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| *Study Program* | **Ph.D. in Economics (RD 99/2011)** | | | | |
| Centro | **Escuela de Doctorado** | | | | |
| *Centre* | **Escuela de Doctorado** | | | | |



El estudiante se encuentra matriculado en el año académico 2023/24 en el plan de estudios indicado
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# “Just” the Flu? Examining Externality Benefits of Influenza Vaccination in the Labor Market

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June 6, 2024

**Abstract**

This study investigates whether and how health benefits from influenza vaccination in the United States affect labor market outcomes. I exploit a random variation in the match between the viruses present in the vaccine and those in circulation to estimate the causal impact of influenza vaccination on employment and wages. I find that influenza vaccination is positively associated with these labor market outcomes. The results suggest that the main mechanisms driving this relationship are an increase in labor productivity and an increase in aggregate demand.

**Keywords:** Influenza Vaccination, Unemployment, Absenteeism, Wages

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# 1 Introduction

Seasonal influenza is a common illness that affects both developed and developing countries, leading to a substantial number of hospitalizations and deaths. According to the Centers for Disease Control and Prevention (CDC), between nine to 41 million flu-related illnesses occur annually in the United States, resulting in up to 52,000 deaths. Influenza vaccination can substantially reduce the severity of illness but compared to other vaccine-preventable diseases the vaccination rates against influenza remain low.

The cost-effectiveness of vaccination campaigns is one of the crucial factors that policymakers consider when making decisions on resource allocation. Recent quasi-experimental studies by Ward (2014) and White (2021) have quantified the direct health benefits of influenza vaccination. However, health interventions, such as influenza vaccination may also play an important role in the formation of human capital and economic development.

Researchers have extensively studied the indirect economic benefits of preventing malaria, tuberculosis, and parasitic worms (Ozier, 2018; Bütikofer and Salvanes, 2020; Baird et al., 2016; Barofsky et al., 2015). They have shown that immunization against these diseases has positive externality effects on labor outcomes and economic development. Yet, it remains an open question whether influenza vaccination yields similar benefits. This study aims to address this gap in the literature by exploring the indirect economic benefits of influenza vaccination in the labor market.

Particularly, this paper is the first to provide evidence on the externality effects of flu vaccines on employment and wages and examine the mechanism behind this relationship. The study utilizes state-by-year vaccination rates from the Behavioral Risk Factor Surveillance System (BRFSS) and year-to-year vaccine match data derived from the CDC influenza surveillance reports. Vaccine matches are defined as the goodness of fit of virus strains' predictions in a given influenza season. These matches occur randomly due to genetic variations in the virus and are unpredictable before the distribution of influenza vaccines (White, 2021). The variable of interest is the interaction between vaccination and match rates which measures the level of effective vaccination. This variable estimates the causal effect of vaccination by comparing states with high and low vaccination rates within flu seasons with different vaccine matches.

In theory, there are a number of channels through which influenza vaccination may affect labor market outcomes. Influenza is associated with chronic illnesses such as asthma, chronic obstructive pulmonary disease, and cardiovascular disease (Kramarz et al., 2001; Poole et al., 2006; Clar et al., 2015). If influenza vaccination reduces the prevalence of these illnesses, it may decrease the number of people who are out of the labor force due to chronic health conditions.

Furthermore, if influenza vaccination decreases absenteeism of the employed, it may improve effective labor time and labor productivity (Koopmanschap et al., 1995; Pauly et al., 2002). This increased productivity may stimulate firms to expand their operations, leading to more job openings. Additionally, higher labor productivity may lead to an increase in wages.

Another channel through which influenza vaccination may affect labor demand is through an increase in aggregate demand. If higher labor productivity leads to an increase in employment and wages, workers' labor income will increase. These income gains may stimulate aggregate demand for goods and services even in those sectors that are not directly affected by a health channel (Guerrieri et al., 2022). The increase in aggregate demand is expected to be more profound if the agents are borrowing-constraint.

Finally, influenza vaccination may directly increase aggregate demand due to improved health of consumers. Better health is associated with higher marginal utility of consumption (Finkelstein et al., 2013). Hence, individuals with better health may be more willing to increase their non-health-related expenditures.

The results suggest that a one standard deviation increase in effective vaccination (i.e., 12 percentage points) is associated with more than a one percentage point decrease in the unemployment rate. The findings also show that effective vaccination is associated with higher wages. The estimated effects appear to be driven by labor demand factors since there is a strong and statistically significant relationship between effective vaccination and job openings. The association between labor force participation rate and effective vaccination is small in magnitude and not statistically significant at conventional levels.

The estimates of effective vaccination on employment and wages are quite homogeneous across demographic groups with the exception of employment effects by parental status. The relationship between effective vaccination and employment appears to be stronger among respondents with children compared to those without children. By exploring the heterogeneity between industries, I find that the effects of vaccination on employment and wages are larger within high-contact industries compared to their counterparts. I also show that in these industries, an increase in effective vaccination is associated with a decrease in absenteeism and an increase in output per worker. These results provide suggestive evidence that an increase in effective labor time and labor productivity is one of the channels through which vaccination affects employment and wages.

The results also suggest that the association between employment and wages is larger in magnitude within industries that exhibit stronger responses to changes in labor income (hereafter, high-$\beta$ industries). These industries do not experience a larger increase in labor productivity when effective vaccination is high. Therefore, an increase in aggregate demand driven by higher labor income in high-contact industries appears to be another channel through which effective vaccination impacts labor market outcomes. To provide additional evidence for this mechanism, I investigate the effects of influenza vaccination on labor market outcomes in high-$\beta$ industries in states with high and low shares of borrowing-constraint agents[1]. The findings suggest that the relationship between influenza vaccination and labor market outcomes is larger in magnitude in the states that have a higher share of the borrowing-constraint agents.

I also provide evidence that effective vaccination increases consumption. The Cur-

[1]This measure is proxied by the share of homeowners since house can be used as collateral

rent Population Survey contains information on weekly spending on eating in bars and restaurants. I show that effective vaccination is positively associated with consumption in the food service industry. Moreover, the effects are larger for those respondents who work in high-contact industries and thus have a higher probability of getting infected with influenza viruses. These results provide suggestive evidence that influenza vaccination may also directly stimulate aggregate demand due to improved health of consumers.

Finally, to better understand the transmission of vaccination externalities in the labor market, I analyze the impact of effective vaccination in local labor markets defined by state, county, and metropolitan state area (MSA). To do so, I use actual vaccination rates for a specific geographic area and include state-by-time fixed effects in the regressions that estimate the benefits of vaccination on county or MSA levels. In other words, I compare the estimates obtained with between-state variation with the estimates obtained with within-state variation. The results suggest that the effect of vaccination on absenteeism is similar within labor markets defined by different geographic areas. However, the externality benefits of vaccination on employment in the labor markets defined by MSA and county are smaller compared to the employment effects in the labor market encompassed by state. These findings are not surprising since if the sectors are tradable, the positive externality effects of influenza vaccination may spread to the neighboring counties/MSAs which would be captured by state-by-time fixed effects.

The remainder of the paper is structured as follows. In Section 2, I provide background information on vaccine match and describe my contribution to the literature. Section 3 describes data and empirical strategy. In Section 4, I discuss the results and provide a series of robustness checks. Finally, Section 5 concludes.

# 2 Background

## 2.1 Vaccination and Vaccine Match

Influenza vaccination is a powerful tool to protect against the disease. However, individual vaccination decisions are likely to be endogenous as those people who face a greater risk of getting sick or may experience complications from the flu are more inclined to opt for vaccination. Even though vaccination on a state level is less susceptible to self-selection bias, states with a higher share of the elderly and other vulnerable groups tend to exhibit higher average vaccination rates. To explore exogenous spillover effects of vaccination White (2021) suggests interacting local vaccination rate with the vaccine match which occurs randomly.

Vaccine match is determined by the goodness of virus strains' predictions. Each year, the World Health Organization monitors influenza virus strains that circulate around the world. Based on this surveillance data, experts predict the most likely strains to circulate in the next influenza season. These strains serve as the basis for vaccine production. Depending on how similar the predicted virus strains are to the actual ones circulating in a given year, vaccine match is calculated, ranging from zero to one with one denoting the maximum match.

Vaccine mismatches may occur for several reasons. First, viruses may mutate over time. These changes in the virus strains may be small but accumulate over time which is referred to as "antigenic drift". A mismatch may occur if antigenic drifts are not considered for the production of influenza vaccines (White, 2021).[2] Another reason why mismatches may occur is because the influenza vaccine can only include a maximum of four virus strains. If the predictions on the predominant viruses were wrong, then the match rate may be smaller than one (White, 2021).

Since vaccine match is unknown prior to the beginning of the influenza season, it

[2]Mismatches may also occur if viruses mutate abruptly, which is referred to as "antigenic shift". However, these mismatches are not studied in the paper.

cannot affect vaccination decisions. Thus, the interaction between state-level vaccination rates and vaccine match measures the exogenous benefits of effective vaccination if controlled for actual state-level vaccination rates, which absorb the endogeneity of vaccination decisions in a given state.

## 2.2 Literature Review

This study contributes to the research on the economic burden of preventable diseases and the benefits of their eradication. One of the diseases that has been extensively discussed in the literature is malaria. Studies have shown that malaria eradication campaigns increase educational attainment, literacy, and wage employment (Barofsky et al., 2015; Lucas, 2010). Furthermore, the incidence of malaria has been negatively associated with economic growth and productivity (Sachs and Malaney, 2002; Hong, 2011; Sarma et al., 2019).

Another cost-effective measure that has drawn the attention of scholars is deworming. Mass deworming has positive externality effects on health, school participation, and years of schooling (Ozier, 2018; Miguel and Kremer, 2004). Moreover, Bleakley (2007) and Baird et al. (2016) report improvements in long-term labor outcomes for children exposed to deworming. Finally, Bütikofer and Salvanes (2020) finds that tuberculosis testing and vaccination campaigns in Norway in 1940 had positive externality effects beyond health outcomes. The authors show that school cohorts residing in municipalities with high pre-treatment tuberculosis incidence benefit more from the campaign in terms of education, height, longevity, and earnings.

The current study contributes to understanding how immunization against preventable diseases impacts economic outcomes. Influenza is one of the most common diseases in both developed and developing countries. Thus, evaluating whether and how the externality effects of influenza vaccination go beyond health benefits could help to better inform policy-makers about the potential returns on investment in vaccination programs.

The effect of influenza on health and economic outcomes has been mainly discussed in the context of in-utero or early-life exposure to influenza pandemics. In-utero exposure to pandemics has been shown to negatively impact health later in life, educational attainment, income, and socioeconomic status (Almond and Mazumder, 2005; Almond, 2006; Kelly, 2011; Lin and Liu, 2014). Additionally, Schwandt (2018) exploits the variation in society-wide seasonal influenza spread and maternal influenza hospitalization. The author finds that in-utero exposure to seasonal influenza is negatively associated with earnings later in life.

Extensive research has been conducted to investigate the effect of COVID-19 on unemployment, job losses, and inequality (Guerrieri et al., 2022; Aum et al., 2021; Bluedorn et al., 2023; Alon et al., 2022; Coibion et al., 2020; Montenovo et al., 2022; Adams-Prassl et al., 2020 Abo-Zaid and Sheng, 2020). By employing a two-sector model, Guerrieri et al. (2022) shows that a (partial) shutdown in a contact-intensive sector may lead to contractions in aggregate demand in a sector that is not directly affected by a shutdown. The authors show that the secondary effect exists if the elasticity of substitution between sectors is lower than the intertemporal elasticity of substitution. However, this assumption may be further relaxed if the markets are incomplete and some share of agents are borrowing-constraint. Their theoretical findings provide important intuition for understanding why health shocks may have larger effects than expected. However, pandemics substantially differ from seasonal influenza since they lead to quarantine measures that significantly disrupt economic activity. This paper adds to this literature by estimating the economic effects of more frequent and less severe health shocks.

The works of Ward (2014) and White (2021) are particularly relevant to this study. Ward (2014) employs a triple difference design based on a vaccination program in Ontario and annual vaccine efficiency, revealing that effective vaccination decreases work absences and influenza and pneumonia-related hospitalizations. White (2021) utilizes variation in effective vaccination rates, and finds that effective vaccination reduces pneumonia-related mortality and work absences. This paper relies on and extends the work of White

(2021) by providing evidence on the impact of influenza vaccination on labor market outcomes beyond absenteeism and identifying the underlying mechanisms.

Finally, since one of the channels through which influenza vaccination may affect labor market outcomes is a decrease in absenteeism, this paper also contributes to the research on absenteeism costs. By estimating a conventional hedonic wage equation, Allen (1983) finds a small output loss from absenteeism. Specifically, a 10 percentage point increase in absenteeism is associated with a 2.1% decrease in wages and a 1.6% decrease in labor productivity. However, by employing a theoretical model, Pauly et al. (2002) suggests that in team production settings where absent workers cannot be easily replaced by perfect substitutes, absenteeism costs may be higher than wages. The importance of worker substitutability in evaluating the indirect costs of absenteeism was further discussed by Koopmanschap et al. (1995). The authors also differentiated between long- and short-term absenteeism with short-term absenteeism representing a lower bound of the estimated costs. Koopmanschap et al. (1995) estimate that, on average, reducing absenteeism by 2% may decrease friction costs worth 0.5% of net national income. Furthermore, the authors find that the elasticity between absenteeism and labor productivity is around 0.8.

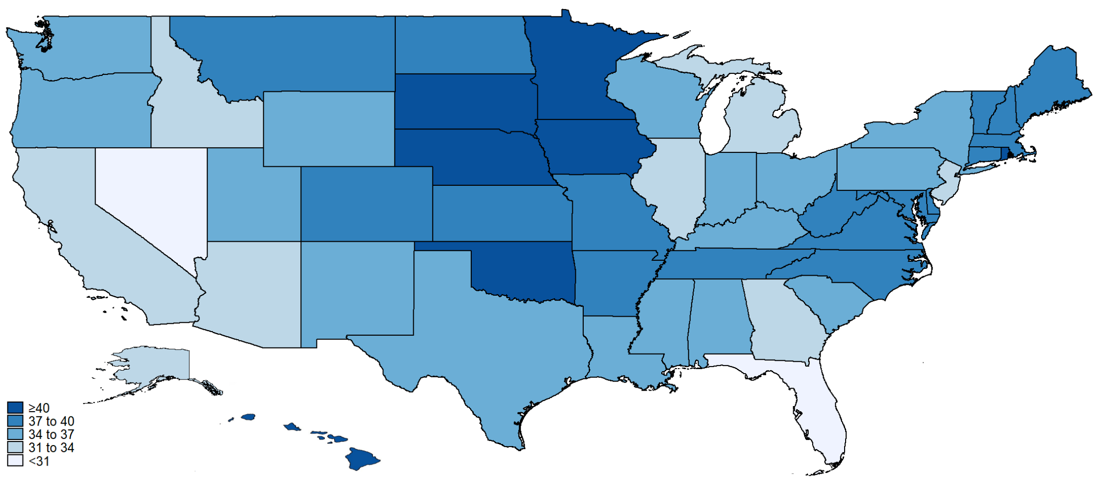
The following studies provide theoretical background on the costs of absenteeism. However, these studies have either relied on observational data or theoretical frameworks. By employing a quasi-experimental setting, the current study helps better evaluate the benefits of decreased absenteeism, particularly absenteeism associated with reducing influenza-related absences.

# 3 Data and Empirical Strategy

## 3.1 Data

The data analysis is performed by flu seasons which range from July to June.[3]. The data on state-level vaccination rates come from the Behavioral Risk Factor Surveillance System. BRFSS is a health-related telephone survey which among other questions provides information on the individual vaccination status. Survey weights are used to calculate vaccination rates by state.

**Figure 1. Flu Vaccination Coverage by State**




Notes: The map shows the average vaccination rates by state from the flu season 2000/01 to 2015/16. The data come from BRFSS

The average variation coverage between states over the period 2000/01-2015/16 is shown in Figure 1. The vaccination coverage ranges from 28.5% to 47%. Two states have vaccination coverage less than 31% and six states have average vaccination coverage over 40%.

Figure 2a shows actual vaccination and match rates over time for the states that in a given flu year have vaccination rates below and above the median (thereafter low- and high-vaccinated states). The figure shows that the vaccination rate increases over time but

[3]For example, flu season 2000/2001 ranges from July 2000 to June 2001

there are no systematic differences between high- and low-vaccinated states. Furthermore, there is no evidence suggesting that vaccination coverage was higher during seasons with elevated flu activity, such as the 2009-2010 pandemic.

Figure 2b shows the interaction between actual vaccination and match rate (i.e., effective vaccination) for the high- and low-vaccinated states. The vaccine match appears to be random over time, without any discernible pattern. The gap in effective vaccination between high- and low-vaccinated states increases when the vaccine match is high and it is almost negligible when the vaccine match is low.

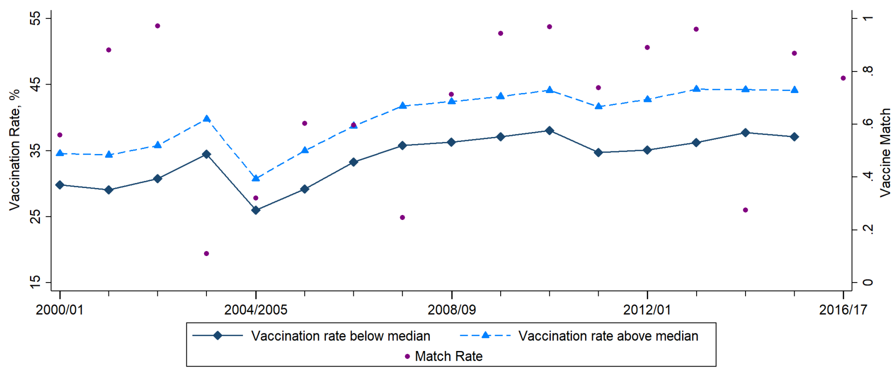
State-level data on employment-to-population ratio, unemployment rate, and labor force participation ratio come from the Local Area Unemployment Statistics (LAUS). To determine whether the employment effects are driven by demand factors or voluntary resignations, the study utilizes the Job Openings and Labor Turnover Survey, which offers data on job openings, hiring, quitting, and layoff rates.[4]

The data on individual labor market outcomes and restaurant spending are from the Current Population Survey. The variables of interest are employment, the natural logarithm of wages, and absenteeism due to illnesses. To investigate the effects on employment, the analysis excludes retired individuals and those attending school, while the effects on wages are only investigated for employed individuals. Finally, since the CPS only interviews full-time employed individuals regarding their reasons for working part-time or being absent from work, only full-time employed respondents are considered to study the impact of vaccination on absenteeism. Employment takes value one if a person is employed and zero otherwise and respondents are considered to be absent due to illness if they miss work or work part-time due to their own medical problems.

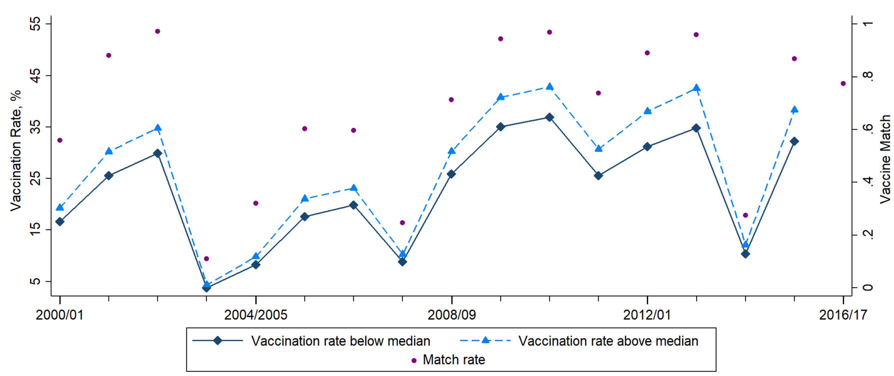
Next, to investigate the mechanism of increased demand in the hospitality industry I focus on two indicators. First, a dummy variable which takes the value of one if a respondent spends any positive amount on eating in a bar or restaurant. Second, a variable

[4]The rates are calculated by dividing the data element level by employment and multiplying by 100.

**Figure 2.** **Actual and Effective Vaccination Over Time**




**Panel A: Actual Vaccination**




**Panel B: Effective Vaccination**

Notes: The graph shows the average actual and effective vaccination from the flu season 2000/01 to 2015/16. The data come from BRFSS that denotes the logarithm of inflation-adjusted spending in a bar or restaurant.

Descriptive statistics are provided in Table 1. It shows that the average employment to population ratio is 62.8%, while average unemployment is 5.6%.

**Table 1. Descriptive Statistics**

| | (1) | (2) |
|---|---|---|
| | Mean | St. Dev. |
| Employment Rate | 62.76671 | 4.644446 |
| Unemployment Rate | 5.553951 | 1.924584 |
| LFP Ratio | 66.42214 | 4.197045 |
| Openings Rate | 2.999112 | .6914703 |
| Hiring Rate | 3.807527 | .7619283 |
| Layoff Rate | 1.511458 | .3976997 |
| Quits Rate | 1.951011 | .4933104 |
| Share 0-14 | 20.27553 | 1.966586 |
| Share 15-44 | 42.11305 | 2.726935 |
| Share 45-64 | 24.40012 | 2.800599 |
| Share +65 | 13.21129 | 2.005757 |

Notes: The data come from LAUS, JOLTS, and Bureau Census. Labor market outcomes are seasonally adjusted.

## 3.2 Empirical Strategy

I start my analysis by investigating the externality effects of influenza vaccination on employment outcomes. To do so, I estimate the following equation 1:

$$Y_{smy} = \beta_0 + \beta_1(V_{sy} * M_y) + \beta_2 V_{sy} + \beta_4 X_{smy} + \delta_{my} + \gamma_s + \epsilon_{smy} \tag{1}$$

where $Y_{smy}$ denotes the outcome variable in state $s$, month $m$, and year $y$. $V_{sy} * M_y$

stands for the state-level vaccination rate in a given flu year multiplied by vaccine match. This interaction term is a variable of interest and is referred to as the effective vaccination rate. $V_{sy}$ represents the actual vaccination rate and absorbs the endogenous part of the relationship between vaccination and labor market outcomes. $X_{smy}$ denotes state-level time-varying control variables such as the share of age groups, the share of individuals with high-school and bachelor's degrees, average month temperature, and precipitation, the logarithm of lagged per capita GDP growth and bartik-type of control.[5][6] The vectors $\delta_{my}$ and $\gamma_s$ stand for state and month-by-year fixed effects. They absorb state-specific time-invariant components and common time shocks. Finally, if the model is estimated on the individual level, I also control for individual-level time-varying characteristics $X_{s(i)my}$, such as age, education, sex, marital, and parental status.

The identification strategy compares the difference in outcomes between low- and high-vaccinated states during flu seasons with high match rates to the difference in outcomes during flu seasons with relatively low match rates. (White, 2021). To investigate the impact of seasonal influenza, the flu years 2008-2009 and 2009-2010 are excluded from the analysis due to the H1N1 pandemic.

[5]Bartik-type of control is constructed by using base level super-sector industry shares by state in 2000 and national employment growth in the given super-sectors over time. This control variable takes care of the endogeneity that might arise from the fact that states react differently to employment shocks (Blanchard and Katz, 1992)

[6]Since weather controls are not available for the District of Columbia and Hawaii, they are excluded from the main analysis. Moreover, the number of observations for the District of Columbia in BRFSS is too low to construct representative vaccination rates

# 4 Results

## 4.1 Main Results

In this section, I analyze the impact of actual and effective vaccination on labor market outcomes. Table 2 shows the estimated effects of influenza vaccination on the unemployment rate, employment-to-population ratio, and labor force participation ratio. The estimates of the actual vaccination rates show the effect of vaccination when the match rate is zero (White, 2021). The results suggest that state-level vaccination rates are highly endogenous: states with higher vaccination rates have higher unemployment rates and labor force participation ratios.

**Table 2. Effective Vaccination and Labor Market Outcomes**

| | (1) | (2) | (3) |
|---|---|---|---|
| | Unemployment rate | Employment ratio | LFP ratio |
| Vaccination*Match | -0.1280*** | 0.0901*** | 0.0142 |
| | (0.0240) | (0.0246) | (0.0187) |
| Vaccination | 0.0972*** | -0.0025 | 0.0588** |
| | (0.0248) | (0.0306) | (0.0280) |
| Observations | 7938 | 7938 | 7938 |

Notes: The data come from the LAUS. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are the unemployment rate, employment-to-population ratio, and labor force participation. The regressions include the full set of state-level control variables described in the section 3.2.
* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

The variables of interest are the interaction terms between vaccination and match rates. The results suggest that a one percentage point increase in effective vaccination is associated with a 0.128 percentage point decrease in the unemployment rate and a 0.09 percentage point increase in the employment-to-population ratio. Considering that one standard deviation of effective vaccination is approximately 12 percentage points, these results are large in magnitude. The estimated effect of effective vaccination on labor force participation is small in magnitude and not statistically significant. These findings suggest that effective vaccination appears to help unemployed individuals find jobs, but does not encourage more people to enter the labor force.

Similar findings are presented in Table 3. The estimates of effective vaccination on hiring and opening rates are positive and statistically significant at conventional levels. This suggests that employment effects appear to be driven by labor demand factors since firms tend to post more vacancies in states with higher effective vaccination. The estimated effect of the interaction term on the quit rates is also positive and statistically significant. Considering that the quit rates are usually due to voluntary job-to-job transitions, this finding aligns with the previously discussed estimates. The association between effective vaccination and layoff rate is not statistically significant.

**Table 3. Effective Vaccination and Labor Market Turnovers**

| | (1)<br>Opening Rate | (2)<br>Hiring Rate | (3)<br>Quit Rate | (4)<br>Layoff Rate |
|---|---|---|---|---|
| Vaccination*Match | 0.0143** | 0.0140** | 0.0113** | 0.0050 |
| | (0.0060) | (0.0064) | (0.0043) | (0.0032) |
| Vaccination | -0.0101 | -0.0030 | 0.0018 | -0.0060 |
| | (0.0068) | (0.0104) | (0.0067) | (0.0053) |
| Observations | 7,938 | 7,938 | 7,938 | 7,938 |

Notes: Notes: The data come from the JOLTS. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are the opening, hiring, quit, and layoff rates. The regressions include the full set of state-level control variables described in the section 3.2.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

Next, by using CPS data, I evaluate the externality benefits of vaccination on labor market outcomes by demographic characteristics. Figures 3a and 3b present the estimates of effective vaccination on employment and wages for various demographic groups. Consistent with the previous results, the findings suggest that effective vaccination is associated with an increase in employment and wages across most demographic groups. The relationship between effective vaccination and labor outcomes is quite homogenous across demographic groups with some minor exceptions. Particularly, the relationship between effective vaccination and employment is stronger for younger individuals and individuals with children.

## 4.2 Mechanisms

To determine the channels through which vaccination affects employment and hiring rates, I estimate the impact of effective vaccination on the logarithm of employment and wages by industry.[7] First, I classify industries by physical proximity. An industry is considered high physical proximity if the physical proximity index is greater than 60.[8]

The estimates in Table 4 show that the estimated effects of vaccination on both wages and employment are larger in magnitude in high-contact industries. Additionally, the estimates in Panels C of Table 4 suggest that effective vaccination reduces absenteeism in high-contact industries by 0.36 percentage points.

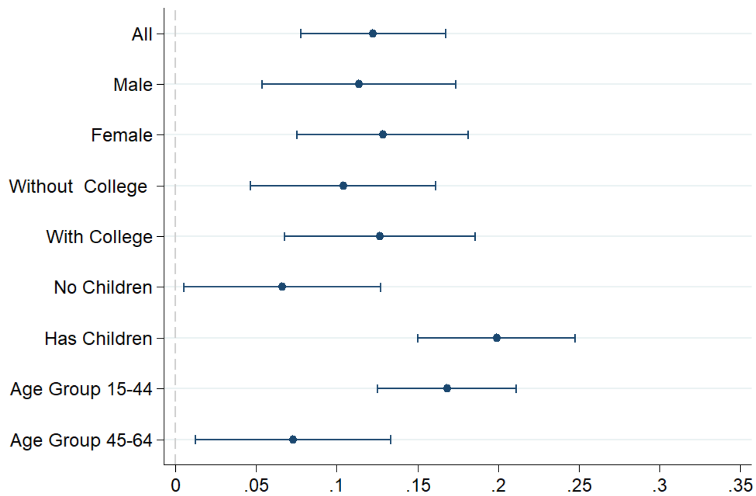
These findings provide evidence that one of the mechanisms driving the relationship between vaccination and job openings is an increase in labor productivity. The exact relationship between absenteeism and labor productivity depends on the substitutability of workers and the possibility of postponing tasks to the future. However, even if a worker can be substituted, absenteeism decreases the effective labor time (Koopmanschap et al., 1995; Pauly et al., 2002).

To provide further evidence on this channel I explore the relationship between vaccination and output per worker. The findings suggest that a one standard deviation increase in effective vaccination increases output per worker by 1.8%.

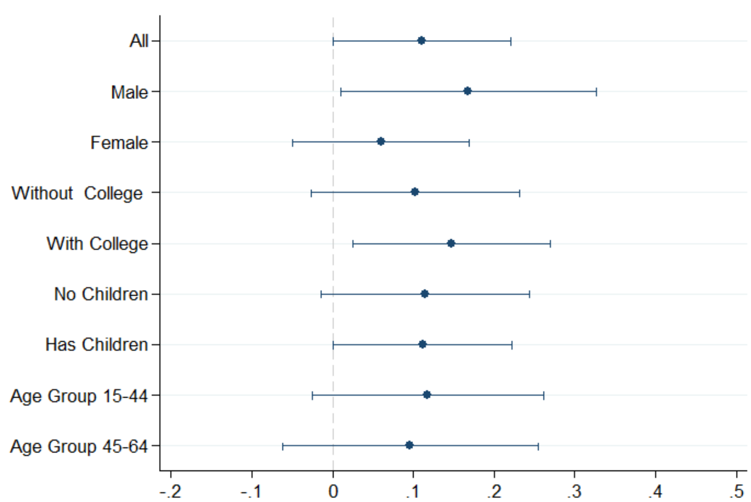
[7]The industries are defined by the Bureau of Labor Statistics aggregation into supersectors.

[8]The classification by physical proximity is based on Famiglietti et al. (2020) and Azzimonti et al. (2020). Therefore high-contact industries include such industries as leisure and hospitality, education and health services, construction, retail trade, and other services.

**Figure 3.** **Estimated Effects by Demographic Characteristics**




**Panel A: Employment**




**Panel B: Wages**

Notes: The data come from the CPS. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are employment and the logarithm of wages. The regressions include the full set of state- and individual-level control variables described in section 3.2.

Next, I investigate whether the benefits of vaccination in high-contact industries may stimulate aggregate demand in industries that are not directly affected by changes in absenteeism and labor productivity. By theoretically analyzing the effects of (partial) shut-

**Table 4. Effective Vaccination and Labor Market Outcomes by Industry**

| | (1) High Proximity | (2) Low Proximity | (3) High Beta | (4) Low Beta |
|---|---|---|---|---|
| **Panel A: Employment** | | | | |
| Vaccine*Match | 0.2341*** | 0.1203 | 0.2516* | 0.1010* |
| | (0.0831) | (0.0752) | (0.1260) | (0.0577) |
| Observations | 7,752 | 7,764 | 7,776 | 7,740 |
| **Panel B: Wages** | | | | |
| Vaccine*Match | 0.1297* | 0.1001 | 0.1806** | 0.0181 |
| | (0.0759) | (0.0716) | (0.0783) | (0.0774) |
| Observations | 639,389 | 560,590 | 644,422 | 555,557 |
| **Panel C: Absenteeism** | | | | |
| Vaccine*Match | -0.0310*** | 0.0014 | -0.0079 | -0.0200*** |
| | (0.0103) | (0.0081) | (0.0101) | (0.0071) |
| Observations | 3,600,754 | 4,194,251 | 4,223,837 | 3,571,168 |
| **Panel D: Output per Worker** | | | | |
| Vaccine*Match | 0.1524** | -0.0340 | 0.0137 | -0.0167 |
| | (0.0704) | (0.0913) | (0.0914) | (0.0862) |
| Observations | 1,824 | 1,798 | 1,824 | 1,798 |

Notes: The data on employment come from the CES; the data on wages and absenteeism come from the CPS; the data on the logarithm of output per worker come from the BEA and the CES. The estimates are obtained with a two-way fixed effects OLS model. The regressions include the full set of state- and individual-level control variables described in the section 3.2.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

downs Guerrieri et al. (2022) show that spillovers from one sector to another are likely when markets are incomplete and the elasticity of substitution between sectors is relatively lower than the intertemporal elasticity of substitution. Market incompleteness and share of budget-constrained individuals play a major role in determining the strength of spillovers between sectors. This is because if individuals are budget-constrained, their marginal propensity to consume is high. Hence, an increase in labor income of workers in the high-contact industries may stimulate aggregate demand in sectors that are not directly affected by influenza vaccination.

To investigate the presence of this channel I classify industries by their response to business cycles (a proxy for changes in labor income) following the approach by Blanchard and Katz (1992). Particularly, I estimate the following regression:

$$\Delta N_{it} = \alpha_i + \beta \Delta N_t^{-i} + \epsilon_{it}$$

where $N_{it}$ is the logarithm of the national employment in the industry $i$ and $N_t^{-i}$ is the logarithm of the total national employment excluding the employment in the industry $i$. By doing so, I approximate labor income in all the industries except industry $i$ with the corresponding employment. If $\beta$ is greater than one, then the industry is classified as a high-$\beta$ industry.[9]

The findings show that the association between effective vaccination and labor market outcomes is stronger in high-$\beta$ industries. Furthermore, there is no evidence that the impact of effective vaccination on absenteeism in high-$\beta$ industries is larger compared to low-$\beta$ industries. Hence, it appears that the mechanism driving the relationship between effective vaccination and employment in high-$\beta$ industries is distinct from a change in labor productivity. This provides suggestive evidence that an increase in the labor income

[9]High-$\beta$ industries include construction, manufacturing, wholesale trade, retail trade, transportation and warehousing, information, and professional and business services. The same classification is obtained if I regress employment growth in each industry on the growth in total disposable income and classify high-$\beta$ industries as those that have $\beta$ higher than the median.

of workers in high-contact industries may further contribute to higher labor demand in industries that are not directly affected by fluctuations in labor productivity.

To provide additional evidence for the aggregate demand channel, I estimate the effects of vaccination on labor market outcomes for two sets of states: states that have the baseline share of homeowners below and above the median.[10]. Ownership of the dwelling can serve as collateral, that is why I use it as a proxy for the share of budget-constrained agents. In theory, states with a lower share of homeowners (higher share of budget-constrained agents) should have larger effects on aggregate demand.

**Table 5. Effective Vaccination and Labor Market Outcomes: by Dwelling Ownership**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | High-$\beta$, N | High-$\beta$, O | Low-$\beta$, N | Low-$\beta$, O |
| **Panel A: Employment** | | | | |
| Vaccine*Match | 0.3262* | 0.1516* | 0.1000 | 0.1555* |
| | (0.1626) | (0.0815) | (0.0793) | (0.0905) |
| Observations | 4,050 | 3,726 | 4,014 | 3,726 |
| **Panel B: Wages** | | | | |
| Vaccine*Match | 0.2285*** | -0.0028 | 0.1375* | 0.0620 |
| | (0.0663) | (0.2299) | (0.0788) | (0.1355) |
| Observations | 380,137 | 302,540 | 347,791 | 264,663 |

Notes: The data on employment come from the CES; the data on the share of home-owners by state come from the ACS; Columns 1 and 3 (2 and 4) show the results that the share of homeowners below (above) median. The estimates are obtained with a two-way fixed effects OLS model. The regressions include the full set of state- and individual-level control variables described in the section 3.2.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

Table 5 shows the relationship between vaccination and labor market outcomes high-

[10]The data on homeownership in the base year (2000) is approximated from the American Community Survey

and low-$\beta$ industries for the states that have a share of homeowners in a base year below the median (columns one and three) and above the median (columns two and four). The findings suggest that the association between vaccination and labor market outcomes is larger in states with a lower share of homeowners. These results may also be driven by the differential effects of vaccination on absenteeism. However, the estimates in the Appendix Table 8 show that, if any difference, the impact of vaccination on absenteeism is larger in the states with a higher share of homeowners.

Finally, another mechanism through which vaccination may affect employment is increased demand due to consumers' improved health. When consumers are in better health, their marginal propensity to consume is ]higher, hence influenza vaccination may also directly stimulate aggregate demand.

To investigate this channel I use data from the CPS on the expenditure for eating in bars and restaurants. The first column in Table 6 shows the relationship between effective vaccination and spending in the food services industry. The results suggest that a one standard deviation increase (0.12) in effective vaccination increases the average spending on eating in a restaurant by 2.9$.

However, this result alone does not imply that the estimated effect is driven by improved health since as shown above aggregate demand may also increase due to the income effect. To provide suggestive evidence that improved health may affect spending on restaurants directly, I estimate the association between effective vaccination and demand for food services for respondents who work in high- and low-contact sectors. Those who work in high-contact sectors have larger health benefits from influenza vaccination. Hence if their demand for the food industry increases more compared to their counterparts, the direct health channel cannot be ruled out. Column two of Table 6 shows the results for respondents in high-contact industries and column three for their counterparts. Since the relationship between vaccination and spending in restaurants is larger for respondents working in high-contact industries, the findings provide suggestive evidence for a direct health channel in stimulating aggregate demand.

## 4.3 Heterogeneity by Geographic Area

To better understand the spillover effects of vaccination, I estimate the externality effects of vaccination by geographic area of the labor market. In particular, columns one, two, and four of Table 7 report the estimates obtained with equation 1; the full sample in column one, the sample that has county identifiers in column two, and the sample that has identifiers of Metropolitan Statistical Areas (MSAs) in column four. Columns three and five estimate the following model:

$$Y_{limy} = \beta_0 + \beta_1(V_{ly} * M_y) + \beta_2 V_{ly} + \beta_3 X_{limy} + \gamma_l + (\delta_{my} * \kappa_s) + \epsilon_{limy} \tag{2}$$

where $Y_{limy}$ is an individual outcome in location l (county or MSA), $V_{ly} * M_y$ is the measure of effective vaccination in location l, $X_{limy}$ is a set of individual characteristics, the vector $\gamma_l$ denotes location fixed effect. Finally, $\delta_{my} * \kappa_s$ is a set of state-by-time fixed effects. In other words, estimates in columns one, two, and four are obtained by utilizing between-state variation while estimates in columns three and four utilize within-

**Table 6. Effective Vaccination and Demand for Food Services Industry**

| | (1) | (2) | |
|---|---|---|---|
| | Spending | Spending | Spending |
| Vaccine*Match | 24.106*** | 36.735*** | 27.134** |
| | (6.819) | (9.772) | (11.240) |
| Observations | 1,364,244 | 340,059 | 334,230 |

Notes: The data come from the CPS. Column 1 estimates the effect of effective vaccination on inflation-adjusted restaurant spending for the whole sample, and column 2 (3) shows the effects for the respondents working in high-contact (low-contact) industries. The estimates are obtained with a two-way fixed effects OLS model. The regressions include the full set of state- and individual-level control variables described in the section 3.2.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

state variation. The variations in the flu vaccination coverage by county and MSA are presented in figures B.1 and B.2.

The results show an interesting pattern.[11] The findings suggest that as the area of the labor market expands, the externality effect of vaccination on employment increases. The estimates of effective vaccination in the labor market defined by the county are more than twice smaller in magnitude than the same estimates in the labor market defined by the state. A similar pattern of results but with a smaller absolute difference is evident for the comparison between the labor markets defined by the state and MSA. However, the impact of effective vaccination on absenteeism is of comparable magnitude between labor markets defined by different geographic areas. This suggests that the spillover effects of vaccination from one county (MSA) to another are larger in terms of economic benefits than in terms of health benefits.

## 4.4 Robustness Checks

This section presents a series of robustness and specification checks. First I examine how sensitive the estimates are to the choice of fixed effects. Table C.1 shows that the estimates are not sensitive to omitting state-fixed effects and including state-specific trends.

To ensure that the results are not contaminated by the effects of vaccination during pandemic years, I excluded flu years 2008/09 and 2009/10 for the main analysis. Table 5 shows that the estimates are robust to including the following years even though, as expected, the estimated effects are slightly larger in magnitude. Furthermore, the findings are robust to excluding the year with vaccine shortage, using alternative vaccination and match measures, described in section 5 and estimating the effects for an alternative set of states.

Next, I investigate whether the results are robust to using alternative estimation strate-

[11] The estimates in samples with available state and county identifiers are larger than in the full sample. This is because county and MSA identifiers are available only in highly populated counties and MSAs.

**Table 7. Effective Vaccination and Employment: Geographic Heterogeneity**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | State | State C-Sample | County | State M-Sample | MSA |
| **Panel A: Employment** | | | | | |
| Vaccine*Match | 0.1291*** | 0.2433*** | 0.1023*** | 0.2733*** | 0.1733*** |
| | (0.0259) | (0.0470) | (0.0291) | (0.0660) | (0.0553) |
| Observations | 13,387,286 | 1,930,325 | 1,930,325 | 2,024,148 | 2,024,148 |
| **Panel B: Absenteeism** | | | | | |
| Vaccine*Match | -0.0149** | -0.0306* | -0.02427 | -0.0220 | -0.02981 |
| | (0.0062) | (0.0166) | (0.0158) | (0.01900) | (0.0267) |
| Observations | 8,026,155 | 1,173,983 | 1,173,983 | 1,241,754 | 1,241,754 |

Notes: The data on employment and absenteeism come from the CPS. The estimates in columns 1, 2, and 4 are obtained by estimating equation 3.2; full sample in column 1, sample with county identifiers in column 2, and sample with MSA identifiers in column 4. The estimates in columns 3, and 5 are obtained by estimating equation 2; in column 3 location is referred to county, and in column 5 location is referred to MSA.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

gies. In the main analysis, I controlled for the actual vaccination rates to capture the endogeneity of vaccination across states. Other ways to estimate the effects would be to exclude the actual vaccination rates from the regression but use an instrumental variables strategy (IV) or interact time-varying match rates with preexisting vaccination rates in the baseline year. Panel A of Table C.4 presents the estimates of the interaction between state-level vaccination rates in the flu year 1999/2000 interacted with time-varying match rates. Under the assumption that the difference between vaccination rates across states is constant over time, this identification strategy should yield estimates of comparable magnitude to those presented in the main specification. The findings confirm that estimates are robust to using a time-invariant measure of vaccination instead of controlling for the actual vaccination rates.

Furthermore, estimates in panel B of Table C.4 show that the results are robust to estimating the effects with an IV strategy. In this specification, the interaction between time-varying match and vaccination rates is instrumented by the interaction between time-invariant vaccination rate in the flu year 1999/2000 and time-varying match rates.

Finally, the identification strategy works under the assumption that the difference between outcomes of high- and low-vaccinated states depends on match rates. Table C.3 presents the estimates of the placebo test, where match rates are randomly reshuffled 1000 times. The results show that the median effect of effective vaccination when the match rate is random is negligible in magnitude, which confirms the usage of the match rates for the construction of effective vaccination.

# 5 Conclusions

Vaccination is a powerful tool to prevent infectious diseases. However, the indirect economic benefits of vaccination are often excluded from the cost-benefit analysis of vaccination campaigns. This study investigates the indirect economic benefits of vaccination, specifically within the labor market.

To study the causal effects of vaccination, the paper exploits variation in vaccine matches (i.e., goodness of fit of virus strains' predictions). In particular, the identification strategy compares the difference between high- and low-vaccinated states when the vaccine match is high with the difference between high- and low-vaccinated states when the vaccine match is low.

The study provides evidence of the positive impact of vaccination on employment and wages. In particular, the results suggest that one standard deviation increase in vaccination is associated with more than a one percentage point decrease in the unemployment rate and a 1.4 percent increase in wages. The results appear to be homogenous across demographic groups but there is substantial heterogeneity across industries. The relationship between vaccination and labor market outcomes is stronger within high-$\beta$ industries and industries with high physical proximity.

This heterogeneity across industries provides suggestive evidence for the channels through which vaccination affects labor market outcomes. The direct channel appears to be an increase in labor productivity which is evident through a decrease in absenteeism and an increase in output per worker within industries with high physical proximity. The other two channels are related to the increase in aggregate demand.

Overall, this study underscores the importance of considering the broader economic benefits of health interventions. The findings provide evidence that influenza vaccination not only promotes a healthier workforce but also enhances labor productivity and stimulates aggregate demand.

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# Online Appendix

## Appendix A: Details on Vaccination and Match Rates

The data on state-year-level vaccination rates come from the Behavioral Risk Factor Surveillance System (BRFSS). BRFSS is a large-scale telephone survey which among other questions includes a question on vaccination status. The exact format of the question on the vaccination status varies over time, however, the most common format is the following: ”A flu shot is an influenza vaccine injected into your arm. During the past 12 months, have you had a flu shot?”. For the main specification, a respondent is classified as vaccinated against the flu if, during the current flu season, the respondent answered ”yes” to this question.

However, since the usual transmission of vaccines is between September to December, giving a positive answer to the flu vaccine question during these months may refer to the previous or current flu season. For example, an affirmative answer to this question in November may mean that the respondent received the flu shot in the current year in October or in the previous year in December (White (2021)). Hence, to avoid this ambiguity, a robustness check is performed with the alternative vaccination measure. This vaccination measure is obtained by omitting the answers between September and December.

Match rates are defined as the percentage of virus strains in the vaccine that match actual virus strains and are derived by using the calculator described in White (2021). The match rate used in the main specification is defined as the “strict” match, which means that the viruses in the vaccine exactly match the circulating viruses (White, 2021). The alternative measure is defined as a “loose” match which means that virus strains in the vaccine provide some level of protection against the circulating strains.

# Appendix B: Additional Tables and Figures

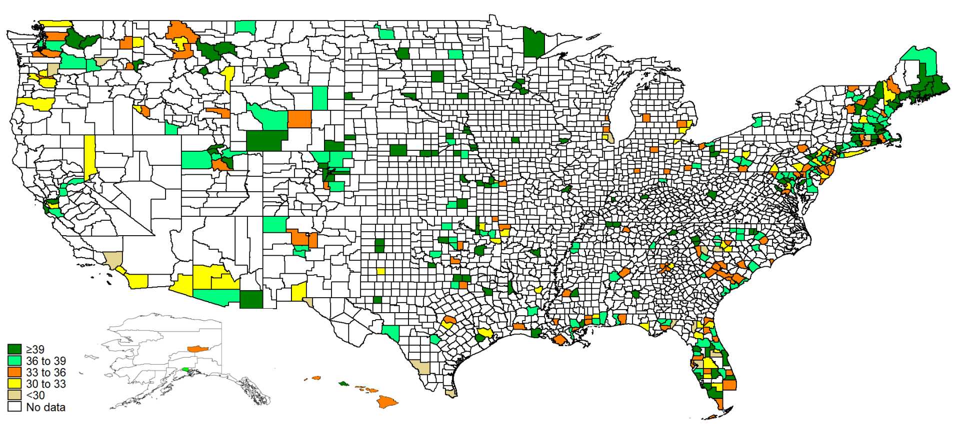
**Table 8.** **Effective Vaccination and Absenteeism: Heterogeneity by Dwelling Ownership**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Whole Sample | Whole Sample | High Contact | High Contact |
| Vaccine*Match | -0.0096 | -0.0169 | -0.0307** | -0.0419** |
| | (0.0079) | (0.0165) | (0.0122) | (0.0182) |
| Observations | 4,745,509 | 3,280,646 | 2,170,878 | 1,486,437 |

Notes: The data on absenteeism come from the CPS; the data on the share of home-owners by state come from the ACS; Columns 1 and 3 (2 and 4) show the results that the share of homeowners below (above) median. The estimates are obtained with a two-way fixed effects OLS model. The regressions include the full set of state- and individual-level control variables described in the section 3.2.

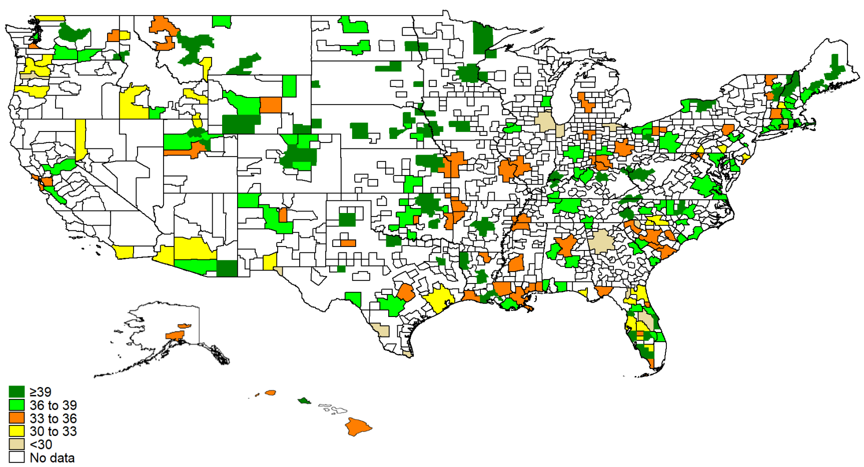
* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

**Figure B.1.** **Flu Vaccination Coverage by County**




Note: Based on the data from BRFSS from 2000/01 to 2015/16

**Figure B.2.** **Flu Vaccination Coverage by Metropolitan Statistical Area**




Note: Based on the data from BRFSS from 2003/04 to 2015/16. The sample size is reduced due to a change in MSA administrative division

## Appendix C: Robustness Checks

**Table C.1. Effective Vaccination and Unemployment: Specification Checks**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Unemployment | Unemployment | Unemployment | Unemployment |
| Vaccination*Match | -0.1280*** | -0.1141*** | -0.1002*** | -0.1280*** |
| | (0.0240) | (0.0229) | (0.0322) | (0.0240) |
| Vaccination | 0.0972*** | 0.0969*** | -0.0341 | 0.0980*** |
| | (0.0248) | (0.0228) | (0.0246) | (0.0248) |
| Observations | 7938 | 7938 | 7938 | 7938 |
| Month-year FE | X | X | X | X |
| State FE | X | X | - | - |
| State Trends | - | X | - | X |

Notes: The data come from the LAUS. The estimates show various specification checks with the first column representing the main specification. The dependent variable is the unemployment rate. The regressions include the full set of state-level control variables described in the section 3.2.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

**Table C.2. Effective Vaccination and Labor Market Outcomes: Robustness Checks**

| | Alternative Vaccination | Alternative Match | Include N1H1 | Drop 2004/05 | All States | Without Alaska |
|---|---|---|---|---|---|---|
| Vaccine*Match | -0.1047*** | -0.1088*** | -0.1477*** | -0.1178*** | -0.1212*** | -0.1291*** |
| | (0.0230) | (0.0269) | (0.0255) | (0.0226) | (0.0237) | (0.0236) |
| Vaccine | 0.0780*** | 0.0949*** | 0.1126*** | 0.0896*** | 0.0915*** | 0.0863*** |
| | (0.0216) | (0.0278) | (0.0241) | (0.0253) | (0.0251) | (0.0222) |
| Observations | 7938 | 7938 | 9114 | 7350 | 8262 | 7776 |

Notes: The data come from the LAUS. The estimates are obtained with a two-way fixed effects OLS model. The dependent variable is the unemployment rate. The regressions include the full set of state-level control variables described in the section 3.2. Column 1 uses an alternative definition of vaccination rate; column 2 uses an alternative definition of match rate; column 3 includes years with the N1H1 pandemic, column 4 drops the years with vaccine shortage, column 5 includes all states and column 6 excludes Alaska.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

**Table C.3.** **Effective Vaccination and Labor Market Outcomes: Placebo Test**

| | (1) Unemployment rate | (2) Employment ratio | (3) LFP ratio |
|---|---|---|---|
| Vaccination*Match | 0.0111 | -0.0064 | -0.0025 |
| | (0.0697) | (0.0554) | (0.0296) |
| Observations | 7938 | 7938 | 7938 |

Notes: The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are the unemployment rate, employment-to-population ratio, and labor force participation. The control variables include the shares of males, white population, and age groups. The match rates are shuffled 1000 times. The table reports the median of the estimated coefficients and the standard deviation of the estimated coefficients (in parenthesis).

**Table C.4.** **Effective Vaccination and Labor Market Outcomes**

| | (1) Unemployment rate | (2) Employment ratio | (3) LFP ratio |
|---|---|---|---|
| **Panel A: Reduced Form** | | | |
| Vaccination*Match | -0.1095*** | 0.0784** | 0.0133 |
| | (0.0324) | (0.0297) | (0.0313) |
| Observations | 7938 | 7938 | 7938 |
| **Panel B: IV** | | | |
| Vaccination*Match | -0.1212*** | 0.0869*** | 0.0147 |
| | (0.0339) | (0.0332) | (0.0341) |
| Observations | 7938 | 7938 | 7938 |

Notes: The data come from the LAUS. The dependent variables are the unemployment rate, employment-to-population ratio, and labor force participation. The regressions include the full set of state-level control variables described in the section 3.2 except vaccination rate. The estimates in Panel A are obtained with a two-way fixed effects OLS model, where the match rate is interacted with the vaccination rate in the flu year 1999/2000. The estimates in Panel B are obtained with a two-stage least squares estimator, where the interaction between time-varying vaccination and match rates is instrumented with the interaction between time-varying match rate and vaccination rate in the flu year 1999/2000.

* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level