62)	(0.49)	(0.73)	(0.74)	(0.88)	(0.94)
Married	-2.79***	1.17*	-3.96***	2.64***	3.73***	11.80***	4.95***
	(0.58)	(0.64)	(0.24)	(0.51)	(0.48)	(0.41)	(0.30)
Male	13.03***	19.37***	-6.34***	13.68***	14.13***	8.17***	14.53***
	(1.54)	(1.30)	(0.39)	(0.51)	(0.40)	(0.50)	(0.34)
Less than high school diploma	-4.93***	-0.34	-4.60***	3.35***	4.24***	-14.71***	-19.78***
	(0.88)	(0.96)	(0.39)	(0.73)	(0.72)	(0.52)	(0.45)
High school diploma or GED	-0.32	4.17***	-4.49***	5.59***	6.29***	-8.75***	-14.59***
	(0.48)	(0.29)	(0.35)	(0.39)	(0.39)	(0.35)	(0.36)
US citizen	1.44**	0.55	0.89***	0.14	0.04	7.12***	7.11***
	(0.69)	(0.69)	(0.17)	(0.31)	(0.35)	(0.93)	(0.50)

[a] The sample includes 48,020 adults who were on Medicaid at some point during the past year and 267,734 low-income adults not on Medicaid in the past year. All regression results were estimated using linear probability models or linear regression of logged outcomes that controlled for age, race/ethnicity, sex, Medicaid status, marital status, education, citizenship status, state and year fixed effects as well as interactions between Medicaid status and state, Medicaid status and year, and state and year. The coefficient estimates for state and year fixed effects and interactions between Medicaid status and state, Medicaid status and year, and state and year are omitted for brevity. Survey weights were used to produce nationally representative estimates and errors were clustered at the state level. Estimates for binary variables (worked at least one week last year, usually worked full time, usually worked part time) represent percentage point effects. Estimates for logged variables are in terms of log points. The "Mean log occupation wage" represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. Standard errors are shown below estimates in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix Table 3. Triple Difference Results using a Concurrent Vision Coverage Indicator[a]

Full sample		
Worked at least one week last year	1.44	0.78
	(1.76)	(1.65)
Usually worked full time last year (vs. part time or no work)	3.60***	1.86***
	(0.80)	(0.66)
Usually worked part time last year (vs. full time or no work)	-2.16*	-1.08
	(1.29)	(1.38)
Employed last year		
Usual hours worked last year (log)	5.90***	3.66**
	(1.37)	(1.56)
Usually worked full time last year (vs. part time)	5.63***	3.27**
	(1.07)	(1.26)
Hourly wage last year (log)	-1.06	-1.65
	(1.95)	(1.71)
Mean log occupation wage	2.27***	0.60
	(0.59)	(0.94)
Vision coverage variable	One year lag	Concurrent

[a] Estimates reported in the table represent the coefficient for the interaction between the vision coverage indicator and Medicaid status. Standard errors are shown below estimates in parentheses. All regression results were estimated using linear probability models or linear regression of logged outcomes that controlled for age, race/ethnicity, sex, Medicaid status, marital status, education, citizenship status, state and year fixed effects as well as interactions between Medicaid status and state, Medicaid status and year, and state and year. Survey weights were used to produce nationally representative estimates and errors were clustered at the state level. Estimates for binary variables (worked at least one week last year, usually worked full time, usually worked part time) represent percentage point effects. Estimates for logged variables are in terms of log points. The "Mean log occupation wage" represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. * p<0.10, ** p<0.05, *** p<0.01.

Appendix Table 4. Triple Difference Results using Alternative Weights and Unweighted Data[a]

	Model 1	**Model 2**	**Model 3**
Full sample			
Worked at least one week last year	1.44	0.67	0.81
	(1.76)	(1.89)	(1.45)
Usually worked full time last year (vs. part time or no work)	3.60***	3.17***	3.22***
	(0.80)	(0.82)	(0.69)
Usually worked part time last year (vs. full time or no work)	-2.16*	-2.50*	-2.41**
	(1.29)	(1.44)	(1.02)
Employed last year			
Usual hours worked last year (log)	5.90***	5.83***	5.71***
	(1.37)	(1.47)	(1.08)
Usually worked full time last year (vs. part time)	5.63***	5.59***	5.42***
	(1.07)	(1.22)	(0.99)
Hourly wage last year (log)	-1.06	-1.27	-1.89
	(1.95)	(2.31)	(1.84)
Mean log occupation wage	2.27***	2.49***	1.94**
	(0.59)	(0.63)	(0.74)
Weight variable	**standard**	**alternative**	**none**

[a] Estimates reported in the table represent the coefficient for the interaction between the vision coverage indicator and Medicaid status. Standard errors are shown below estimates in parentheses. All regression results were estimated using linear probability models or linear regression of logged outcomes that controlled for age, race/ethnicity, sex, Medicaid status, marital status, education, citizenship status, state and year fixed effects as well as interactions between Medicaid status and state, Medicaid status and year, and state and year. Weights are as indicated in the table and errors were clustered at the state level. Estimates for binary variables represent percentage point effects. Estimates for logged variables are in terms of log points. The "Mean log occupation wage" represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. * p<0.10, ** p<0.05, *** p<0.01.

Appendix Table 5. Triple Difference Results using Data Prior to the Great Recession[a]

Full sample		
Worked at least one week last year	1.44	-0.01
	(1.76)	(2.35)
Usually worked full time last year (vs. part time or no work)	3.60***	2.16*
	(0.80)	(1.23)
Usually worked part time last year (vs. full time or no work)	-2.16*	-2.17
	(1.29)	(1.74)
Employed last year		
Usual hours worked last year (log)	5.90***	4.50**
	(1.37)	(2.20)
Usually worked full time last year (vs. part time)	5.63***	3.99**
	(1.07)	(1.90)
Hourly wage last year (log)	-1.06	7.03***
	(1.95)	(1.81)
Mean log occupation wage	2.27***	3.05*
	(0.59)	(1.69)
Sample Period	2001-2012	2001-2007

[a] Estimates reported in the table represent the coefficient for the interaction between the vision coverage indicator and Medicaid status. Standard errors are shown below estimates in parentheses. All regression results were estimated using linear probability models or linear regression of logged outcomes that controlled for age, race/ethnicity, sex, Medicaid status, marital status, education, citizenship status, state and year fixed effects as well as interactions between Medicaid status and state, Medicaid status and year, and state and year. Survey weights were used to produce nationally representative estimates and errors were clustered at the state level. Estimates for binary variables represent percentage point effects. Estimates for logged variables are in terms of log points. The "Mean log occupation wage" represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix Table 6. Triple Difference Results by Age and Marital Status

	Under age 35	At least age 35	p-value for difference	Married	Unmarried	p-value for difference
Full sample						
Worked at least one week last year	1.38	1.54	0.90	-0.81	3.33	0.02
	(1.74)	(1.87)		(1.91)	(2.26)	
Usually worked full time last year (vs. part time or no work)	3.51*	3.63***	0.97	2.76**	4.07***	0.50
	(2.02)	(1.21)		(1.25)	(1.35)	
Usually worked part time last year (vs. full time or no work)	-2.13	-2.08*	0.98	-3.58***	-0.74	0.05
	(2.13)	(1.17)		(0.93)	(1.72)	
Employed last year						
Usual hours worked last year (log)	5.87**	5.71**	0.96	6.51***	5.00***	0.41
	(2.58)	(2.43)		(1.28)	(1.75)	
Usually worked full time last year (vs. part time)	5.49	5.76***	0.95	6.38***	4.01*	0.39
	(3.31)	(1.59)		(0.79)	(2.25)	
Hourly wage last year (log)	-2.20	0.42	0.42	-3.84**	3.40	0.13
	(2.02)	(2.92)		(1.84)	(3.92)	
Mean log occupation wage	3.69**	1.29*	0.21	3.98***	1.45	0.17
	(1.41)	(0.76)		(1.11)	(1.20)	

[a] Estimates reported in the table represent the triple difference estimate from models with full interactions between the subgroup characteristic of interest and all explanatory variables. Standard errors are shown below estimates in parentheses. All regression results were estimated using linear probability models or linear regression of logged outcomes that controlled for age, race/ethnicity, sex, Medicaid status, marital status, education, citizenship status, state and year fixed effects as well as interactions between Medicaid status and state, Medicaid status and year, and state and year. Survey weights were used to produce nationally representative estimates and errors were clustered at the state level. Estimates for binary variables represent percentage point effects. Estimates for logged variables are in terms of log points. The "Mean log occupation wage" represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix Table 7. Intent-to-Treat Analysis[a]

Sample	Less than high school education	Family income less than 400 FPL
Full sample		
Worked at least one week last year	-0.32	0.36
	(1.33)	(0.34)
Usually worked full time last year (vs. part time or no work)	0.33	0.99**
	(1.09)	(0.50)
Usually worked part time last year (vs. full time or no work)	-0.65	-0.64
	(0.51)	(0.47)
Employed last year		
Usual hours worked last year (log)	0.79**	0.66
	(0.38)	(0.59)
Usually worked full time last year (vs. part time)	0.91*	1.08*
	(0.50)	(0.62)
Hourly wage last year (log)	-0.39	0.48
	(1.03)	(0.47)
Mean log occupation wage	0.75**	0.28*
	(0.32)	(1.62)

[a] Source: 2002-2013 CPS ASEC. The sample includes adults ages 22-64 who were not on Medicare and did not receive SSI income in the past year; other sample exclusions are as indicated. All regression results were estimated using linear probability models that controlled for age, race/ethnicity, sex, marital status, education, citizenship status, state and year fixed effects. Survey weights were used to produce nationally representative estimates and errors were clustered at the state level. The table shows the coefficient estimates on the vision coverage indicator. Standard errors are shown below estimates in parentheses. Estimates for binary variables (employed last week, worked at least one week last year, usually worked full time, usually worked part time, service occupation, managerial/professional occupation) represent percentage point effects. Estimates for logged variables are in terms of log points. The "Mean log occupation wage" represents the mean of the log wage for the full non-elderly adult CPS sample by occupation category (from CPS variable occ1990) excluding farming/fishing occupations and any categories with fewer than 100 observations. * p<0.10, ** p<0.05, *** p<0.01.