Just the Flu? Examining Externality Benefits of Influenza Vaccination in the Labor Market

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Abstract

This study investigates the effects of influenza vaccination in the United States on 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 impact of influenza vaccination on employment and wages. The findings indicate a positive association between vaccination and labor market outcomes in high- and low-contact non-tradable sectors. However, this association is small and not statistically significant in tradable sectors. The results suggest that the main mechanisms behind this relationship are an increase in labor productivity and a surge in aggregate demand driven by higher labor income of workers affected by a labor productivity shock. These findings provide new evidence that aggregate supply shocks in some sectors may cause demand fluctuations in sectors that are not directly affected.

Keywords: Influenza Vaccination, Employment, 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 reduce the severity of illness, but compared to other vaccine-preventable diseases, vaccination rates against influenza remain low (White, 2021). To promote and finance vaccination campaigns, policymakers need to consider their cost-effectiveness. Recent quasi-experimental studies by Ward (2014) and White (2021) have estimated the direct health benefits of influenza vaccination. However, it remains an open question whether this immunization campaign may have indirect payoffs.

This paper is the first to provide evidence on the externality effects of flu vaccines on employment and wages and examine the mechanisms 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 strain 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, influenza vaccination may affect labor market outcomes both through aggregate supply and aggregate demand channels. There are a number of mechanisms through which influenza vaccination may change aggregate demand. First, since better health is associated with a higher marginal utility of consumption (Finkelstein et al., 2013), consumers may increase their non-health-related expenditures. In particular, healthier individuals may be more likely to engage in outdoor activities, such as dining out. Second, lower infection rates may reduce the fear of getting the flu, encouraging spending in sectors that require physical contact. Third, if influenza vaccination reduces absenteeism in the states without paid sick leave, workers will have higher disposable income which may encourage them to spend more. All of these effects may be exacerbated by network spillovers. For example, dining out is often a group activity, and if one member of a group is not willing to participate, others may choose to stay home as well. Regardless of the mechanism in place, an increase in aggregate demand would induce firms to hire more workers.

On the aggregate supply side, influenza vaccination may affect labor market outcomes through an increase in labor productivity, but the sign of the effect on employment and wages is ambiguous. On the one hand, if influenza vaccination increases labor productivity but aggregate demand remains unchanged, then employment may decrease because firms will require fewer workers to produce the same level of output (Gali, 1999; Blanchard, 1989).[1] On the other hand, if aggregate demand increases accordingly, then firms may expand their operations, leading to more job openings and higher wages.

Similar to the effects of COVID-19, the effects of influenza may be disproportional across sectors. Those sectors that rely heavily on face-to-face interactions (hereafter, high-contact sectors) may be more affected both on aggregate demand and aggregate supply sides. Jobs in these sectors have a higher likelihood of flu transmission among coworkers which may result in a larger decrease in labor productivity. On the other hand, individuals may be more likely to reduce consumption of goods and services in high-contact sectors when influenza outbreaks occur. The asymmetric nature of the effects of influenza across sectors may generate spillovers from the high-contact sectors to the sectors that are directly affected (Guerrieri et al., 2022). The spillovers may occur if

[1] Aggregate demand would remain unchanged if prices are sticky and monetary accommodation is limited (Gali, 1999).

workers in high-contact sectors are financially constrained, because a decrease in workers' labor income may reduce aggregate demand not only for high-contact but also for low-contact sectors. A decrease in aggregate demand in not directly affected sectors may also occur due to an input-output structure of production (Guerrieri et al., 2022). A disruption in output in high-contact sectors which usually serve as a downstream of the chain may reduce the demand for goods in services in the upstream of the chain.

This study provides evidence that influenza vaccination has a positive effect on employment and wages. The results suggest that at the average match rate, a one standard deviation increase in vaccination (i.e., five percentage points) is associated with a 0.3 percentage points increase in the employment-to-population ratio and a 0.5% increase in wages. The estimated effects appear to be driven by labor demand factors, as there is a strong relationship between effective vaccination and job openings.

By investigating the heterogeneity in the effects of vaccination by demographic characteristics, I find that the relationship between effective vaccination and labor market outcomes is quite homogeneous across demographic groups. In contrast, by exploring the heterogeneity between sectors, I show that the effects of vaccination on employment and wages are larger in high-contact sectors compared to their counterparts. The results also suggest that in these sectors, an increase in effective vaccination is associated with a decrease in absenteeism and an increase in output per worker. These findings provide evidence that an increase in effective labor time is one of the channels through which vaccination may affect employment and wages.

I also show that influenza vaccination is positively associated with employment in low-contact non-tradable sectors. However, this association is small and not statistically significant in low-contact tradable sectors. These results suggest that there are positive spillover effects through an aggregate demand channel because while non-tradable sectors heavily rely on local demand, tradable sectors rely more on national or global demand (Mian and Sufi, 2014). Next, I examine whether aggregate demand is affected due to the input-output chain of production or consumers' labor income. To provide evidence on the latter mechanism, I investigate the effects of influenza vaccination on the labor market outcomes in states with high and low shares of hand-to-mouth households.[2] Hand-to-mouth households have a higher marginal propensity to consume and in theory, an increase in labor income in the states with a higher share of hand-to-mouth households would have larger effects on aggregate demand. The findings provide evidence for this pattern. The effect of influenza vaccination on consumption and labor market outcomes is larger in magnitude in the states with a higher share of hand-to-mouth households. To examine the supply chain channel, I explore if the effects of influenza vaccination are larger in the low-contact non-tradable sectors that are more likely to be used as intermediate inputs. I find that employment effects are larger in these sectors compared to downstream low-contact sectors which provides the evidence for the supply chain channel.

Finally, to better understand the transmission of vaccination externalities in the labor market, I analyze the impact of effective vaccination in labor markets defined at the state, county, and metropolitan state area (MSA) levels. 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 effects of vaccination on employment are smaller in magnitude in labor markets defined at the MSA and county levels compared to labor markets defined at the state level. These findings are not surprising because positive externality effects of vaccination may spread to the neighboring counties or metropolitan areas 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 outline 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. Section 5 outlines a theoretical framework and section 6

[2] This measure is proxied by the share of homeowners whose status of mortgage is free and clear (Cloyne et al., 2020).

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 with poor health may be more likely to get a flu vaccine. 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 these 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).[3] 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

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

match rate may be lower than one (White, 2021).

Since vaccine match is unknown prior to the beginning of the influenza season, it 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. The latter would absorb the endogeneity of vaccination decisions in a given state.

2.2 Related Literature and Contribution

This study contributes to several stands of the literature. First, it is related to the research on the economic burden of preventable diseases and the benefits of their eradication. While there is growing evidence that immunization against such common diseases as malaria, tuberculosis, and parasite worms has positive partial equilibrium effects, (Bütikofer and Salvanes, 2020; Bleakley, 2007; Baird et al., 2016; Lucas, 2010; Barofsky et al., 2015 Ozier, 2018; Miguel and Kremer, 2004), there is no consensus on the general equilibrium effects of health improvements on the economy. Some studies find that better health is positively associated with economic growth and productivity (Bloom et al., 1998; Strauss and Thomas, 1998; Gallup and Sachs, 2000; Sachs and Malaney, 2002; Shastry and Weil, 2003; Hong, 2011; Sarma et al., 2019; Bloom et al., 2019), while others find no or negative relationship between health improvements and economic development (Acemoglu and Johnson, 2007, 2014; Hansen and Lønstrup, 2015).

The effect of influenza on economic outcomes has only been studied using a partial equilibrium approach by comparing the outcomes of cohorts that have been exposed to influenza outbreaks with the outcomes of their counterparts (Almond and Mazumder, 2005; Almond, 2006; Kelly, 2011; Lin and Liu, 2014; Schwandt, 2018). This study contributes to the literature by examining how immunization against one of the most common diseases affects labor market outcomes by using a general equilibrium approach. Investigating whether 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 works of Ward (2014) and White (2021) are particularly relevant to this study. Ward (2014) uses a triple difference design based on a vaccination program in Ontario and annual vaccine efficiency and shows that effective vaccination decreases work absences 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 builds on and extends the work of White (2021) by providing evidence on the impact of influenza vaccination on labor market outcomes and examining the underlying mechanisms.

Since influenza vaccination may affect labor market outcomes through an increase in effective labor time which may be asymmetric across sectors, this paper also contributes to the research on absenteeism costs and spillover effects of aggregate supply shocks. The previous studies on absenteeism either provide theoretical background on the costs of absenteeism (Pauly et al., 2002) or rely on correlations rather than causal effects (Allen, 1983; Koopmanschap et al., 1995). Similarly, the spillover effects of aggregate supply shocks have been mostly studied by using a theoretical framework. By analyzing a two-sector model, Guerrieri et al. (2022) shows that a (partial) shutdown in a high-contact 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. Guided by a theoretical framework of Guerrieri et al. (2022) with an adjustment to an open economy, I employ a quasi-experimental setting to examine the mechanisms behind spillover effects of aggregate supply shocks.

Finally, extensive research has been conducted to investigate the effect of COVID-19 on unemployment, job losses, and inequality (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). 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.

3 Data and Empirical Strategy

3.1 Data

This section describes the data used in this study. The data on match rates are derived from the CDC surveillance reports by using a calculator developed by White (2021). To assign match rates I redefine years as "flu-years" running from July through June. For example, the flu year 2001/2002 starts in July 2001 and ends in June 2002. This redefinition is necessary because the CDC provides data on virus circulations for influenza seasons rather than for calendar years. In most specifications, the data are for 2001-2016. Furthermore, following White (2021), I exclude the flu-years 2008/09 and 2009/10 due to the H1N1 pandemic.[4]

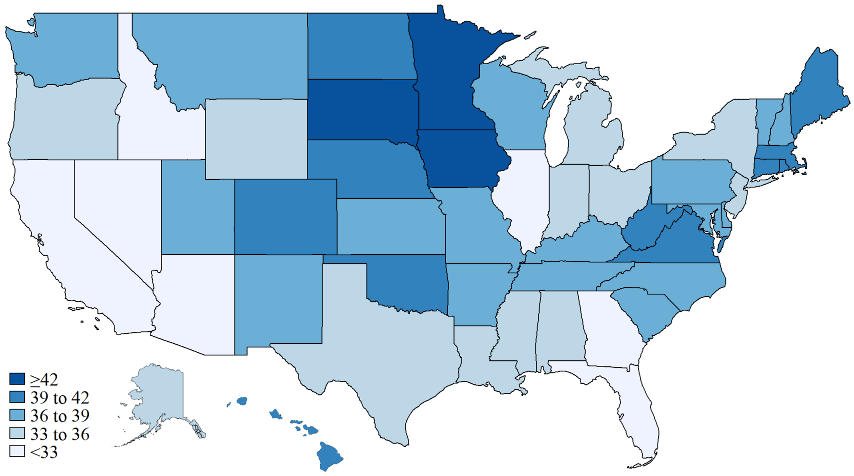
The data on state-by-flu-year vaccination rates come from the Behavioral Risk Factor Surveillance System. BRFSS is a health-related telephone survey which among other questions provides information on the individual vaccination status. Survey weights are used to calculate vaccination rates by state. The variation in the vaccination rates across states between 2000/01 and 2016/17 is shown in Figure 1. The vaccination rates range from 28.7% to 47.1%. Two states have vaccination rates below 31% and six states have vaccination rates above 41%.[5]

Figure 2a shows the actual vaccination rate and vaccine match over time for the states

[4]The data on match rates is available from July 1993, but the data on labor market turnovers is available only from January 2001. Therefore, to analyze the same sample for all labor market outcomes, I restrict it to January 2001.

[5]The states with vaccination rates below 31% are Florida and Nevada and the states with vaccination rates above 41% are Hawaii, Iowa, Minnesota, Nebraska, and South Dakota

Figure 1. Flu Vaccination Coverage by State

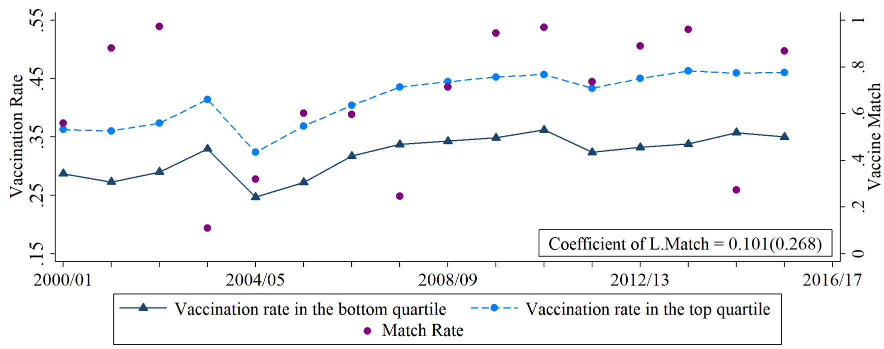


Notes: Based on BRFSS. The map shows the average vaccination rates by state from the flu season 2000/01 to 2016/17.

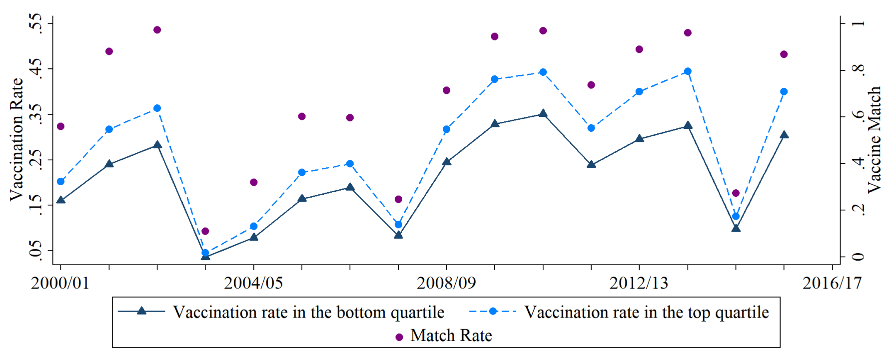
that in a given flu-year have vaccination rates in the bottom and top quartiles (hereafter, low- and high-vaccinated states). The figure shows that the vaccination rate increases over time but there are no systematic differences between high- and low-vaccinated states. Furthermore, there is no evidence suggesting that vaccination coverage was higher during seasons with elevated flu activity, such as the H1N1 pandemic. The vaccine match appears to be random over time, without any discernible pattern. To examine it more formally, I test whether the match rates can be predicted by their lags, lags of labor market outcomes, or a linear time trend. I find no evidence that any of these variables are predictive of match rates (see Appendix Table C.2). Similarly, Appendix Table C.3 shows that the relationship between vaccination and match rates is small and not statistically significant suggesting that individual vaccination decisions are not affected by match rates. Moreover, I find no evidence that states with higher baseline vaccination rates, employment-to-population ratios, or labor-force participation ratios respond differently to match rates.

Figure 2b shows the interaction between actual vaccination and match rate (i.e., effective vaccination) for the high- and low-vaccinated states. 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.

Figure 2. Actual and Effective Vaccination Over Time



Panel A: Actual Vaccination



Panel B: Effective Vaccination

Notes: Based on BRFSS. The graph shows the actual and effective vaccination rates from the flu season 2000/01 to 2016/17.

State-level data on the employment-to-population ratio and labor force participation ratio come from the Local Area Unemployment Statistics (LAUS). To determine whether the employment effects are driven by labor 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.[6] Summary statistics for labor market

[6]The rates are calculated by dividing the data element level by employment and multiplying

outcomes based on these data are shown in Appendix Table C.1. Additionally, to study employment effects by sector, I use data from the Current Employment Survey (CES).

The individual-level data come from the Current Population Survey. The variables of interest are employment, the natural logarithm of inflation-adjusted hourly wages, absenteeism due to illnesses (hereafter, absenteeism), and restaurant consumption. The analysis sample excludes retired individuals and those attending school, while the effects on wages are investigated only for employed individuals.[7] Furthermore, since the CPS only interviews full-time workers about their reasons for working part-time or being absent from work, the measure of absenteeism due to illness is constructed only for those who work at least 35 hours per week. Employment is coded as one if an individual is employed and zero otherwise. Respondents are classified as absent due to illness if they miss work or work part-time due to their own medical problems. The data on restaurant consumption are available only until 2015 and the spending is top-coded to 250$.[8]

Panels A and C of Figure 3 show the evolution of absenteeism and employment for high- and low-vaccinated states. High-vaccinated states tend to exhibit higher absenteeism than their counterparts. However, when the vaccine match is close to one, the difference in absenteeism between these states becomes smaller. Panel B of Figure 3 provides more direct evidence for this pattern by plotting the relationship between match rates and differences in absenteeism between high- and low-vaccinated states. Panel C shows that the employment-to-population ratio also appears to be higher in states with vaccination rates in the top quartile of the distribution, and this gap increases when match

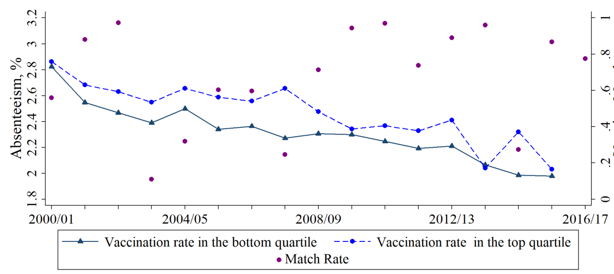
by 100.

[7]To derive hourly wages, I divide weekly earnings by the reported number of hours the respondent usually worked at the job. Since some values of hourly wages are below minimum wage or top coded, following Autor et al. (2008), I trim the top and bottom three percentiles of the wage distribution.

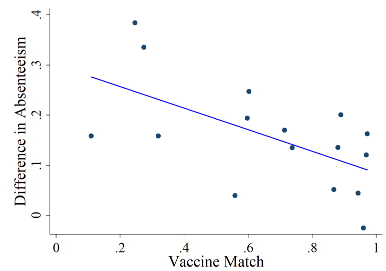
[8]The top codes vary between years with the lowest top code being 250 in 2011. To make data consistent across years, I top-coded the consumption in all the years to 250. Both restaurant consumption and weekly earnings are in 2000$

rates are close to one. This figure provides the first evidence of a negative correlation between absenteeism and influenza vaccination and a positive correlation between employment and vaccination.

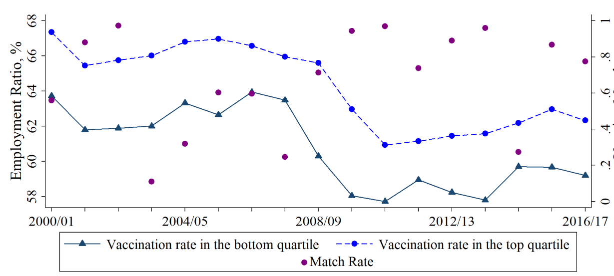
Figure 3. Absenteeism and Employment in Low- and High-Vaccinated States



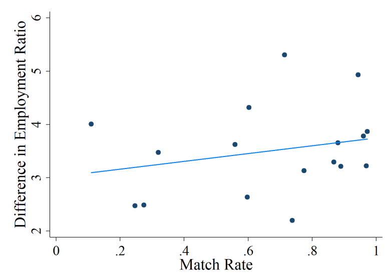
Panel A: Absenteeism



Panel B: $\rho_{\textbf{absenteeism,match}}$



Panel C: Employment



Panel D: $\rho_{\textbf{employment,match}}$

Notes: Based on CPS, CES, and CDC surveillance reports.

3.2 Empirical Strategy

Following White (2021), to investigate the externality effects of influenza vaccination on labor market outcomes by using a quasi-experimental design, 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} is the outcome variable in state s, month m, and year y. The actual vaccination rate is denoted by V_{sy}, and M_y is the match rate. The variable of interest is $V_{sy} * M_y$ which measures the level of effective vaccination. The vector X_{smy} includes state-level time-varying control variables such as average monthly temperature and precipitation, the annual population share for age groups, the lagged GDP growth, and Bartik-type control.[9,10] State fixed effects are denoted by γ_s, and δ_{my} are month-by-year fixed effects. These variables absorb state-specific time-invariant components and common time shocks. Finally, if the model is estimated on the individual level, I also include individual-level time-varying characteristics $X_{s(i)my}$, such as age, education, sex, marital, and parental status.

The identification strategy compares the differences in outcomes between low- and high-vaccinated states in flu seasons with high match rates against the same differences in flu seasons with relatively low match rates. (White, 2021). The variable of interest which is a function of exogenous shocks and other variables is commonly referred to as "formula treatment" (Borusyak and Hull, 2023). The identification strategy relies on the assumption that match rates are as good as randomly assigned. If this assumption holds, then conditional on actual vaccination, effective vaccination measures the causal effect of influenza vaccination.

[9]Bartik-type control is constructed by using base-level super-sector 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).

[10]Due to the unavailability of weather controls for the District of Columbia and Hawaii, I exclude them 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

Table 1 shows the estimated effects of influenza vaccination on the employment-to-population-ratio, and labor force participation ratio. The estimates of the actual vaccination rates represent the effect of vaccination when the match rate is zero (White, 2021). The results suggest that state-level vaccination rates are endogenous: states with higher vaccination rates tend to have higher labor force participation ratios.

Table 1. Effective Vaccination and Labor Market Outcomes

	(1)	(2)
	Employment ratio	LFP ratio
Vaccination*Match	0.098***	0.021
	(0.027)	(0.019)
Vaccination	0.011	0.055*
	(0.030)	(0.028)
Mean of D.V.	0.621	0.658
State FE	Yes	Yes
Time FE	Yes	Yes
Observations	8,232	8,232

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 variable of interest is the interaction between actual vaccination and match rates. Based on the estimates in Table 1, a one percentage point increase in effective vaccination is associated with a 0.097 percentage point increase in the employment-to-population ratio. This suggests that in an average match season, a one standard deviation increase in actual vaccination (i.e., five percentage points) leads to a 0.33 percentage point increase in the employment-to-population ratio. The magnitude of this estimate appears to be surprisingly large but not implausible considering the mechanisms through which influenza vaccination may affect employment. Section 4.6 will discuss the plausibility of these estimates in greater detail. On the other hand, the effect of the interaction term on labor force participation is small in magnitude and not statistically significant. Hence, influenza vaccination appears to help unemployed individuals find jobs but does not encourage more people to enter the labor force.

Table 2. Effective Vaccination and Labor Market Turnovers

	(1)	(2)	(3)	(4)
	Opening Rate	Hiring Rate	Quit Rate	Layoff Rate
Vaccination*Match	0.015**	0.013**	0.011**	0.004
	(0.006)	(0.007)	(0.004)	(0.003)
Vaccination	-0.010	-0.003	-0.000	-0.007
	(0.007)	(0.010)	(0.006)	(0.005)
Mean of D.V.	0.031	0.040	0.020	0.015
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	8,232	8,232	8,232	8,232

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

The relationship between influenza vaccination and labor market turnover is presented in Table 2. Influenza vaccination has a positive effect on hiring and job opening rates but no effect on layoff rates, providing further evidence that the employment effects tend to be driven by labor demand. The association between effective vaccination and quit rates is also positive and statistically significant. Given that quit rates are typically driven by voluntary job-to-job transitions, this finding is consistent with the previously discussed estimates.

Next, by using CPS data, I examine the impact of effective vaccination on labor market outcomes by demographic characteristics. Figures 4a and 4b show that the relationship between effective vaccination and labor market outcomes is quite homogeneous across demographic groups with some minor exceptions. Particularly, the estimated effect of influenza vaccination on employment is larger for those who are younger or have children.

4.2 Mechanisms

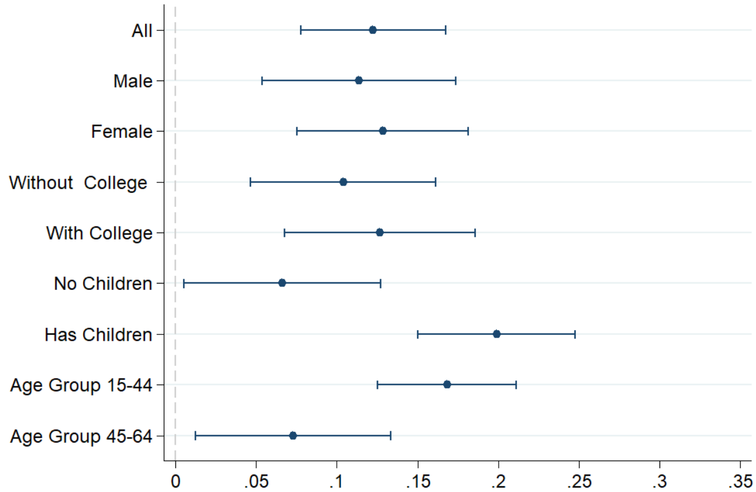
To determine the channels through which vaccination may affect employment and wages, I estimate its impact by sector.[11] First, I classify sectors by contact intensity.[12]

The estimates in Table 3 show that the effects of vaccination on wages and employment are larger in magnitude in high-contact sectors. The findings also suggest that in an average match season, a one standard deviation increase in vaccination reduces absenteeism in high-contact sectors by 0.1 percentage points (a 5% decrease with respect to the mean). These results provide evidence that influenza vaccination may affect labor market outcomes through a labor productivity channel. The exact relationship between absenteeism and labor productivity depends on the substitutability of workers and the possibility of postponing tasks to the future (Koopmanschap et al., 1995; Pauly et al.,

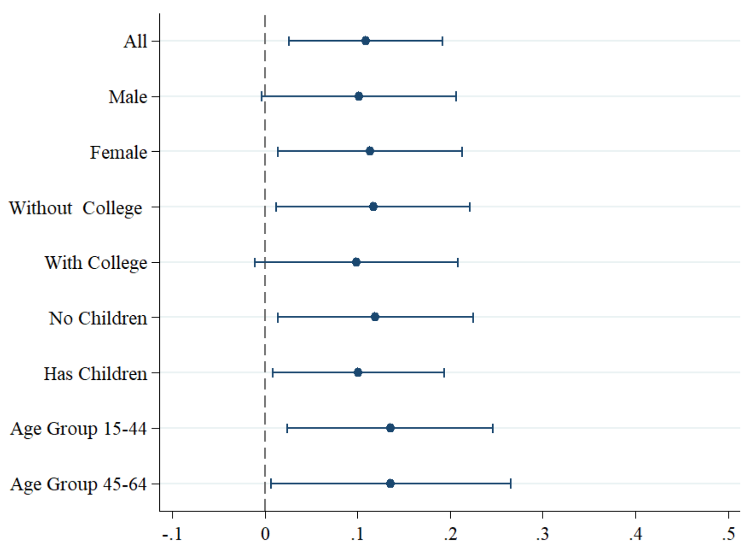
[11]The sectors are defined by the 2-digit North American Industry Classification System (NAICS).

[12]A sector is considered high-contact if the physical proximity index is greater than 65 which corresponds to the fourth quartile of physical proximity by a 2-digit industry. The classification by physical proximity is based on merging O*NET 20.1 version data on physical proximity by occupation with the Occupational Employment and Wage Statistics (OEWS) data on occupational employment by industry. Therefore, high-contact sectors include leisure and hospitality, education and health services, construction, and retail trade.

Figure 4. **Estimated Effects by Demographic Characteristics**



Panel A: Employment



Panel B: Hourly 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.

2002). However, several studies show that absenteeism has an impact on labor productivity (Koopmanschap et al., 1995; Miller et al., 2008).

Table 3. **Effective Vaccination and Labor Market Outcomes by Sector**

	(1) High, Non-Tradable	(2) Low, Non-Tradable	(3) Low, Tradable
Panel A: Absenteeism			
Vaccine*Match	-0.031***	-0.007	-0.001
	(0.010)	(0.010)	(0.011)
Mean of D.V.	0.023	0.024	0.021
Observations	3,849,380	1,747,026	2,731,213
Panel B: Ln(Employment)			
Vaccine*Match	0.231**	0.218**	-0.033
	(0.098)	(0.082)	(0.107)
Mean of D.V.	6.589	6.430	6.180
Observations	8,064	7,728	7,716
Panel C: Ln(Hourly Wages)			
Vaccine*Match	0.141**	0.073	0.089
	(0.057)	(0.068)	(0.080)
Mean of D.V.	2.522	2.603	2.730
Observations	959,413	384,801	614,268
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: Column 1 shows the estimates for high-contact non-tradable sectors, column 2 for low-contact non-tradable, and column 3 for low-contact tradable sectors. The data on employment come from the CES; the data on wages and absenteeism come from the CPS. 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

To provide further evidence on this mechanism, I examine the relationship between vaccination and labor productivity measured by output per worker and output per hour.[13]The findings in Appendix Table C.4 suggest that at the average match rate, a one standard deviation increase in influenza vaccination in high-contact sectors is associated with a 0.56% and 0.66% increase in output per worker and output per hour, respectively.

Next, I investigate whether influenza vaccination may stimulate aggregate demand in sectors that tend to experience smaller direct effects. Guerrieri et al. (2022) show that aggregate supply shocks may generate sectoral spillovers through the input-output network of production and consumer responses. The transmission through the latter mechanism may occur if agents are financially constrained and the elasticity of substitution between sectors is relatively lower than the intertemporal elasticity of substitution. The share of financially constrained workers in directly affected sectors plays an important role in determining the strength of this channel. This is because if these types of workers experience income losses, they are more likely to decrease their spending. On the other hand, the supply chain may serve as a transmission mechanism for sectoral spillovers because an aggregate supply shock to downstream sectors may induce demand fluctuations in upstream sectors.

As theoretically shown in Section 5, the sectoral spillovers should be larger in non-tradable sectors, as tradable sectors mostly rely on national or global demand. That is why I further classify low-contact sectors by tradability.[14] The estimates in Table 3 show that even though the effects of influenza vaccination on effective labor time are much smaller in low-contact sectors, the employment effects in low-contact non-tradable are

[13]To analyze the effects of vaccination on these outcomes, I impose additional sample restrictions described in Appendix B.

[14]The classification is based on Spence and Hlatshwayo (2012) who rely on the physical concentration of industries. I define sectors as non-tradable if their tradability is below 50%. According to this classification, low-contact non-tradable sectors include public administration, other services, real estate and rental leasing, wholesale trade, administrative and waste services, and management of companies and enterprises. All high-contact sectors are non-tradable.

relatively large. In contrast, these effects are close to zero and not statistically significant in low-contact tradable sectors.

To examine whether sectoral spillovers occur through consumer responses, I estimate the effects of influenza vaccination on restaurant consumption, which is the only type of consumption available from the CPS. This type of consumption may capture several effects. First, it may be directly affected if households tend to dine out more when they are healthier or when their fear of getting sick is lower. Second, the demand for restaurant consumption may be affected as a response to a change in prices which may occur due to an aggregate supply shock. Finally, workers in directly affected sectors may increase their restaurant consumption due to changes in their labor income. The latter channel would indicate sectoral spillovers and its impact would be larger among financially constrained households. Since the state-level financial data are not available, I follow Cloyne et al. (2020) who show that in the absence of financial data, homeownership status may serve as a proxy for hand-to-mouth households (H2M). The authors find that mortgagors and renters react stronger to income shocks, and that is why they can be classified as H2M households. I use their finding to investigate the effects of influenza vaccination on consumption and labor market outcomes for two sets of states: states that have a lagged share of mortgagors and renters above and below the median (hereafter H2M and NH2M sample).[15]

Table 4 shows the effects of influenza vaccination on consumption and absenteeism in states with a high and low share of hand-to-mouth households. The estimates suggest that the relationship between vaccination and absenteeism is similar in both sets of states. However, the effect of vaccination on restaurant consumption is three times larger in states with a higher share of hand-to-mouth households. These results provide evidence for the sectoral spillovers through the consumption channel. Similar findings are presented in Table 5, which shows the association between vaccination and labor market outcomes in these sets of states. The estimates suggest that the relationship between vaccination and

[15]The data on homeownership status is approximated from the American Community Survey.

Table 4. Estimated Effects of Vaccination on Consumption and Absenteeism by Dwelling Ownership

	(1) Overall	(2) H2M	(3) NH2M
Panel A: Restaurant Consumption			
Vaccine*Match	25.827***	28.503***	18.613
	(7.237)	(8.177)	(11.831)
Mean of D.V.	29.89	30.94	28.34
Observations	796,905	442,860	354,045
Panel B: Absenteeism			
Vaccine*Match	-0.016***	-0.017**	-0.012
	(0.006)	(0.008)	(0.009)
Mean of D.V.	0.023	0.023	0.023
Observations	8,499,256	4,512,469	3,986,787
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: The data on the share of homeowners by state come from the ACS and the data on restaurant consumption and absenteeism come from the CPS. Columns 1 and 2 show the results for states with the share of homeowners with status free and clear below (H2M) and above (NH2M) the 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

labor market outcomes is larger in states with a higher share of hand-to-mouth households.

To explore whether the supply chain disruptions may contribute to the sector spillovers, I examine the effects of influenza vaccination for upstream and downstream low-contact non-tradable sectors. I find that the association between influenza vaccination and employment is larger in sectors that tend to serve as inputs for high-contact sectors (see

Appendix Table C.6).[16] These findings provide evidence that supply chains may amplify the sectoral spillovers of influenza vaccination.

Table 5. Effective Vaccination and Labor Market Outcomes: by H2M status

	(1)	(2)	(3)	(4)
	High, H2M	High, NH2M	Low, H2M	Low, NH2M
Panel A: Ln(Employment)				
Vaccine*Match	0.360**	0.064	0.308***	0.033
	(0.153)	(0.099)	(0.092)	(0.143)
Mean of D.V.	6.881	6.336	6.687	6.194
Observations	3,738	4,326	3,690	4,038
Panel B: Ln(Hourly Wages)				
Vaccine*Match	0.174**	0.055	0.050	0.133
	(0.068)	(0.084)	(0.085)	(0.098)
Mean of D.V.	2.560	2.472	2.643	2.547
Observations	506,691	452,722	213,554	171,247
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

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

Finally, influenza vaccination may also directly affect aggregate demand in high-contact sectors. Table 4 shows that influenza vaccination is positively associated with restaurant consumption. As discussed before, the findings in this table provide evidence that to some extent these effects are indirect and are driven by fluctuations in labor in-

[16]These sectors are real estate and rental leasing, administrative and waste services, and management of companies

come. However, the reduced form estimates cannot disentangle to what extent restaurant consumption changes as a result of aggregate supply shocks, directly through changes in consumer behavior, or indirectly through fluctuations in labor income. However, as discussed in Guerrieri et al. (2022) the nature of the shock (i.e., aggregate demand or aggregate supply) in directly affected sectors does not change the transmission mechanisms for sectoral spillovers.

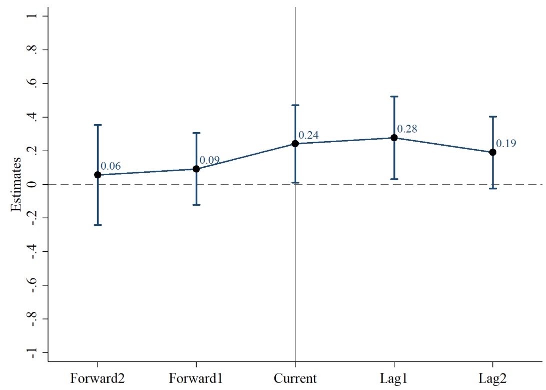
4.3 Dynamics

To rule out the presence of pre-trends and evaluate the persistence of the estimated effects, I enrich the main specification with the variables which interact actual vaccination with match rates in prior and forward flu seasons. Figure 5 presents the estimates of actual vaccination interacted with up to two years forward, current, and up to two years lagged match rates for high-contact non-tradable, low-contact non-tradable, and low-contact tradable sectors.

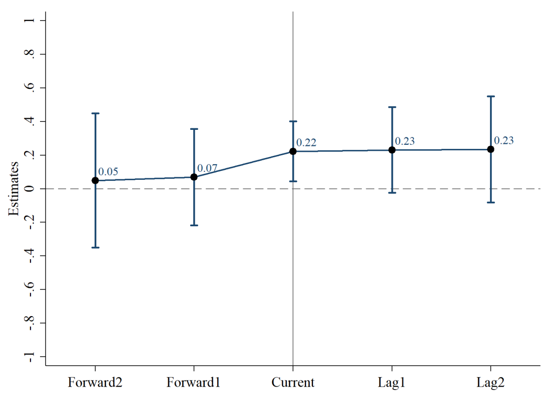
The findings show little evidence of pre-trends. The estimates of the interaction between actual vaccination and forward match rates are small in magnitude and not statistically significant for all the sectors. Consistent with the results presented in Table 3, the interaction of actual vaccination with the current match rate has a positive statistically significant effect on employment in high-contact and low-contact non-tradable sectors. The estimated effect persists for 1-2 years and it is more short-lived in low-contact non-tradable sectors.

Similarly to the estimates in Table 3, the interaction between actual vaccination and the current match rate does not have a sizable and statistically significant effect for tradable sectors. The effect of actual vaccination interacted with the two-year lagged match rate is negative and large in magnitude, even though not statistically significant at conventional levels. A decrease in employment in the tradable sector may happen due to labor mobility between sectors if wages and job openings in the affected sectors increase.

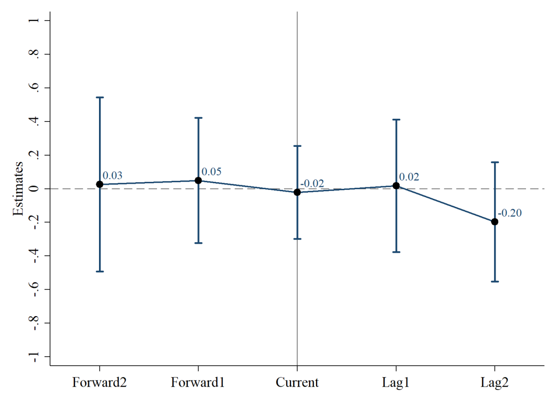
Figure 5. Effective Vaccination and Employment by Sector



Panel A: High-contact non-tradable



Panel B: Low-contact non-tradable



Panel C: Low-contact tradable

Notes: The data on employment come from the CES. The estimates are obtained with a two-way fixed effects OLS model. The regressions include the full set of state control variables described in the section 3.2. The 95% confidence intervals are obtained with standard errors clustered at the state level.

4.4 Heterogeneity by Geographic Area

To better understand the spillover effects of vaccination, I estimate the externality effects of vaccination by the definition of the labor market. In particular, columns one, two, and four of Table 6 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:

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

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 γ_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-state variation. The variations in the flu vaccination coverage by county and MSA are presented in Appendix Figures C.1 and C.2.

The results show an interesting pattern.[17] 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 at the county level are more than twice smaller in magnitude than the same estimates in the labor market defined at the state level. A similar pattern of results but with a smaller absolute difference is evident for the comparison between the labor markets defined at the state and MSA levels. This pattern of results is consistent with the findings in Borjas (2006) and suggests that there are economic spillover effects from one county or MSA to another. These spillover effects

[17] 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 6. Effective Vaccination and Employment: Geographic Heterogeneity

	(1) State	(2) State C-Sample	(3) County	(4) State M-Sample	(5) MSA
Panel A: Employment					
Vaccine*Match	0.117***	0.224***	0.097***	0.248***	0.201***
	(0.027)	(0.045)	(0.027)	(0.073)	(0.049)
Mean of D.V.	0.752	0.754	0.754	0.763	0.763
Observations	13,312,836	1,840,434	1,8404,34	1,934,843	1,934,843
Panel B: Absenteeism					
Vaccine*Match	-0.016***	-0.036*	-0.021	-0.027	-0.028
	(0.006)	(0.018)	(0.017)	(0.018)	(0.027)
Mean of D.V.	0.023	0.022	0.022	0.023	0.023
Observations	8,499,256	1,195,356	1,195,356	1,262,745	1,262,745

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

are captured by common state-by-time shocks which makes the estimates in columns three and five smaller compared to the estimates in columns two and four.

4.5 Robustness Checks

This section presents a series of robustness and specification checks. First, I examine how sensitive the estimates are to the inclusion of state-specific trends. Table D.1 shows that the estimates are robust to this specification change.

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 D.2 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 Appendix A, and estimating the effects for an alternative set of states.

Next, I investigate whether the results are robust to using alternative estimation strategies. 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 D.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 fairly constant over time, this identification strategy should yield estimates of comparable magnitude to those presented in the main specification. The findings provide evidence 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 D.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.

The identification strategy relies on the assumption that the difference between outcomes of high- and low-vaccinated states depends on match rates. Table D.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 reshuffled is negligible in magnitude.

Finally, I study the effects of vaccination by using a quasi-experimental setting in Canada. In October 2000, Ontario implemented the Universal Influenza Immunization Program (UIIP) which aimed at providing free influenza vaccines for the entire population. Following Ward (2014), I employ the triple-difference estimation design shown in equation 3, to estimate the effect of influenza vaccination on employment.

$$\begin{aligned} Y_{pt} = \alpha_1 \left(\text{UIIC}_p \times \text{Post}_t \times m_{py}\right) + \alpha_2 \left(\text{UIIC}_p \times \text{Post}_t\right) + \\ \alpha_3 \left(\text{Post}_t \times m_{py}\right) + \alpha_4 \left(\text{UIIC}_p \times m_{py}\right) + \mathbf{X}'_{pt}\Pi + \kappa_t + \phi_p + u_{pt} \end{aligned} \tag{3}$$

where Y_{pym} denotes employment to population ratio in province p, month m, and year y. UIIC_p takes value one if the province is Ontario, $Post_t$ takes value one if the flu year is greater or equal to 2000, and m_{py} is the province-by-flu-year match rate. Vector X_{pt} includes province-by-time control variables, such as match rate in levels, share of five age groups, weather controls, lagged GDP growth, and batik-type of control. Lastly, κ_t and ϕ_p are time and province fixed effects, respectively.

The triple-difference estimates with actual and reshuffled match rates are shown in Table D.5. The findings suggest that at the average match rate (i.e., 0.7), the UIIC appears to increase the employment-to-population ratio by 0.37 percentage points. Given that the adoption of the program is associated with an 8.7 percentage point increase in vaccination rates, the magnitude of the estimate is of lower but comparable to the estimated effect of influenza vaccination in the US.

4.6 Discussion

This paper finds that influenza vaccination has a surprisingly large effect on employment. It provides evidence that asymmetric health effects across sectors and subsequent sectoral spillovers appear to explain the magnitude of the relationship between vaccination and labor market outcomes. As Guerrieri et al. (2022) argued, due to sectoral spillovers, there is a difference between a 100 percent decrease in the output in half of the sectors and a 50 percent decrease in output in the whole economy. Since this study is the first to examine sectoral spillovers due to influenza vaccination, it is important to reconcile the magnitude of the estimated effects with other related studies.

I start with the relationship between absenteeism and labor productivity. Absenteeism has been shown to affect labor productivity especially if workers cannot be easily substituted and in the presence of the team production function (Koopmanschap et al., 1995). The estimated elasticity of output per worker to absenteeism in other studies ranges from -0.1 to -0.03 (Zhang et al., 2017; Rondinella and Silipo, 2023). This study finds that a one percentage point increase in effective vaccination is associated with a 0.03 percentage point decrease in absenteeism in high-contact sectors (1.3% with respect to the mean) and a 0.17 percent increase in output per hour, which implies the elasticity of output per worker to absenteeism to be -0.13. This estimate is slightly higher than those from the previous studies, which may be due to the fact that some workers may go to work while being ill but are less productive due to having influenza.

Another important elasticity to consider is the elasticity of employment to labor productivity. Most studies examine the effect of an increase in labor productivity caused by technology shocks. Due to displacement effects, these studies find no or negative relationship between technology adoption and employment (Autor and Salomons, 2018; Acemoglu and Restrepo, 2018; Acemoglu and Restrepo, 2020). Moreover, as argued by Gali (1999), an increase in labor productivity may lead to lower employment if aggregate demand does not adjust accordingly. Since influenza vaccination does not have displacement effects, the findings of this paper are more comparable to studies that examine the effect of an increase in labor productivity on employment caused by the training of workers (Naval et al., 2020; OECD, 2004). Naval et al. (2020) find that an increase in on-the-job training increases both employment and labor productivity but the authors do not explicitly discuss the elasticity of employment with respect to labor productivity. Moreover, the effect of influenza vaccination on employment in high-contact sectors may also come through an increase in aggregate demand but the reduced form estimates cannot disentangle the relative importance of these channels.

Another elasticity that needs to be discussed is the elasticity of consumption to employment and income. Previous studies find that the onset of unemployment is associated with a 6-10 percent decrease in spending (Ganong and Noel, 2019; Baker and Yannelis, 2017). This relationship is stronger with the absence of unemployment insurance. For these individuals, the spending decreases by 12-20 percent. The average elasticity of consumption to income is estimated to be around 0.3 (Baker and Yannelis, 2017). Importantly, H2M households tend to be more responsive to income changes (Kaplan and Violante, 2014; Baker and Yannelis, 2017). This paper finds that a one percentage point increase in effective vaccination increases employment-to-population ratio and wages by 0.098 percentage points (0.16% with respect to the mean) and 0.1 percent, respectively, while restaurant consumption increases by 0.258 dollars (0.8% with respect to the mean). These findings suggest that demand for restaurant consumption increases both directly and indirectly. Direct effects may arise due to a higher willingness to dine out of healthier individuals, while indirect effects due to income effects. Comparing the estimate of an increase in restaurant consumption to the elasticity of consumption to income suggests that the direct effects are relatively large. The indirect effects might be slightly larger than estimated from the previous studies because spending on restaurants tends to be 1.15-1.3 times more affected than the average spending and high-contact sectors have a higher share of H2M households. For example, the share of H2M households in accommodation and food services is 1.3 times higher than the average, and the share of H2M households in retail trade and health services is 1.13 times higher than the average (Beraldi and Malgieri, 2024).

Finally, to analyze spillover effects from high-contact sectors to low-contact non-tradable sectors, consider the elasticity of employment to consumption. Mian and Sufi (2014) finds that the elasticity of non-tradable employment to consumption in other studies is around 0.48. The findings suggest that a one percentage point increase in effective vaccination is associated with a 0.218 percent increase in employment. This estimate may capture the effect of vaccination on employment in low-contact non-tradable sectors through several channels: an indirect increase in demand due to consumer responses and input-output structure of production and an increase in effective labor time. The effect of effective vaccination on absenteeism in low-contact non-tradable sectors is quite noisy but suggests that a one percentage point increase in effective vaccination appears to decrease absenteeism by 0.007 percentage points (0.29% decrease with respect to the mean).

5 Theoretical Framework

To provide a more formal intuition for the transmission mechanisms across sectors, I extend the Guerrieri et al. (2022) model to an open economy following Mian and Sufi (2014). By analyzing a two-sector model, Guerrieri et al. (2022) show that a shock that (partially) shuts down one sector, can lead to demand shortages in another sector. This transmission occurs if the inter-temporal elasticity of substitution is larger than the elasticity of substitution between sectors. A negative aggregate supply shock in one sector makes goods in another sector relatively cheaper stimulating the demand for goods in a non-directly affected sector. On the other hand, when the supply of the disrupted sector falls, the prices of its goods increase which makes today's consumption basket more expensive relative to future consumption. This effect induces consumers to postpone the consumption of both goods to the future. The condition stated above ensures that the latter force is stronger. Furthermore, sectoral spillovers become more pronounced if some share of households do not have access to credit. Due to a financial constraint, agents also lose their labor income which further exacerbates a decrease in consumption in the fully active sector.

To analyze the implications of the Guerrieri et al. (2022) model in the open economy, suppose that consumers in fully identical states s derive utility from the consumption of two goods A and B. Households face a constant elasticity of substitution between goods ϵ and constant inter-temporal elasticity of substitution σ.

$$\sum_{t=0}^{\infty} \beta^t U\left(c_{\mathrm{A}st}, c_{\mathrm{B}st}\right)$$

$$U\left(c_{\mathrm{A}st}, c_{\mathrm{B}st}\right) = \frac{\sigma}{\sigma-1}\left(\phi^{\frac{1}{\epsilon}} c_{\mathrm{A}st}^{\frac{\epsilon-1}{\epsilon}} + (1-\phi)^{\frac{1}{\epsilon}} c_{\mathrm{B}st}^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}\frac{\sigma-1}{\sigma}}$$

Sector A is high-contact and non-tradable while sector B is low-contact and freely tradable across states. The shipment costs are equal to zero. Prices in a non-tradable sector are stare-specific but prices in a tradable sector are identical between states. Households face the following budget constraint:

$$\mathrm{P}_{\mathrm{A}st} c_{i\mathrm{A}st} + \mathrm{P}_{\mathrm{B}t} c_{i\mathrm{B}st} + a_{ist} \leq \mathrm{W}_{jst} n_{jst} + (1 + i_{st-1})\, a_{ist-1},$$

where W_{jst} are wages in sector j in which agent i works, $\mathrm{P}_{\mathrm{A}st}$ and $\mathrm{P}_{\mathrm{B}t}$ are prices for goods A and B, $a_i t$ are bond holdings and i_{st} is a nominal interest rate. Furthermore, a random share μ of workers do not have access to credit (i.e., $a \geq 0$).

Labor is supplied inelastically, and the production technology in each sector j is linear: $\mathrm{Y}_{jst} = \mathrm{N}_{jst}$. Share ϕ of agents work in sector A and share $1 - \phi$ work in sector B. There is no labor mobility between states or between sectors. Non-tradable goods can be sold only within a state. However, the demand for tradable goods in each state also relies on the demand from other states. By imposing market clearing conditions: $\mathrm{C}_{\mathrm{A}st} = \mathrm{Y}_{\mathrm{A}st}$ and $\sum_{s=1}^{n} \mathrm{C}_{\mathrm{B}st} = \sum_{s=1}^{n} \mathrm{Y}_{\mathrm{B}st}$. Firms are competitive, which implies that in equilibrium, $\mathrm{W}_{jst} = \mathrm{P}_{jst}$. In a steady state $\mathrm{W}^*_{\mathrm{A}s} = \mathrm{W}^*_{\mathrm{B}s} = \mathrm{P}^*_{\mathrm{A}s} = \mathrm{P}^*_{\mathrm{B}} = 1$.

In period zero each state faces a different labor productivity shock in sector A which causes workers' labor productivity in sector A to go to $1 - \delta_s$.

Full Nominal or Real Wage Rigidity

As a result of labor productivity shock, employment in sector A in each state s decreases to $(1 - \delta_s)$, because $n_{\mathrm{A}0s} = \frac{\mathrm{Y}_{\mathrm{A}0s}}{\mathrm{Y}^*_{\mathrm{A}s}} = \frac{(1-\delta_s)\phi}{\phi} = (1 - \delta_s)$.

To analyze changes in employment in sector B, one needs to consider the ratio between actual and potential output, where actual output is derived from the market clearing condition and potential output is equal to $1 - \phi$. Following Guerrieri et al. (2022), it can be shown that consumption of the goods in each state in period zero is equal to:[18]

[18]The consumption function has the following form because constrained agents in sector A ($\mu\phi$) consume their labor income $(1 - \delta_s)\mathrm{W}_{\mathrm{A}is0}$, while the average consumption for all the other

$$C_{As0} = \phi\left(\frac{P_{As0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{W_{Aso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right),$$
$$C_{Bs0} = (1-\phi)\left(\frac{P_{Bs0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{W_{Aso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right).$$

where is P_{s0} is a price index in period zero in each state which is equal to: $P_{s0} = \left(\phi P_{As0}^{1-\epsilon} + (1-\phi)P_{Bs0}^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}$.

Given the tradability of the sectors, the aggregate demand in each sector in period zero is given by: $Y_{Bs0} = C_{Bs0}$ and $\sum_{s=1}^{n} Y_{Bs0} = \sum_{s=1}^{n} C_{Bs0}$. Hence, since firms are symmetric, substituting $W_{As0} = W_{Bs0} = P_{As0} = P_{B0} = P_{0s} = W^* = P^* = 1$ gives the following equation for the output of good B in each state:

$$Y_{Bs0} = \frac{(1-\phi)\sum_{s=1}^{n}(1-\mu\phi\delta_s)}{n}$$

Finally, employment in sector B in state s in period zero can be derived as a ratio between actual and potential output.

$$n_{Bs0} = \frac{Y_{Bs0}}{Y_{Bs}^*} = \frac{Y_{Bs0}}{(1-\phi)} = \frac{\sum_{s=1}^{n}(1-\mu\phi\delta_s)}{n}$$

This result suggests that the larger is n, the less employment in sector B depends on the labor productivity shock in sector A in its state. In contrast, the case of n being equal to one is identical to sector B being fully non-tradable (i.e., model analyzed by Guerrieri et al. (2022)). In such a case, $n_{B0} = 1 - \delta\mu\phi$ which implies that employment in sector B is more affected if the share of financially constrained households μ increases.

No Nominal or Real Wage Rigidity

When real wages are rigid, then there is no involuntary unemployment. Instead, firms adjust their wages. In sector A, firms their wages to $W_{As} = P_{As}(1-\delta_s)$. First, consider the case when sector B is non-tradable. Following this adjustment, firms in sector B decrease

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workers $(1-\mu\phi)$ is derived from the Euler equation is equal to $(\frac{P_0}{P_1})^{-\sigma}$.

their wages and prices if the following condition holds (see the detailed derivations in Appendix E):

$$\sigma > \epsilon - (1-\epsilon)\frac{\ln\left(1-\mu\phi\frac{(1-\delta_s)^{1-\frac{1}{\epsilon}}}{\phi(1-\delta_s)^{1-\frac{1}{\epsilon}}+1-\phi}\right)-\ln(1-\mu\phi)}{\ln\left(\phi(1-\delta_s)^{1-\frac{1}{\epsilon}}+1-\phi\right)}$$

Hence, under flexible prices and wages in both sectors, labor productivity shock in sector A translates into a decrease in wages and prices in sector B if the intertemporal elasticity of substitution is sufficiently larger than the elasticity of substitution between sectors. Similar to the result above, prices and wages are more affected if the share of the financially constrained households increases. If sector B is tradable, then all the firms adjust prices by the same level according to the market clearing condition.

Flexible Prices in Sector A and Real Wage Rigidity in Sector B

Finally, consider the case when prices in sector A are allowed to increase as a result of a labor productivity shock, but wages are downward rigid in both sectors. Since prices in sector B are rigid, the output is rationed by demand. If sector A is non-tradable, then workers in this sector would face involuntary unemployment if the following condition holds:

$$\sigma > \epsilon - (1-\epsilon)\frac{\ln\left(1-\mu\phi^2\frac{(1-\delta)^{\epsilon-1}}{\phi(1-\delta)^{\epsilon-1}+1-\phi}\right)-\ln(1-\mu\phi)}{\ln\left(\phi(1-\delta)^{\epsilon-1}+1-\phi\right)}$$

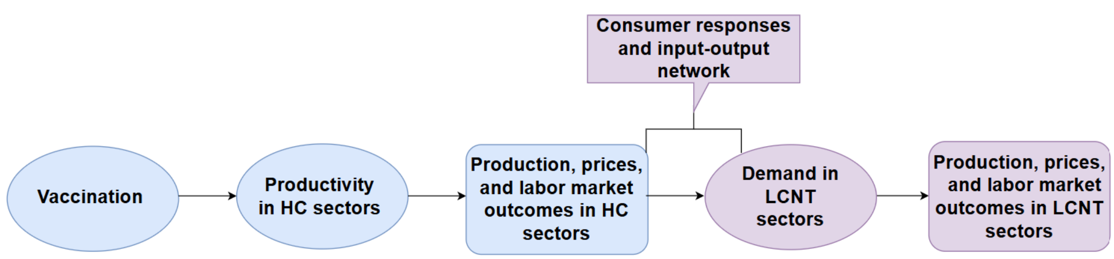
This condition is very similar to the condition above and suggests that if real wages in sector B are rigid, then this sector faces involuntary unemployment if sectors are complementary enough. Again, if sectors are tradable, the spillover effects would be the same in all the states.

These three conditions provide a simple framework for the propagation of shocks across sectors. The flexibility of prices in sector A determines whether an additional assumption of complementarity between sectors is needed while nominal rigidities in sector B determine if the spillover effects are absorbed by employment or wages.

Moreover, as shown in Guerrieri et al. (2022) the transmission of the aggregate supply shocks may be exacerbated if sector B serves as an intermediate input for sector A. This is because if production in sector A falls, the firms in this sector would decrease the demand for the intermediate inputs.

In short, the channels for sectoral transmission are depicted in Figure 6. The diagram shows that a shock to labor productivity in high-contact sectors may affect labor market outcomes in low-contact non-tradable sectors through consumer responses and the input-output network structure of production. The changes in consumption may be driven by two forces: the changes in the price index and the income losses of workers who are hit by a labor productivity shock. Furthermore, the transmission of aggregate demand shocks in one sector (e.g, lower willingness to dine out because of getting flu) would happen through the same channels in the presence of nominal rigidities (Guerrieri et al., 2022).

Figure 6. Flow Diagram



Notes: HCNT and LCNT stand for high- and low-contact non-tradable sectors, respectively.

6 Concluding Remarks

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

To study the causal effects of vaccination, this paper exploits variation in vaccine matches (i.e., the goodness of fit of virus strains' predictions). 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 findings provide evidence of the positive impact of vaccination on employment and wages. Specifically, the results suggest that at the average match rate, a one standard deviation increase in vaccination is associated with a 0.33 percentage point increase in the employment-to-population ratio and a 0.3 percent increase in hourly wages. The effects appear to be homogeneous across demographic groups but there is substantial heterogeneity across sectors. The relationship between vaccination and labor market outcomes is stronger within high-contact non-tradable sectors. Furthermore, vaccination is positively associated with these labor market outcomes in low-contact non-tradable sectors, while this association is small in magnitude and not statistically significant in low-contact tradable sectors.

This sectoral heterogeneity provides suggestive evidence for the channels through which vaccination affects labor market outcomes. The direct channel appears to be an increase in labor productivity, evident through a decrease in absenteeism and an increase in output per worker in high-contact sectors. Another channel appears to be an increase in aggregate demand due to the higher labor income of workers in high-contact sectors.

Overall, this study underscores the importance of considering the broader economic benefits of health interventions. The findings show that influenza vaccination not only promotes a healthier workforce but also enhances labor productivity and stimulates aggregate demand. Moreover, this study provides evidence that aggregate supply shocks in directly affected sectors may lead to demand fluctuations in sectors that are not directly affected.

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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: Data on Labor Productivity

To provide further evidence for the productivity channel, I estimate the effect of vaccination on logarithms of output per worker and output per hour. The data on gross domestic product (GDP) come from the Bureau of Economic Analysis (BEA) and the data on the average number of hours come from the CES. BEA provides quarterly data on GDP by industry from 2005. Output per worker is constructed as GDP in a certain sector over the number of employees in that sector. The classification of sectors is described in section 4.2.

Data on the average number of hours by sector are available from 2007. However, the sector classification is broader than the one used in section 4.2. Particularly the data are available only by supersector. Furthemore, the data for such supersectors as mining and information contain a large number of missing values. That is why I analyze the effects of vaccination only for those supersectors that coincide with the previous classification and have a sufficient number of non-missing values. By doing so, high-contact sectors include construction, education and health services, and leisure and hospitality; low-contact non-tradable sectors include other services and public administration and low-contact tradable sectors include manufacturing.

Appendix C: Additional Tables and Figures

Table C.1. Summary Statistics

	(1) Mean	(2) St. Dev.
Employment Ratio	62.08825	4.644798
LFP Ratio	65.75833	4.257654
Opening Rate	3.128268	.6437396
Hiring Rate	3.907106	.7446626
Layoff Rate	1.494704	.3766591
Quit Rate	2.026421	.4796558
Observations	8,232	8,232

Notes: Based on LAUS, JOLTS, and CES. Labor market outcomes are seasonally adjusted.

Table C.2. Match Rates Predictions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.Match	0.1014	0.0483					
	(0.2684)	(0.2786)					
	(5.9956)	(1.3927)					
L.Empl. ratio			-4.3914	-6.1428			
			(3.5516)	(4.9380)			
L.LFP ratio					-3.7558	7.2946	
					(5.2842)	(18.4196)	
Trend		0.0136		-0.0090		0.0360	0.0143
		(0.0192)		(0.0281)		(0.0600)	(0.0139)
Observations	16	16	16	16	16	16	17

Notes: The data on the labor market outcomes and match rate come from LAUS and CDC reports, respectively. The dependent variable is a match rate from 2000/01 to 2016/17. Monthly labor market outcomes from 2001 to 2016 are averaged by flu-year. Robust standard errors are reported in parentheses.

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

Table C.3. **Vaccination and Match Rate**

	(1)	(2)	(3)	(4)
Match	0.0020	0.0030	0.0159	0.0385
	(0.0020)	(0.0224)	(0.0511)	(0.0559)
Match*Baseline Vacc.		-0.0029		
		(0.0687)		
Match*Baseline Empl.			-0.0212	
			(0.0779)	
Match*Baseline LFP				-0.0537
				(0.0820)
Trend	0.0063***	0.0063***	0.0063***	0.0063***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Observations	833	833	833	833

Notes: The data on the labor market outcomes, match rates, and vaccination rates come from LAUS, CDC reports, and BRFSS respectively. The dependent variable is the vaccination rate by state-flu-year from 2000/01 to 2016/17. All regressions include state-fixed effects. Standard errors are clustered at a state level.

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

Table C.4. Effective Vaccination and Output per worker/hour

	(1)	(2)	(3)
	High, Non-Tradable	Low, Non-Tradable	Low, Tradable
Panel A: Ln(Output per worker)			
Vaccine*Match	0.174**	0.160	-0.264
	(0.075)	(0.097)	(0.221)
Mean of D.V	4.048	4.783	4.997
Observations	1,920	1,840	1,812
Panel B: Ln(Output per hour)			
Vaccine*Match	0.202**	-0.266	-0.062
	(0.077)	(0.251)	(0.435)
Mean of D.V	-0.547	-0.810	1.214
Observations	1,312	960	1,440

Notes: Based on quarterly data starting from 2005 and 2007 in the first and second rows, respectively. Data on output come from the BEA and data on the number of employees and number of hours from the CES. The estimates are obtained with a two-way fixed effects OLS model. 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.5. Effective Vaccination and Restaurant Consumption: Interactions with Demographic Characteristics

	(1)	(2)
	Restaurant Consumption	Restaurant Consumption
Vaccination*Match	22.381	11.944
	(14.448)	(21.772)
Vaccination*Match*H2M	29.225*	47.307
	(17.038)	(30.327)
Vaccination*Match*White	7.799	8.473
	(9.265)	(8.988)
Vaccination*Match*Share_{65}	-0.782*	-0.926**
	(0.418)	(0.407)
Vaccination*Match*Bachelor		0.179
		(0.268)
Mean of D.V.	29.89	29.89
Observations	796,905	796,905

Notes: Based on the CPS. 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 C.6. Effective Vaccination and Input-Output Network

	(1) Downstream	(2) Upstream
Vaccination*Match	0.273^{*}	0.148^{**}
	(0.158)	(0.070)
Mean of D.V	5.013	6.069
Observations	7,728	8,232

Notes: Based on 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

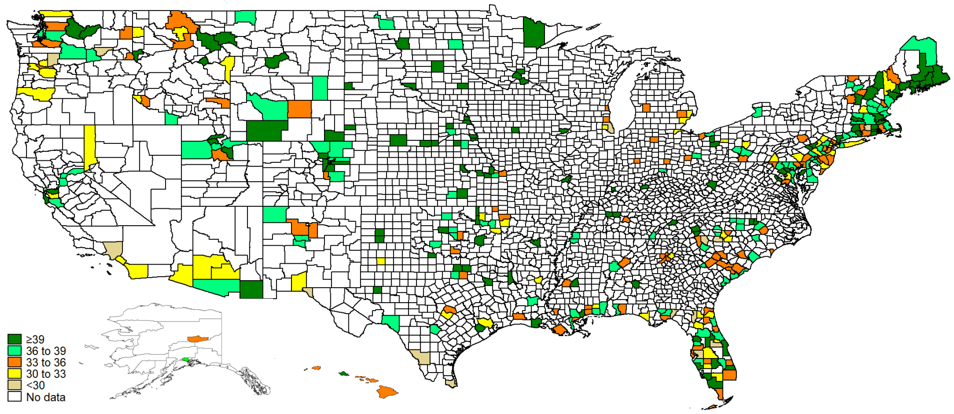
Table C.7. Effective Vaccination by Age Groups and Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment	LFP	Employment	LFP	Employment	LFP	Employment	LFP
Vacc.$_{18-34}$*Match	4.6958*	-1.6805						
	(2.5021)	(2.0752)						
Vacc.$_{35-49}$*Match			6.5550**	-0.7432				
			(2.9205)	(2.1209)				
Vacc.$_{50-64}$*Match					6.8952***	0.9005		
					(2.3910)	(1.7893)		
Vacc.$_{\geq 65}$*Match							9.3343***	4.4495**
							(2.8189)	(2.0278)
Mean of D.V.	62.09	65.76	62.09	65.76	62.09	65.76	62.09	65.76
Observations	8,232	8,232	8,232	8,232	8,232	8,232	8,232	8,232

Notes: The data on the labor market outcomes, match rates, and vaccination rates come from LAUS, CDC reports, and BRFSS respectively. The dependent variables are employment to population ratio and LFP ratio. The variables of interest are the interactions between age-specific vaccination rates and match rates. The regressions include the full set of state-level control variables described in the section 3.2. Standard errors are clustered at a state level.

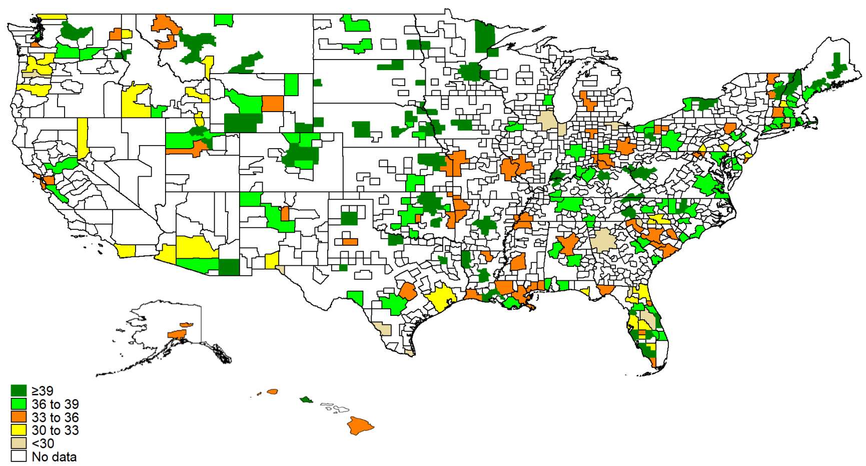
* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

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



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

Figure C.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

Table C.8. **Effective Vaccination and Employment by Vaccination Status**

	(1) Full Sample	(2) Unvaccinated	(3) Vaccinated
Vaccination*Match	0.1351***	0.1107**	0.1114**
	(0.0388)	(0.0456)	(0.0501)
Vaccination	-0.0446	-0.0458	-0.0672
	(0.0409)	(0.0431)	(0.0586)
Observations	3,180,417	2,067,174	1,113,243

Notes: Based on BRFSS. 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 C.9. **Effective Vaccination and Hours Worked Last Week**

	(1) HCNT	(2) LCNT	(3) LCT
Vaccination	2.9178**	-1.8268	-1.3470
	(1.4212)	(1.1967)	(1.0420)
Vaccination*Match	-0.0069	0.0235*	-0.0037
	(0.0195)	(0.0137)	(0.0126)
Observations	4,644,719	2,014,771	2,869,380

Notes: Based on CPS. 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

Appendix D: Robustness Checks

Table D.1. Effective Vaccination and Employment: Specification Checks

	(1) Employment	(2) Employment	(3) Employment	(4) Employment
Vaccination*Match	0.098***	0.065***	0.097***	0.130***
	(0.028)	(0.019)	(0.028)	(0.032)
Vaccination	0.011	-0.019	0.012	-0.021
	(0.030)	(0.028)	(0.030)	(0.034)
Mean of D.V	0.629	0.629	0.629	0.629
Observations	8,232	8,232	8,232	8,232
Month-year FE	X	X	X	X
State FE	X	X	-	X
State Trends	-	X	X	-
Controls	X	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 employment-to-population ratio.
* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

Table D.2. **Effective Vaccination and Employment: Robustness Checks**

	Alter. Vaccination	Alter. Match	Include N1H1	Drop 2004/05	All States	Without Alaska
Vaccine*Match	0.086***	0.104***	0.106***	0.098***	0.089***	0.101***
	(0.025)	(0.035)	(0.026)	(0.027)	(0.028)	(0.027)
Vaccination	-0.053***	-0.004	-0.006	-0.001	0.013	0.010
	(0.019)	(0.034)	(0.030)	(0.031)	(0.029)	(0.030)
Observations	8,226	8,232	9,408	7,644	8,568	8,064

Notes: The data come from the LAUS. The estimates are obtained with a two-way fixed effects OLS model. The dependent variable is the employment-to-population ratio. 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 D.3. **Effective Vaccination and Labor Market Outcomes: Placebo Test**

	(1)	(2)
	Employment ratio	LFP ratio
Vaccination*Match	-0.010	-0.003
	(0.061)	(0.032)
Observations	8,232	8,232

Notes: The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are employment-to-population ratio, and labor force participation. The match rates are shuffled 1000 times. The regressions include the full set of state-level control variables described in the section 3.2. The table reports the median of the estimated coefficients and the standard deviation of the estimated coefficients (in parenthesis).

Table D.4. Effective Vaccination and Labor Market Outcomes: Alternative Identification Strategy

	(1)	(2)
	Employment Ratio	Labor Force
Panel A: Reduced Form		
Vaccine*Match	0.093***	0.023
	(0.032)	(0.033)
Observations	8,232	8,232
Panel B: IV		
Vaccination*Match	0.101***	0.025
	(0.036)	(0.035)
Observations	8,232	8,232

Notes: The data come from the LAUS. The dependent variables are 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 2000/2001. 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 2000/2001.

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

Table D.5. **Vaccination and Employment: Canadian Data**

	Actual Match		Reshuffled Match	
	(1)	(2)	(3)	(4)
$\text{UIIC}_p * \text{P}ost_y * \text{M}atch_{py}$	0.848^{***}	0.532^{*}	0.102	0.089
	(0.186)	(0.250)	(1.349)	(1.071)
Province FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	1,314	1,314	1,314	1,314

Notes: Based on data from Statistics Canada. Columns 1 and 2 report triple-difference estimates from equation 4 with standard errors in parentheses. Columns 3 and 4 report median estimates from reshuffling match rates 1000 times with the standard deviation of the reshuffled values in parentheses.
* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

Table D.6. **Effective Vaccination and GDP by sector**

	(1)	(2)	(3)	(4)
	Total	High, Non-Tradable	Low, Non-Tradable	Low, Tradable
Vaccine*Match	0.223^{*}	0.413^{***}	0.322^{**}	-0.247
	(0.130)	(0.138)	(0.125)	(0.227)
Mean of D.V.	12.11	10.64	11.15	11.14
Observations	1,960	1,956	1,960	1,899

Notes: Based on quarterly data starting from 2005. Data on GDP by sector come from the BEA. The estimates are obtained with a two-way fixed effects OLS model. 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

Appendix E: Derivations

Suppose that consumers in fully identical states s derive utility from the consumption of two goods A and B. Households face a constant elasticity of substitution between goods ϵ and constant inter-temporal elasticity of substitution σ.

$$\sum_{t=0}^{\infty} \beta^t \mathrm{U}\left(c_{\mathrm{A}st}, c_{\mathrm{B}st}\right)$$

$$\mathrm{U}\left(c_{\mathrm{A}st}, c_{\mathrm{B}st}\right) = \frac{\sigma}{\sigma-1}\left(\phi^{\frac{1}{\epsilon}} c_{\mathrm{A}st}^{\frac{\epsilon-1}{\epsilon}} + (1-\phi)^{\frac{1}{\epsilon}} c_{\mathrm{B}st}^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}\frac{\sigma-1}{\sigma}}$$

Sector A is high-contact and non-tradable while sector B is low-contact and freely tradable across states. The shipment costs are equal to zero. Prices in a non-tradable sector are state-specific but prices in a tradable sector are identical between states. Households face the following budget constraint:

$$\mathrm{P}_{\mathrm{A}st} c_{i\mathrm{A}st} + \mathrm{P}_{\mathrm{B}t} c_{i\mathrm{B}st} + a_{ist} \leq \mathrm{W}_{jst} n_{jst} + \left(1 + i_{st-1}\right) a_{ist-1},$$

where W_{jst} are wages in sector j in which agent i works, $\mathrm{P}_{\mathrm{A}st}$ and $\mathrm{P}_{\mathrm{B}t}$ are prices for goods A and B, $a_i t$ are bond holdings and i_{st} is a nominal interest rate. Furthermore, a random share μ of workers do not have access to credit (i.e., $a \geq 0$).

Labor is supplied inelastically, and the production technology in each sector j is linear: $\mathrm{Y}_{jst} = \mathrm{N}_{jst}$. Share ϕ of agents work in sector A and share $1-\phi$ work in sector B. There is no labor mobility between states or between sectors. Non-tradable goods can be sold only within a state. However, the demand for tradable goods in each state also relies on the demand from other states. By imposing market clearing conditions: $\mathrm{C}_{\mathrm{A}st} = \mathrm{Y}_{\mathrm{A}st}$ and $\sum_{s=1}^{n} \mathrm{C}_{\mathrm{B}st} = \sum_{s=1}^{n} \mathrm{Y}_{\mathrm{B}st}$. Firms are competitive, which implies that in equilibrium, $\mathrm{W}_{jst} = \mathrm{P}_{jst}$. In a steady state $\mathrm{W}^*_{\mathrm{A}s} = \mathrm{W}^*_{\mathrm{B}s} = \mathrm{P}^*_{\mathrm{A}s} = \mathrm{P}^*_{\mathrm{B}} = 1$.

In period zero each state faces a different labor productivity shock in sector A which causes workers' labor productivity in sector A to go to $1-\delta_s$.

Full Nominal or Real Wage Rigidity: $W_{As0} = W_{Bs0} = P_{As0} = P_{Bs0} = P_{0s} = W^* = P^* = 1$

As a result of labor productivity shock, employment in sector A in each state s decreases to $(1-\delta_s)$, because $n_{A0s} = \frac{Y_{A0s}}{Y^*_{As}} = \frac{(1-\delta_s)\phi}{\phi} = (1-\delta_s)$.

To analyze changes in employment in sector B, one needs to consider the ratio between actual and potential output, where actual output is derived from the market clearing condition and potential output is equal to $1-\phi$. Following Guerrieri et al. (2022), it can be shown that consumption of the goods in period zero is equal to:[19]

$$
\begin{aligned}
C_{As0} &= \phi\left(\frac{P_{As0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{W_{Aso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right),\\
C_{Bs0} &= (1-\phi)\left(\frac{P_{Bs0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{W_{Aso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right).
\end{aligned}
$$

Given the tradability of the sectors, the aggregate demand in each sector in period zero is given by: $Y_{Bs0} = C_{Bs0}$ and $\sum_{s=1}^{n} Y_{Bs0} = \sum_{s=1}^{n} C_{Bs0}$. Hence, since firms are symmetric, and their output is rationed by demand, substituting $W_{As0} = W_{Bs0} = P_{As0} = P_{Bs0} = W^* = P^* = 1$ gives the following equation for the output of good B in each state:

$$
Y_{Bs0} = \frac{(1-\phi)\sum_{s=1}^{n}(1-\mu\phi\delta_s)}{n}
$$

Finally, employment in sector B in state s in period zero can be derived as a ratio between actual and potential output.

$$
n_{Bs0} = \frac{Y_{Bs0}}{Y^*_{Bs}} = \frac{Y_{Bs0}}{(1-\phi)} = \frac{\sum_{s=1}^{n}(1-\mu\phi\delta_s)}{n}
$$

This result suggests that the larger is n, the less employment in sector B depends on the labor productivity shock in sector A in its state. In contrast, the case of n being equal to one is identical to sector B being fully non-tradable (i.e., model analyzed by Guerrieri

[19]The consumption function has the following form because constrained agents in sector A $(\mu\phi)$ consume their labor income $(1-\delta_s)W_{Ais0}$, while the average consumption for all the other workers $(1-\mu\phi)$ is derived from the Euler equation is equal to $(\frac{P_0}{P_1})^{-\sigma}$.

et al. (2022)). In such a case, $n_{B0} = 1 - \delta\mu\phi$ which implies that employment in sector B is more affected if the share of financially constrained households μ increases.

No Nominal or Real Wage Rigidity

Wages in sector A are set according to the following profit maximization equation: $\Pi_{As0} = P_{As0}(1-\delta_s)n_{As0} - W_{As0}n_{As0}$, which after taking the first order conditions with respect to n_{As0}: $W_{As} = P_{As}(1-\delta_s)$.

If both sectors are non-tradable and prices are flexible, using $W_{As} = P_{As}(1-\delta_s)$ gives the following system of equations:

$$(1-\delta_s)\phi = \phi\left(\frac{P_{As0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{P_{Aso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right) \tag{4}$$

$$(1-\phi) = (1-\phi)[\left(\frac{P_{B0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{P_{Aso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right)] \tag{5}$$

$$P_{s0} = \left(\phi P_{As0}^{1-\epsilon} + (1-\phi)P_{B0}^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}$$

Combining equations 4 and 5 gives: $(1-\delta_s) = (\frac{P_{As0}}{P_{Bs0}})^{-\epsilon}$, which implies that $P_{As0} = P_{Bs0}(1-\delta)^{-\frac{1}{\epsilon}}$ and $P_{s0} = P_{Bso}[\phi(1-\delta)^{1-\frac{1}{\epsilon}} + (1-\phi)]^{\frac{1}{1-\epsilon}}$. Plugging this into 4 gives:

$$P_{B0} = \left[\frac{1-\mu\phi\frac{(1-\delta)^{1-\frac{1}{\epsilon}}}{\phi(1-\delta)^{1-\frac{1}{\epsilon}}+(1-\phi)}}{(1-\mu\phi)(\phi(1-\delta)^{1-\frac{1}{\epsilon}} + (1-\phi))^{\frac{\epsilon-\sigma}{1-\epsilon}}}\right]^{-\frac{1}{\sigma}}$$

Hence $P_{B0} = W_{B0} < 1$ if

$$1-\mu\phi\frac{(1-\delta)^{1-\frac{1}{\epsilon}}}{\phi(1-\delta)^{1-\frac{1}{\epsilon}} + (1-\phi)} > (1-\mu\phi)(\phi(1-\delta)^{1-\frac{1}{\epsilon}} + (1-\phi))^{\frac{\epsilon-\sigma}{1-\epsilon}}$$

Which after taking logarithms implies that:

$$\sigma > \epsilon - (1-\epsilon)\frac{\ln\left(1-\mu\phi\frac{(1-\delta)^{1-\frac{1}{\epsilon}}}{\phi(1-\delta)^{1-\frac{1}{\epsilon}}+1-\phi}\right) - \ln(1-\mu\phi)}{\ln\left(\phi(1-\delta)^{1-\frac{1}{\epsilon}} + 1-\phi\right)}$$

Hence, under flexible prices and wages in both sectors, labor productivity shock in sector A translates into a decrease in wages and prices if the intertemporal elasticity of substitution is sufficiently larger than the elasticity of substitution between sectors. The condition becomes more stringent if the share of the financially constrained households decreases.

If sector B is tradable, then prices and wages in all the states would change by the same amount satisfying the following system of equations:

$$(1-\delta_s)\phi = \phi\left(\frac{P_{As0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{P_{Aso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right)$$

$$N(1-\phi) = (1-\phi)\sum_{s=1}^{n}[\left(\frac{P_{B0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{P_{Aso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right)]$$

$$P_{s0} = \left(\phi P_{As0}^{1-\epsilon} + (1-\phi)P_{B0}^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}$$

Flexible Prices in Sector A and Real Wage Rigidity in Sector B

Finally, consider the case when prices in sector A are allowed to increase as a result of a labor productivity shock, but wages are downward rigid in both sectors. From the profit maximization I obtain that $P_{As0} = \frac{W_{As0}}{1-\delta} = \frac{1}{1-\delta}$.

Since prices in sector A are flexible, we know that:

$$n_{A0s}(1-\delta) = \phi\left(\frac{P_{As0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{W_{As0}}{P_{s0}}n_{Aso} + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right) \tag{6}$$

But since prices in sector B are rigid, the output in sector B is rationed by demand:

$$Y_{B0} = (1-\phi)\left(\frac{P_{B0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{P_{Aso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right) \tag{7}$$

After combining equations 4 and 7, I obtain:

$$Y_{B0} = \frac{(1-\phi)(1-\delta)n_{As0}}{\phi}\left(\frac{P_{As0}}{P_{B0}}\right)^{\epsilon}$$

which implies that

$$n_{B0} = \frac{Y_{B0}}{1-\phi} = \frac{(1-\delta)\, n_{As0}}{\phi} \left(\frac{P_{As0}}{P_{B0}}\right)^{\epsilon} \tag{8}$$

Plugging $W_{As0} = 1$, $P_{As0} = \frac{1}{1-\delta}$, $P_{0s} = (\phi(\frac{1}{1-\delta})^{(1-\epsilon)} + (1-\phi))^{\frac{1}{1-\epsilon}}$ into equation 6, I obtain:

$$n_{As0} = \frac{\phi(1-\mu\phi)(\phi(1-\delta)^{\epsilon-1} + (1-\phi))^{\frac{\epsilon-\sigma}{1-\epsilon}}}{(1-\delta)^{1-\epsilon} - \frac{\phi^2\mu}{\phi(1-\delta)^{\epsilon-1}+(1-\phi))^{\frac{\epsilon-\sigma}{1-\epsilon}}}} \tag{9}$$

Finally, combining equations 8 and 9 and taking logarithms, I obtain that under flexible prices in sector A and real wage rigidities in sector B, a negative labor productivity shock in sector A would translate into a decrease in employment in sector B if the following condition holds:

$$\sigma > \epsilon - (1-\epsilon)\frac{\ln\left(1-\mu\phi^2\frac{(1-\delta)^{\epsilon-1}}{\phi(1-\delta)^{\epsilon-1}+1-\phi}\right) - \ln(1-\mu\phi)}{\ln\left(\phi(1-\delta)^{\epsilon-1}+1-\phi\right)}$$