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

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**Abstract**

This study estimates the causal impact of influenza vaccination on labor market outcomes in the United States. Exogenous variation in vaccination is constructed by interacting state-level vaccination rates with plausibly exogenous match rates – the degree to which the viruses in the vaccine resemble those in circulation. Using a difference-in-differences design, I show that vaccination has a positive impact on labor market outcomes, though this impact is not uniform. Workers in non-tradable sectors experience sizable gains in employment and wages, while there are no effects in low-contact, tradable sectors. Further analysis suggests that the main mechanisms are higher labor productivity in high-contact sectors and sectoral demand spillovers. By using both theory and data, I show that these spillovers are driven by the input-output structure of production and changes in consumers' labor income. These findings highlight how productivity gains in directly affected sectors can generate demand fluctuations in sectors that are not directly exposed.

**Keywords:** Influenza Vaccination, Employment, Labor Productivity, Wages

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# 1 Introduction

There is a consensus that influenza vaccination has important health implications, including reductions in absenteeism, hospitalizations, and mortality (Ward, 2014; White, 2021; Graff Zivin et al., 2023). Yet, little is known about how these health improvements affect labor market outcomes in a multi-sector economy. Examining the broader economic benefits of flu vaccines may not only help policymakers to better evaluate the cost-effectiveness of immunization programs, but also contribute to a more general research on the transmission of economic disturbances. There is a growing literature that investigates the propagation of sector-specific shocks. However, providing causal evidence for the transmission channels may be challenging due to the lack of plausibly exogenous variation. By utilizing a random variation in vaccine effectiveness, this paper studies how influenza vaccination affects labor markets and how this economic impact spills from one sector to another.

Specifically, I utilize state-by-year vaccine take-up rates (hereafter, actual vaccination rates) from the Behavioral Risk Factor Surveillance System (BRFSS) and year-to-year vaccine match data derived from the influenza surveillance reports to construct a measure of effective vaccination.[1] The vaccine match rate is defined as the degree to which the viruses in the vaccine resemble those in circulation. It occurs randomly due to genetic variations in the virus and is unknown prior to the beginning of the influenza season. Following White (2021), I construct a measure of effective vaccination by interacting actual vaccination rates with vaccine matches.

Conditional on actual vaccination rates, plausibly exogenous vaccine matches allow effective vaccination to provide a causal estimate of flu vaccines on labor market outcomes. Intuitively, this difference-in-difference design relies on comparing the differences in outcomes between states with high and low vaccine take-up rates across flu sea-

[1] The main analysis draws in data from 2001 to 2016 across 50 US states.

sons with different vaccine matches.[2] The main outcomes of interest are employment, wages, and the labor market turnovers, which come from the Current Population Survey (CPS) and other surveys conducted by the Bureau of Labor Statistics (BLS).[3]

In theory, effective vaccination may have an impact on output and these labor market outcomes through multiple channels. Fewer missed workdays and lower risks of severe illness may translate into higher labor income for workers, specifically for those without paid sick leave or for the self-employed. For firms, it means fewer disruptions to operations and higher labor productivity, as employees remain present and able to work at full capacity. This increase in labor productivity may induce firms to hire more workers and pay higher wages.[4] Moreover, certain sectors may be affected by flu vaccines because healthier individuals may be more willing to dine out or shop, which might also lead to higher output and labor demand.

Similar to COVID-19, the impact of effective vaccination may be asymmetric across sectors. Specifically, sectors that rely heavily on face-to-face interactions (hereafter, high-contact sectors) may be more affected because these sectors have a higher likelihood of flu transmission among coworkers and consumers. For example, if effective vaccination reduces flu outbreaks, restaurants may face a larger increase in both labor productivity and demand for their services than other sectors.

Building on Guerrieri et al. (2022) framework, I begin my analysis by outlining a simple two-sector model that examines how effective vaccination may propagate across sectors and what drives sectoral spillovers. The model features an open economy with

[2]In other words, when the flu vaccine works well, the gap in the outcomes between states with the high and low vaccine take-up rates is expected to be large. On the other hand, when the flu vaccine does not work, it should not matter if states have a high or low share of vaccinated individuals.

[3]When aggregate state-level data is used, the unit of analysis is at the state-month level. Whereas, when the CPS data is used, the unit of analysis is at the individual-state-moth level.

[4]Note that an increase in labor productivity may lead to higher labor demand if demand for goods increases accordingly. On the other hand, if demand for goods remains unchanged, employment may decrease because firms will require fewer workers to produce the same level of output (Gali, 1999; Blanchard, 1989). Aggregate demand would remain unchanged if prices are sticky and monetary accommodation is limited (Gali, 1999).

a finite number of geographic states, in which one sector is directly hit by a shock to labor market outcomes and output. I assume that this shock varies across states and consider three channels through which it may operate: labor supply, labor productivity, or consumer demand.

The model yields three main predictions. First, regardless of the operating channel, a state-specific shock in one sector may lead to sectoral spillovers by altering local (state-level) demand for goods and services. This implies that since tradable sectors largely rely on national or global demand, the spillovers in these sectors should be weaker. Second, the changes in local demand may be driven by both consumer and producer responses. Third, consumer responses are amplified if households are highly sensitive to income shocks (commonly referred to as hand-to-mouth households), while producer responses primarily affect upstream sectors. The intuition for these mechanisms is as follows. If households in the directly affected sector are hand-to-mouth (H2M), an increase in their labor income, induced by higher employment or wages, may boost consumer demand in the rest of the economy. On the other hand, if a sector faces a shock to its output, spillovers may arise through increased demand for inputs supplied by upstream sectors. For example, if a restaurant faces higher consumer demand, it will buy more goods from its suppliers — farmers, food distributors, and cleaning services.

Guided by the predictions of the model, I begin my empirical analysis by evaluating the overall impact of effective vaccination on local labor markets. Then, I classify industries by contact intensity and tradability and investigate whether the impact of effective vaccination is heterogeneous across sectors with further examining the channels for sectoral spillovers. My causal estimates show that effective vaccination has a positive impact on employment and wages. At the average match rate, a one standard deviation increase in vaccination (i.e., five percentage points) increases employment-to-population rate and wages by 0.3 percentage points and 0.5 percent, respectively. The estimated effects appear to be driven by labor demand factors, as there is a strong relationship between effective vaccination and job openings.

Next, I show that the relationship between effective vaccination and labor market outcomes is rather homogeneous across demographic groups. In contrast, I find that the impact of effective vaccination on employment and wages is larger in high-contact sectors compared to their counterparts. The results also suggest that in these sectors, effective vaccination reduces absenteeism and increases output per worker. These findings provide suggestive evidence that an increase in labor productivity is one of the channels through which effective vaccination may influence employment and wages.

Furthermore, I find strong support for the predictions of the model regarding sectoral spillovers. I show that effective vaccination has a positive impact on employment in low-contact non-tradable sectors. However, this impact is small and not statistically significant in low-contact tradable sectors. To examine whether consumer responses drive sectoral spillovers, I investigate the relationship between effective vaccination and labor market outcomes in states with high and low shares of H2M households.[5] Consistent with the predictions of the model, my causal estimates show that the impact of effective vaccination on consumption and labor market outcomes is larger in the states with a higher share of H2M households. I also find suggestive evidence for the input-output channel. Specifically, I show that the relationship between effective vaccination and employment is stronger in low-contact non-tradable sectors that are more likely to be used as intermediate inputs.

To understand the spatial spillovers of vaccination externalities in the labor market, I analyze the impact of effective vaccination in labor markets defined at the state, county, and metropolitan statistical 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 at the county or MSA levels.[6] In other words, I compare the estimates obtained with between-state variation with the estimates obtained

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

[6]To study the spatial spillovers, I use the CPS data between 2004 and 2012 for a subset of counties and MSAs.

with within-state variation. The results suggest that the relationship between effective vaccination and employment is 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.

Lastly, to examine the benefits of effective vaccination on labor market outcomes in a different setting, I exploit the universal influenza immunization campaign (UIIC) in Ontario. In July 2000, Ontario started to subsidize influenza vaccines for all residents, which increased flu vaccination coverage in the province by eight percentage points (Ward, 2014). By employing a triple-difference design that exploits the introduction of UIIC and variation in match rates, I find that an increase in effective vaccination in Ontario has a positive impact on employment. The magnitude of the estimated effect is comparable to that presented for the US setting.

Taken together, this study provides the first causal evidence that influenza vaccination may have ripple economic effects, generating both sectoral and spatial spillovers. These findings suggest that a policy aimed at increasing vaccine take-up may yield substantial economic benefits. Although this paper does not directly assess such policies, prior research indicates that universal vaccination programs, correcting misconceptions about vaccines, or offering small financial incentives can increase vaccination rates at relatively low cost (Ward, 2014; Bronchetti et al., 2015; Sacks and Sydnor, 2025). Furthermore, my analysis provides novel causal evidence on the role and mechanisms of sectoral spillovers, contributing to a better understanding of how sector-specific shocks propagate through the economy.

The remainder of the paper is structured as follows. Section 2 provides background information on vaccine match, outlines my contribution to the literature, and presents a theoretical framework for sectoral spillovers. Section 3 describes data and empirical strategy. Section 4 discusses the results and provides a series of robustness checks. Section 5 concludes.

# 2 Background

## 2.1 Vaccination and Vaccine Match

Influenza vaccination is a powerful tool to protect against the disease. However, individual vaccination decisions are highly endogenous. Similarly, states with a higher share of the elderly and other vulnerable groups tend to exhibit higher than average vaccine take-up. To overcome this challenge and construct a plausibly exogenous measure of effective vaccination, White (2021) proposes interacting potentially endogenous state-level actual vaccination rates with vaccine matches, which are argued to be randomly determined.

In detail, vaccine match captures the goodness of the virus strains' predictions. Each year, the World Health Organization (WHO) monitors the influenza virus strains that circulate worldwide. Based on these surveillance data, the WHO predicts the most likely strains to circulate in the next influenza season. These strains serve as the basis for vaccine production. Therefore, vaccine match rates reflect how well the predicted strains resemble the actual ones. The match rate is zero if the prediction fails completely, and it is one when all the circulating virus strains are included in the vaccine.

Variation in vaccine matches (or mismatches) may be driven by virus mutations, commonly referred to as "antigenic drift". Alternatively, mismatches may occur because the influenza vaccine can only include a maximum of four virus strains. If the predictions on the predominant viruses were wrong, then the match rate may be lower than one (White, 2021).[7] Given that the vaccine match is unknown prior to the beginning of the influenza season, it cannot affect vaccination decisions. Thus, conditional on actual vaccination rates, the interaction between state-level vaccine take-up and match rates measures the exogenous benefits of effective vaccination.

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

## 2.2 Related Literature and Contribution

This study contributes to several strands 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 individual-level gains and even positive spillover effects on human capital (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 has only been studied on long-term individual-level outcomes. The previous literature compared health and wages of cohorts that have been exposed to influenza outbreaks in-utero or during childhood, with the outcomes of their counterparts (Almond and Mazumder, 2005; Almond, 2006; Kelly, 2011; Lin and Liu, 2014; Schwandt, 2018). In this study I use a general equilibrium approach to examine how immunization against one of the most common diseases affects labor market outcomes. Investigating whether the externality effects of influenza vaccination go beyond health benefits could help to better inform policymakers about the potential returns on investment in vaccination programs.

The works of Ward (2014), White (2021), and Graff Zivin et al. (2023) are particularly relevant to this study. Ward (2014) uses a triple difference design based on a universal vaccination program in Ontario and annual vaccine match. The author finds that effective vaccination decreases work absences and pneumonia-related hospitalizations. Similarly, White (2021) utilizes variation in effective vaccination rates and finds that effective vaccination reduces pneumonia-related mortality and work absences in the US. Graff Zivin et al. (2023) highlights the importance of joint efforts to control pollution and influenza outbreaks. The authors show that influenza vaccination neutralizes the relationship between pollution and influenza hospitalizations. I build on White (2021) and Ward (2014) and examine the indirect payoffs of effective vaccination, specifically its impact on labor market outcomes.

Since effective vaccination may affect labor market outcomes through changes in absenteeism and labor productivity, which might be asymmetric across sectors, this paper also contributes to the research on absenteeism costs and sectoral spillovers. Previous studies on absenteeism either provide theoretical background on the costs of absenteeism (Pauly et al., 2002) or study correlations rather than causal effects (Allen, 1983; Koopmanschap et al., 1995). On the other hand, sectoral spillovers have been studied both theoretically and empirically. By analyzing a two-sector model, Guerrieri et al. (2022) show 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.[8] I extend their model to an open economy and provide causal micro-evidence on sectoral spillovers. These findings will contribute to other empirical papers that emphasize the role of consumer demand as a driver of sectoral spillovers (Moretti, 2010; Mian and Sufi, 2014; Faggio and Overman, 2014; Gathmann et al., 2020; East et al., 2023).[9]

Finally, my work is also related to the extensive literature that examines the effects of COVID-19 on labor market outcomes and inequality (Aum et al., 2021; Bluedorn et al.,

[8]Furthermore, Baqaee and Farhi (2022) find that complementarities in production amplify sectoral spillovers of supply shocks but mitigate those of demand shocks.

[9]Some of these studies also show that agglomeration effects largely contribute to the size of sectoral spillovers. Since in my setting, all firms in the same sector are assumed to be equally affected, this channel is not discussed here.

2023; Alon et al., 2022; Coibion et al., 2020; Montenovo et al., 2022; Adams-Prassl et al., 2020; Abo-Zaid and Sheng, 2020). While both COVID-19 and influenza are serious health shocks, pandemics differ from the flu due to the lockdown measures. My work measures the causal effects of less severe but more frequent health shocks.

## 2.3 Theoretical Background

As mentioned in the introduction, there are several channels through which effective vaccination may influence labor market outcomes. It may alter labor supply, labor productivity, and consumer demand. However, under nominal wage rigidity, regardless of the mechanism in place, the sectoral transmission of the shocks occurs through the input-output network and/or changes in the real income of workers in the directly affected sectors.

In this section, I propose a model to provide a formal intuition for sectoral spillovers. I assume that the directly affected sector is high-contact (H) and non-tradable, and the sector that is not directly affected is low-contact (L) and can be either non-tradable or tradable. I begin by analyzing the case when the low-contact sector is tradable and focus on the case when influenza vaccination affects labor supply in the high-contact sector under the assumption of nominal wage rigidity. To do so, I extend the model in Guerrieri et al. (2022) and incorporate a setting of an open economy following Mian and Sufi (2014). The other two mechanisms and implications under alternative assumptions are also briefly discussed in this section and Appendix Section A5.

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 $H$ and $L$. Households face a constant elasticity of substitution between goods $\epsilon$ and a constant inter-temporal elasticity of substitution $\sigma$.

$$\sum_{t=0}^{\infty} \beta^t U\left(c_{Hst}, c_{Lst}\right)$$

$$U\left(c_{Hst}, c_{Lst}\right) = \frac{\sigma}{\sigma - 1}\left(\phi^{\frac{1}{\epsilon}} c_{Hst}^{\frac{\epsilon-1}{\epsilon}} + (1-\phi)^{\frac{1}{\epsilon}} c_{Lst}^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}\frac{\sigma-1}{\sigma}}$$

The shipment costs are equal to zero. I begin with assuming that sector $H$ is non-tradable and sector $L$ is tradable. This implies that prices in sector $H$ are state-specific, but prices in sector $L$ are identical between states. Households face the following budget constraint:

$$P_{Hst} c_{iHst} + P_{Lt} c_{iLst} + a_{ist} \leq W_{jst} n_{jst} + \left(1 + i_{st-1}\right) a_{ist-1},$$

where $W_{jst}$ are wages in sector $j$ in which agent $i$ works, $P_{Hst}$ and $P_{Lt}$ are prices for goods $H$ and $L$, $a_{it}$ are bond holdings and $i_{st}$ is a nominal interest rate. Furthermore, a random share $\mu$ 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: $Y_{jst} = N_{jst}$. Share $\phi$ of agents work in sector $H$ and share $1-\phi$ work in sector $L$. There is no labor mobility between states or 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: $C_{Hst} = Y_{Hst}$ and $\sum_{s=1}^{n} C_{Lst} = \sum_{s=1}^{n} Y_{Lst}$. Firms are competitive, which implies that in equilibrium, $W_{jst} = P_{jst}$. Without a loss of generality, in a steady state, prices and wages in both sectors are normalized to one.[10]

In period zero, each state $s$ faces a different labor supply shock in sector $H$, which causes workers' labor supply to fall to $1-\delta_s$. To clear the goods market, prices in sector $H$ have to increase in equilibrium, which implies that firms in sector $H$ are making positive profits. Following Guerrieri et al. (2022), I assume that these firms are symmetrically owned by households who are not borrowing-constrained. Prices in sector $L$ remain equal to wages.

To analyze changes in employment in sector $L$, consider the ratio between actual and potential output, where actual output is derived from the market clearing condition and

[10]This normalization comes from the assumption that the taste parameters in the utility function $\phi$ and $1-\phi$ are equal to shares of households working in each sector.

potential output is equal to $1-\phi$. Constrained agents in sector $H$ ($\mu\phi$) consume their labor income $(1-\delta_s)W_{Hs0}$, while the average consumption for all the other workers $(1-\mu\phi)$ is derived from the Euler equation and is equal to $(\frac{P_{s0}}{P_{s1}})^{-\sigma}$. Hence, consumption of the goods in period zero is equal to:

$$C_{Hs0} = \phi\left(\frac{P_{Hs0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{W_{Hso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right),$$
$$C_{Ls0} = (1-\phi)\left(\frac{P_{L0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{W_{Hso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right)$$

where $P_{st}$ is a price index in period $t$ in each state which is equal to:

$$P_{st} = \left(\phi P_{Hst}^{1-\epsilon} + (1-\phi)P_{Lt}^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}$$

Since sector $L$ is tradable and firms are symmetric, market clearing condition $\sum_{s=1}^{n} Y_{Ls0} = \sum_{s=1}^{n} C_{Ls0}$ implies that the output of good $L$ in each state is equal to:

$$Y_{Ls0} = \frac{(1-\phi)\sum_{s=1}^{n}\left(\frac{P_{L0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{W_{Hso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right)}{n}$$

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

$$n_{Ls0} = \frac{Y_{Ls0}}{Y_{Ls}^{*}} = \frac{Y_{Ls0}}{(1-\phi)} = \frac{\sum_{s=1}^{n}\left(\frac{P_{L0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{W_{Hso}}{P_{s0}}(1-\delta_s) + (1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right)}{n}$$

This result suggests that if sector $L$ is tradable, state-specific shocks are spread out equally across the country, and the larger $n$ is, the less employment in sector $L$ depends on the labor supply shock in sector $H$ in its state. In contrast, the case of sector $L$ being non-tradable is identical to the model analyzed by Guerrieri et al. (2022). In such a case, $n_{Ls0} = (1-\delta_s)(\frac{P_{Hs0}}{P_{Ls0}})^{-\epsilon}$ and employment in sector $L$ decreases if the following condition holds:

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

This condition implies that a labor supply shock in sector $H$ translates into a decrease in employment in sector $L$ if the intertemporal elasticity of substitution is sufficiently larger than the elasticity of substitution between sectors (in other words, if sectors are complementary enough). Moreover, the condition becomes more stringent if the share of hand-to-mouth households goes to zero.

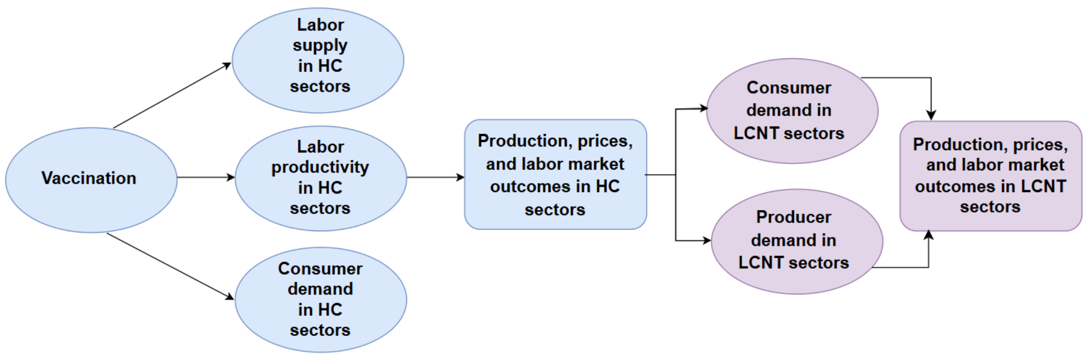
Additionally, as shown in Guerrieri et al. (2022), the transmission of the aggregate supply shocks may be exacerbated if sector $L$ serves as an intermediate input for sector $H$. This is because if production in sector $H$ falls, the firms in this sector would decrease the demand for the intermediate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

As stated above, under nominal wage rigidity, the transmission mechanism would be similar if influenza vaccination affects labor productivity or consumer demand. If a negative shock to effective vaccination reduces labor productivity in sector $H$, and prices in this sector increase to clear the goods market, then the real income of workers in both sectors would decrease due to an increase in CPI (see Appendix Section A5 for further details). On the other hand, if prices in sector $H$ are sticky, a negative labor productivity shock in this simple framework would induce firms to stop hiring workers because the marginal productivity of labor would be lower than the real wage. Similarly, if prices in both sectors are sticky, then a negative shock to the consumer demand in sector $H$ would decrease the employment of workers in this sector, which would have similar implications as a negative labor supply shock (see Guerrieri et al., 2022 for further details).

Finally, under the assumption of flexible wages, the shocks would have different implications in sector $H$, and the spillover effects would be absorbed by wages and prices rather than employment. A negative labor supply shock in sector $H$ would increase the prices and wages in this sector. A negative labor productivity shock would decrease the wages but increase the prices in sector $H$, and a negative consumer demand shock would decrease both the wages and prices in sector $H$.

In short, the key predictions of the model are the following. First, if labor cannot move across sectors or states, spillovers occur only in non-tradable sectors. Second, as illustrated in Figure 1, shocks to consumer demand, labor supply, or productivity in high-contact sectors can transmit to low-contact non-tradable sectors through producer or consumer demand. Third, such spillovers operate through two channels: changes in the price index and changes in the wages of workers directly affected by the shocks. Finally, the presence of hand-to-mouth households amplifies these sectoral spillovers.

**Figure 1. Flow Diagram**




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

# 3 Data and Empirical Strategy

## 3.1 Data

This study utilizes data on health and labor market outcomes in the US and Canada. I begin by describing the US data. In most specifications, the analysis sample includes 50 US states between 2001 and 2016. Following White (2021), I exclude the influenza seasons 2008/09 and 2009/10 due to the H1N1 pandemic.[11]

[11]The data on vaccination rates are available from the 1993/94 influenza season. However, I restrict my sample to 2001 for the following reasons. First, the data on labor market turnovers are available only from January 2001. Second, the sample size in BRFSS used to calculate vaccination rates for the 1993/94-1999/2000 seasons is at least twice as small as in the later seasons. Therefore, to harmonize the sample and to use state-level vaccination rates based on a larger sample, I restrict my analysis sample to January 2001. Furthermore, since I aim to restrict my sample to the pre-COVID period and need to use flu seasons

*US Vaccine Data.* My primary variables of interest are nationwide vaccine match rates, which vary by influenza season, and actual vaccination rates, which vary over time and by state, metropolitan statistical areas, and counties.[12] The data on vaccine match rates are derived from the Centers for Disease Control and Prevention (CDC) surveillance reports by using a calculator developed by White (2021).[13] Following White (2021), to assign vaccine match rates, I redefine years as "flu-years" running from July through June.[14] This redefinition is necessary because the CDC provides data on virus circulation for influenza seasons rather than for calendar years.

Similar to White (2021), I construct both "strict" and "loose" vaccine match rates. The first measure characterizes vaccine virus strains as matched if they are identical to the circulating ones. In contrast, the second measure characterizes virus strains as matched even if they offer only some level of protection against the circulating ones. I use the "strict" vaccine match for my main specification and the "loose" vaccine match for the robustness analysis.

The data on state-by-flu-year actual vaccination rates come from the Behavioral Risk Factor Surveillance System.[15] BRFSS is a health-related telephone survey that, among other questions, provides information on the individual vaccination status. Survey weights are used to calculate actual vaccination rates by state (see Appendix section A5 for further details). To derive actual vaccination rates by counties and MSAs, I utilize data from BRFSS SMART, which are available from 2004 to 2012 for a subset of counties and

2017/18 and 2018/19 as leads to perform a placebo test, I restrict my analysis sample to 2016. However, in the Appendix, I show the impact of effective vaccination on labor market outcomes between 1994 to 2022, with and without excluding pandemic seasons. The District of Columbia is excluded because the sample size is too small to calculate representative vaccination rates.

[12]Here, time refers to influenza season.

[13]The reports can be accessed at Centers for Disease Control and Prevention (2025b).

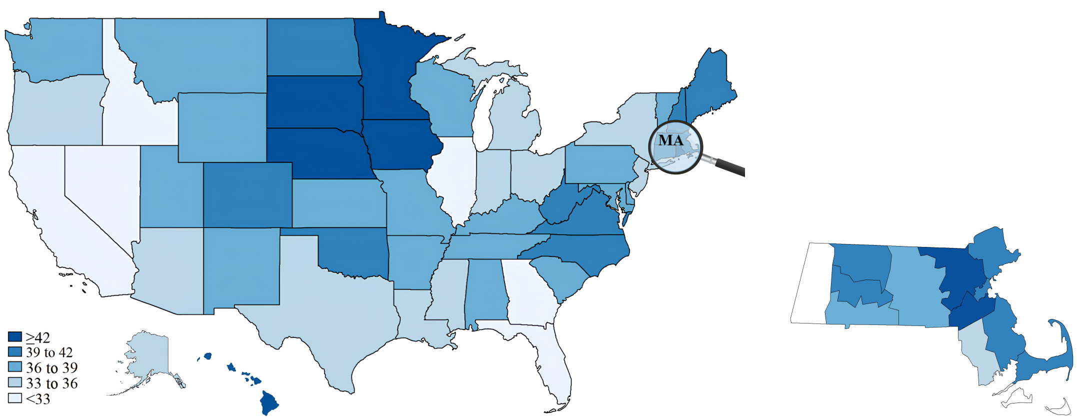
[14]For example, the flu year 2001/2002 starts in July 2001 and ends in June 2002.

[15]These data can be accessed at Centers for Disease Control and Prevention (2025a).

MSAs.[16]

Figure 2 presents the variation in average vaccine take-up across states. The average actual vaccination rate ranges from 29 to 47 percent. Two states have rates below 32 percent, while six states have rates above 42 percent.[17] There is also substantial variation within states. For example, in Massachusetts, which is one of the states with the largest available data at the county level, rates range from 34 to 45 percent (see Figure 2b). Appendix Figures C.2 and C.1 show variation in average vaccine take-up between counties and MSAs for all the states.

**Figure 2. Geographical Variation in Vaccination Rates**




**Panel A: US States** **Panel B: MA Counties**

Notes: Based on the BRFSS and BRFSS SMART. Panel A map shows the average vaccination rates by state from the flu season 2000/01 to 2016/17. Panel B shows the average vaccination rates by county for Massachusetts from 2003/2004 to 2010/2011.

Next, Figure 3a shows the variation in vaccine match and actual vaccination rates over time. The latter is presented for the group of states that in a given flu-year have actual vaccination rates in the bottom and top quartiles (hereafter, low- and high-vaccinated

[16]The data are available from 2002 onward. However, since interview month identifiers are available only until 2012 and administrative divisions of counties and MSAs underwent significant changes after 2003, I focus on this period to calculate vaccination rates by counties and MSAs.

[17]The states with rates below 32 percent are Florida and Nevada, while those with rates above 42 percent are Hawaii, Iowa, Minnesota, Nebraska, Rhode Island, and South Dakota.

states). The figure shows that actual vaccination rates increase over time, but the gap in vaccine take-up between high- and low-vaccinated states remains relatively constant.[18] The vaccine match appears to be random over time, without any discernible pattern.[19] 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 rates, or labor-force participation ratios respond differently to match rates.

Figure 3b presents the evolution of the effective vaccination rate for the high- and low-vaccinated states. By construction, 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.

*US Outcomes.* The data on labor market outcomes come from multiple sources. State-level data on the employment-to-population rate and labor force participation rate come from the U.S. Bureau of Labor Statistics (2025b).[20] To determine whether the employment effects are driven by labor demand factors or voluntary resignations, the study utilizes data from the U.S. Bureau of Labor Statistics (2025a), which offers data on job openings, hiring, quitting, and layoff rates.[21] Summary statistics for labor market outcomes based on these data are shown in Appendix Table C.1. Additionally, to study employment effects by industry, I use data from the U.S. Bureau of Labor Statistics (2025d). The variable of interest in this case is the natural logarithm of employment.[22]

[18]Furthermore, there is no evidence suggesting that vaccination coverage was higher during seasons with elevated flu activity, such as the H1N1 pandemic.

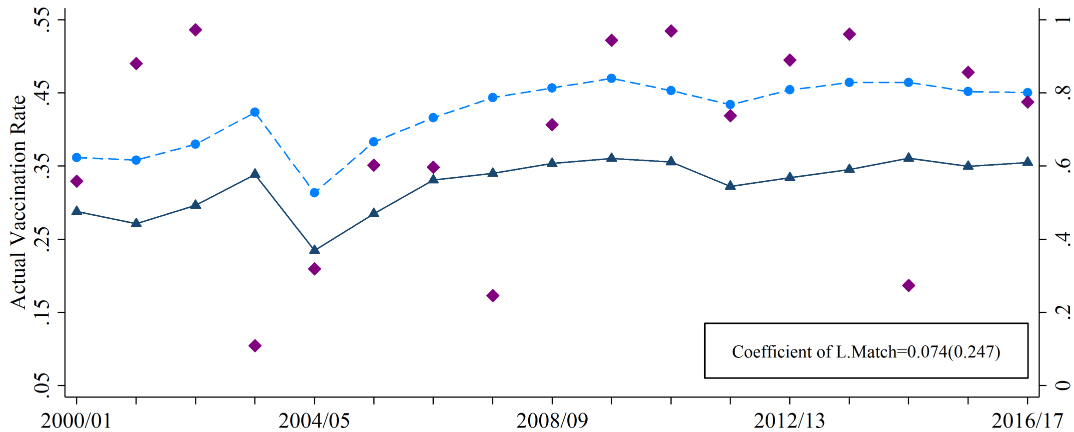
[19]The match rate does not appear to follow any specific trend or to be correlated with its lags.

[20]I am using data revised on March 5, 2025.

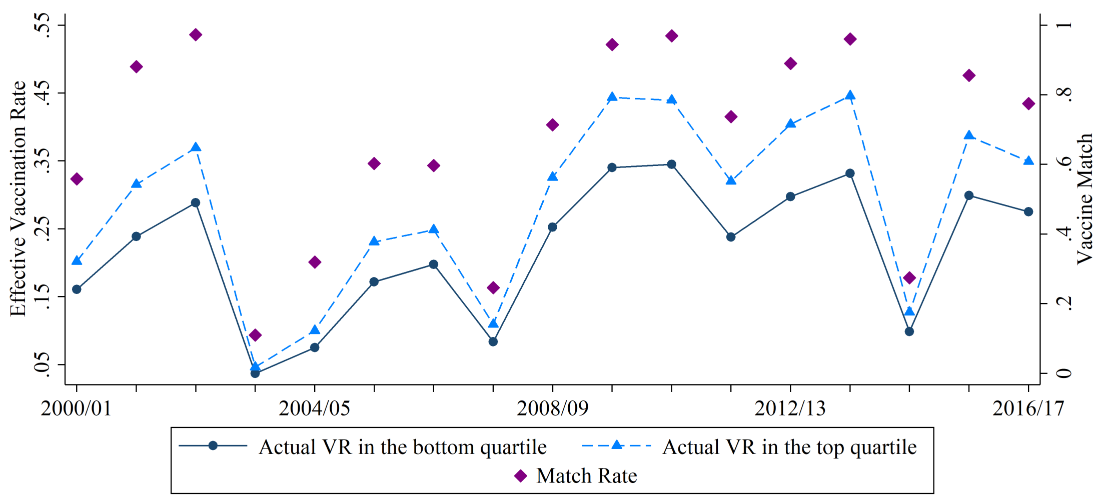
[21]The rates are calculated by dividing the data element level by employment and multiplying by 100.

[22]When these data sets are used, the unit of analysis is at the state-by-month level. Employment data for

**Figure 3. Actual and Effective Vaccination Rates Over Time**




**Panel A: Actual Vaccination Rates**




**Panel B: Effective Vaccination Rates**

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

The individual-level data come from the Current Population Survey.[23] The variables of interest are employment, the natural logarithm of inflation-adjusted hourly wages, absenteeism due to illnesses (hereafter, absenteeism), and weekly restaurant consumption in dollars. Note that the analysis sample excludes retired individuals and those attending school. Moreover, the effects on wages are investigated only for employed individuals. Employment is coded as one if an individual is employed and zero otherwise. To derive hourly wages, I divide weekly earnings by the reported number of hours the respondent usually worked at the job.[24]

Absenteeism is used as a proxy for labor productivity. The exact relationship between absenteeism and labor productivity depends on the substitutability of workers and the possibility of postponing tasks to the future (Koopmanschap et al., 1995; Pauly et al., 2002). However, several studies show that absenteeism has an impact on labor productivity (Koopmanschap et al., 1995; Miller et al., 2008) with an elasticity of around -0.1.

Given that 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. Respondents are classified as absent due to illness if, during the reference week, they miss work or work less than 35 hours due to their own medical problems. Other measures of labor productivity include output per worker and output per hour. To analyze the effects of vaccination on these outcomes, I impose additional sample restrictions described in Appendix B.[25]

Restaurant consumption serves as a proxy for consumer demand. These data are avail-

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certain industries are unavailable for some states. Hence, when the CES data are used, the sample excludes some states.

[23]The data can be accessed at Sarah Flood and Westberry (2024).

[24]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.

[25]Note that the unit of analysis for absenteeism and all the other outcomes from the CPS is at the individual-state-month level, while the unit of analysis for output-per-worker and output-per-hour is at the state-quarter level.

able only until 2015, and the spending is top-coded to 250$.[26] Lastly, I also use the CPS data to study the spatial spillovers of influenza vaccination, i.e, to examine the impact of effective vaccination by using a within-state variation.

To provide descriptive evidence on the impact of effective vaccination on employment and absenteeism rates, I examine variation in these outcomes between high- and low-vaccinated states across different match years. Panels A and B of Figure 4 present the evolution of absenteeism and employment rates for high- and low-vaccinated states, while Panels C and D plot how the gap in these outcomes between high- and low-vaccinated states relates to match rates. Figure 4 shows that high-vaccinated states tend to exhibit higher absenteeism than their counterparts. However, when the vaccine match is close to one, the gap in absenteeism between these states becomes smaller. Employment-to-population rate also appears to be higher in states with vaccination rates in the top quartile of the distribution, and this gap increases when match rates are close to one. These figures provide the first evidence that effective vaccination is negatively associated with absenteeism and positively associated with employment rate.

*US controls.* To address the potential confounders, I collect data on temperature, precipitation, population shares, and lagged growth of Gross Domestic Product (GDP).[27]

*Canadian data.* In the Canadian setting, I examine the impact of the Universal Influenza Immunization Program (UIIP) in Ontario, which was launched in July 2000. To do so, I utilize data on match rates and labor market outcomes from the 1994/95 to 2005/2006 flu seasons.[28] The data on employment-to-population rate and LFP rate at the province-by-month level come from the Statistics Canada (2025a).

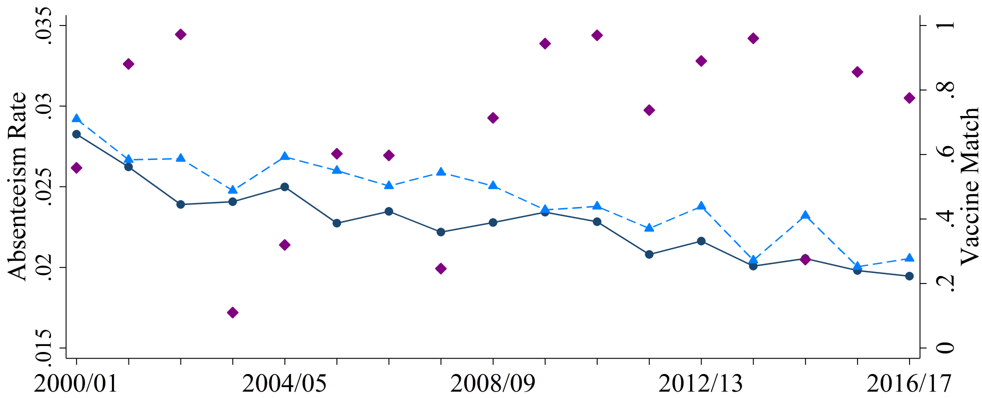
To derive flu-year vaccine match in Canada, I use data on influenza activity from the

[26]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$. Both restaurant consumption and weekly earnings are in 2000$.

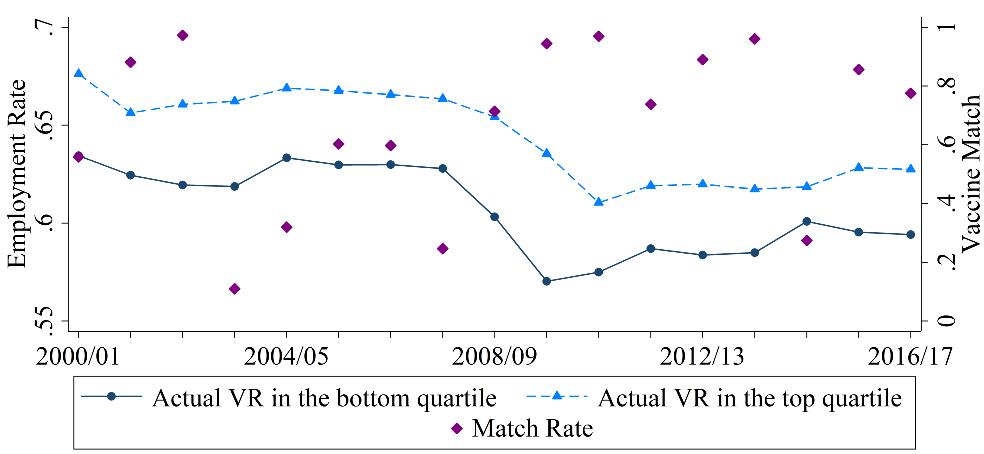
[27]Weather controls come from the NOAA National Centers for Environmental Information (2025); population shares come from the U.S. Census Bureau (2025); and GDP from the U.S. Bureau of Economic Analysis (2025). I use the following population shares: 0-14, 15-24, 25-44, 45-64, and 65+.

[28]I focus on this period to align my results with Ward (2014).

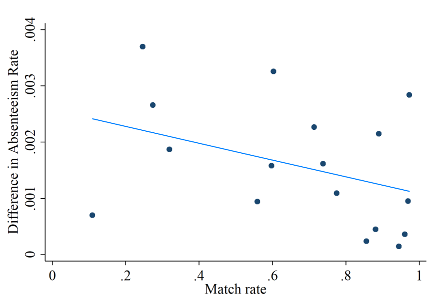
**Figure 4.** **Absenteeism and Employment in Low- and High-Vaccinated States**



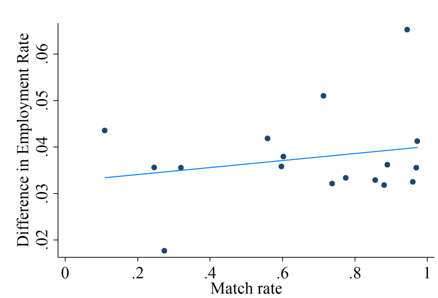

**Panel A: Absenteeism**




**Panel B: Employment**




**Panel C:** $\rho_{\textbf{absenteeism,match}}$




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

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

Public Health Agency of Canada (2010), which are available at both the national and provincial levels. However, to be consistent with the US specification and to avoid small sample bias as well as missing data for some provinces in certain flu-years, I use national match rates for the main specification.[29] The province-level match rates are used for the robustness analysis. Lastly, I obtain data on the same control variables as in the US setting.[30]

## 3.2 Empirical Strategy

To causally estimate the impact of the flu vaccines on labor market outcomes, I exploit the plausibly exogenous variation in effective vaccination (White, 2021) and estimate the difference-in-differences equation (1) as follows:

$$Y_{smt} = \beta_0 + \beta_1(V_{st} \times MR_t) + \beta_2 V_{st} + \beta_4 X_{smt} + \delta_{mt} + \gamma_s + \epsilon_{smt} \tag{1}$$

where $Y_{smt}$ is the outcome variable in state $s$, month $m$, and flu-year $t$.[31] $V_{st}$ denotes the actual vaccination rate, and $MR_t$ denotes the match rate. The variable of interest is $V_{st} \times MR_t$, which measures the level of effective vaccination. The vector $X_{smt}$ includes state-level time-varying control variables such as average monthly temperature and precipitation, the annual population share for five age groups, and lagged GDP growth. State fixed effects are denoted by $\gamma_s$, and $\delta_{mt}$ are month-by-year fixed effects. These variables absorb state-specific time-invariant components and common time shocks.

[29] Note that the match rate calculator developed by White (2021) requires data on sub-typing of detected influenza A viruses. This information is not available for the earlier flu-years. That is why I calculate the match rate for Canada as a simple ratio of matched strains to the total number of antigenically characterized strains. In the robustness check, I replace the missing sub-typed influenza A viruses with the antigenically characterized viruses.

[30] Data on weather controls come from Environment and Climate Change Canada (2025); on population shares from the Statistics Canada (2025b); and on GDP from the Statistics Canada (2025c).

[31] When the CPS data is used, the unit of analysis is at the individual-state-month level, and the individual-level controls $X_{ismt}$ which include age, gender, educational attainment, parental and marital status are added to the equation (1). Moreover, when the outcome denotes output per worker or output per hour, the dependent variable is at the state-quarter level.

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 sometimes 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.[32]

Next, to evaluate the validity of the treatment and to examine the persistence of the estimated effects, I turn to a dynamic specification. To do so, similarly to White (2021), I add the interactions between the actual vaccination rates with the leads and lags of the match rates to the equation (1) and estimate the following model:

$$\begin{aligned} Y_{smt} = \pi_0 + \pi_1(V_{st} \times MR_{t+2}) + \pi_2(V_{st} \times MR_{t+1}) + \pi_3(V_{st} \times MR_t) + \pi_4 \\ (V_{st} \times MR_{t-1}) + \pi_5(V_{st} \times MR_{t-2}) + \pi_6 V_{st} + \pi_7 X_{smt} + \kappa_{mt} + \omega_s + \epsilon_{smt} \end{aligned} \tag{2}$$

In this equation, the interactions $V_{st} \times MR_{t+2}$ and $V_{st} \times MR_{t+1}$ would serve as a falsification test and would examine if future match rates have any impact on the outcomes in the flu season $t$. On the other hand, the interactions $V_{st} \times MR_{t-1}$ and $V_{st} \times MR_{t-2}$ would evaluate the persistence of the effects.

To better understand the spatial spillover effects of vaccination, I also estimate the impact of effective vaccination when the labor market is defined at the metropolitan area or county level. To do so, I estimate the following equation (3) with the individual-level CPS data:

$$Y_{ilmt} = \theta_0 + \theta_1(V_{lt} \times MR_t) + \theta_2 V_{lt} + \theta_3 X_{ilmt} + \phi_l + (\rho_{mt} \times \tau_s) + \epsilon_{ilmt} \tag{3}$$

where $Y_{limt}$ is an individual outcome in location l (county or MSA), and $V_{lt} \times MR_t$ is the measure of effective vaccination in location l. The vector $X_{ilmt}$ denotes a set of individual

[32] In other words, I allow for state-level actual vaccination rates to be endogenous. However, if match rates are as good as randomly assigned, controlling for the expected treatment, which is measured by actual vaccination rates, recenters the realized treatment, which is measured by the effective vaccination.

characteristics, and the vectors $\phi_l$ and $(\rho_{mt} \times \tau_s)$ denote location fixed effects and state-by-time fixed effects, respectively.

Lastly, to evaluate the external validity of my findings, I study the impact of effective vaccination by using a quasi-experimental setting in Canada. In July 2000, Ontario implemented the Universal Influenza Immunization Campaign (UIIC), which aimed at providing free influenza vaccines for the entire population. Following Ward (2014), I employ the triple-difference estimation design shown in equation (4), to estimate the effect of influenza vaccination on employment.

$$\begin{aligned} Y_{pmt} = &\alpha_1 (\text{UIIC}_p \times \text{Post}_t \times MR_t) + \alpha_2 (\text{UIIC}_p \times \text{Post}_t) \\ &+\alpha_3 (\text{UIIC}_p \times MR_t) + \mathbf{X}'_{pmt}\Lambda + \psi_{mt} + \xi_p + u_{pmt} \end{aligned} \tag{4}$$

where $Y_{pmt}$ denotes employment-to-population rate in province $p$, month $m$, and flu-year $t$. $UIIC_p$ is coded as one if the province is Ontario, $Post_t$ is coded as one if the flu-year is greater than or equal to 2000/2001, and $MR_t$ is the flu-year match rate. Vector $X_{pmt}$ includes province-by-time control variables, such as share of five age groups, weather controls, and lagged GDP growth. The vectors $\psi_m t$ and $\xi_p$ are time and province fixed effects, respectively. Note that in this setting, the term $\text{UIIC}_p \times \text{Post}_t$ accounts for unobservable post-period differences in employment-to-population rate in Ontario, for example, any other labor market policies or events that coincided with the introduction of UIIC. In contrast, the term $\text{UIIC}_p \times MR_t$ controls for any differential effects of match rates in Ontario that are common in the pre- and post-period.[33]

# 4 Results

Note that, as described in the previous section, most variables in the analysis either range from zero to one or are expressed in logarithmic form. That is why in most cases, vacci-

[33]Note that the typical triple difference specification would also include the term $\text{Post}_t \times MR_t$. However, since I use the national match rate for the main specification, this term is perfectly collinear with the time fixed effects. When the regional match rate is used, equation (4) also includes the match rate in levels and $\text{Post}_t \times MR_{pt}$.

nation and match rates also range from zero to one, allowing coefficients to be interpreted as the effect of a one percentage point increase. To maintain this interpretation when estimating the impact of effective vaccination on outcomes measured in levels, such as weekly restaurant spending in dollars or weekly hours worked, in these regressions, I multiply the vaccination rate by 100.

## 4.1 Main Results

Table 1 shows the estimated effects of influenza vaccination on the employment-to-population rate and labor force participation rate. Columns one and two only control for state and time fixed effects, while columns three and four add the full set of control variables described in Section 3.2. The coefficients of actual vaccination rates represent the association between vaccination and labor market outcomes when the match rate is zero (White, 2021). The results suggest that the state-level actual vaccination rates are endogenous: states with higher vaccination rates tend to have higher labor force participation rates.

The variable of interest is, however, the effective vaccination rate, which is measured as the interaction between actual vaccination and match rates. The impact of effective vaccination on labor market outcomes is of similar magnitude in the regressions with and without controls, which suggests the validity of the identification strategy. Based on the estimates in column three, a one percentage point increase in effective vaccination increases the employment-to-population rate by 0.09 percentage points. This suggests that in an average match season (i.e, match rate is 0.68), a one standard deviation increase in actual vaccination (i.e., five percentage points) leads to a 0.3 percentage points increase in the employment-to-population rate.[34] The magnitude of this estimate appears to be surprisingly large but not implausible considering the multiple mechanisms through which effective vaccination may affect employment. Section 4.6 will discuss the plausibility of these estimates in greater detail. On the other hand, the impact of effective vaccination

[34] $5 \times 0.68 \times 0.09$

**Table 1. Effective Vaccination and Labor Market Outcomes**

| | (1) Employment rate | (2) LFP rate | (3) Employment rate | (4) LFP rate |
|---|---|---|---|---|
| Vaccination × Match | 0.112*** | 0.030 | 0.089*** | 0.023 |
| | (0.033) | (0.021) | (0.028) | (0.019) |
| Vaccination | -0.010 | 0.057* | 0.011 | 0.052* |
| | (0.032) | (0.030) | (0.032) | (0.030) |
| Mean of D.V. | 0.621 | 0.657 | 0.621 | 0.657 |
| State FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Controls | No | No | Yes | Yes |
| Observations | 8,400 | 8,400 | 8,400 | 8,400 |

Notes: The data come from the LAUS. The unit of analysis is at the state-month level. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are the employment-to-population rate and labor force participation rate. The regressions include the full set of state-level control variables described in the section 3.2. Standard errors are clustered at the state level.

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

on labor force participation is smaller in magnitude and not statistically significant at the conventional levels. These results suggest that effective vaccination appears to mostly help unemployed individuals find jobs rather than encourage more people to enter the labor force.

The relationship between effective vaccination and labor market turnover is presented in Table 2. Effective vaccination has a positive effect on hiring and job opening rates, but it has no effect on layoff rates. These results suggest that the employment effects tend to be driven by labor demand. The relationship 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 estimates documented earlier.

Next, I turn to the CPS data to examine the heterogeneous impact of effective vaccination on labor market outcomes across demographic characteristics. Figures 5a and 5b show that the relationship between effective vaccination and labor market outcomes is rather homogeneous across demographic groups, with some minor exceptions. Particularly, the estimates of effective influenza vaccination on employment are larger for those who are younger or those who have children.

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

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Opening Rate | Hiring Rate | Quit Rate | Layoff Rate |
| Vaccination × Match | 0.014** | 0.017*** | 0.012*** | 0.004 |
| | (0.006) | (0.006) | (0.004) | (0.003) |
| Vaccination | -0.008 | -0.007 | -0.002 | -0.007 |
| | (0.007) | (0.010) | (0.006) | (0.005) |
| Mean of D.V. | 0.031 | 0.039 | 0.020 | 0.015 |
| State FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Observations | 8,400 | 8,400 | 8,400 | 8,400 |

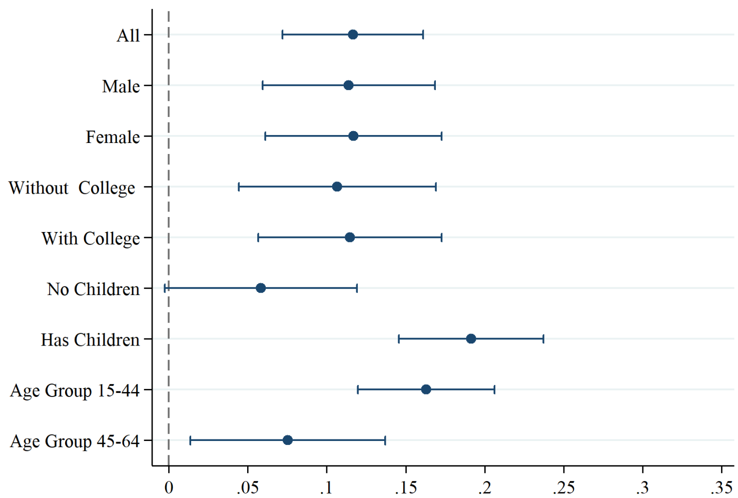
Notes: Notes: The data come from the JOLTS. The unit of analysis is at the state-month level. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are the opening, hiring, quit, and layoff rates. The regressions include the full set of state-level control variables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

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

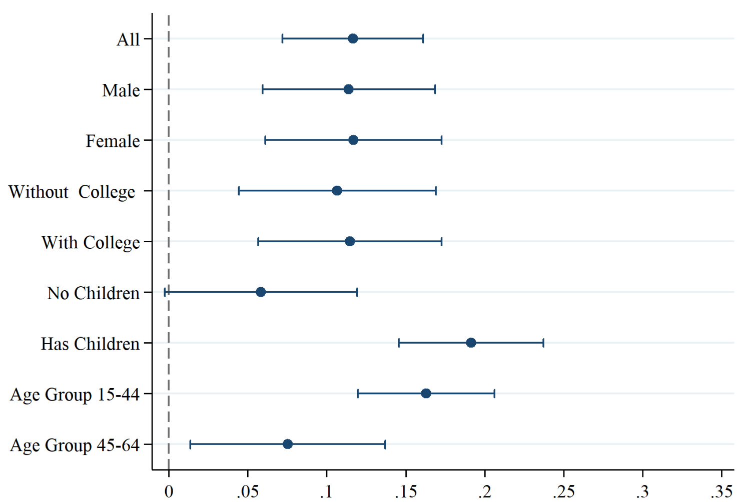
## 4.2 Mechanisms

As discussed above, effective vaccination may affect labor market outcomes through three channels: labor supply, labor productivity, and consumer demand. The results presented in Section 4.1 provide evidence that employment effects are driven by labor demand factors, suggesting that vaccination affects either labor productivity, consumer demand, or

**Figure 5. Estimated Effects by Demographic Characteristics**




**Panel A: Employment**




**Panel B: Hourly Wages**

Notes: The data come from the CPS. The unit of analysis is at the individual-state-month level. 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. 90% confidence intervals are constructed with the standard errors are clustered at the state level.

both. To investigate these mechanisms, I draw on three measures of labor productivity (i.e., absenteeism, output per worker, and output per hour) and use restaurant consumption as a proxy for consumer demand (see Section 3.1 for further details).

The theoretical framework in Section 2.3 suggests that if the impact of effective vaccination is asymmetric across sectors, then sectoral spillovers may amplify its overall effect. To evaluate this hypothesis, I begin my analysis by examining whether the impact of effective vaccination on labor productivity is heterogeneous across sectors. I then evaluate the spillovers on labor market outcomes. Similar to the effects of COVID-19, the direct impact of effective vaccination is expected to be more pronounced in high-contact sectors. The sectoral spillovers, as shown in Section 2.3, are expected to be larger in non-tradable sectors, as tradable sectors mostly rely on national or global demand. That is why I classify the sectors by contact intensity and tradability, which results in the following categories: high-contact non-tradable (HNT), low-contact non-tradable (LNT), and low-contact tradable (LT). Since all high-contact sectors are classified as non-tradable, the high-contact tradable category is omitted.[35]

The estimates in Tables 3 and C.4 indicate that the impact of effective vaccination on labor productivity is larger in high-contact sectors. The findings in Table 3 suggest that in an average match season, a one standard deviation increase in effective vaccination reduces absenteeism in high-contact sectors by 0.1 percentage point (a 5% decrease with

[35] The sectors are defined by the 2-digit North American Industry Classification System (NAICS). I classify a sector as 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. I construct a measure of physical proximity by merging the occupation-level physical proximity index from the O*NET 20.1 database with occupational employment data for each sector. The occupational employment shares within each sector are then used as weights to compute the sector-specific physical proximity index. Therefore, high-contact sectors include leisure and hospitality, education and health services, construction, and retail trade. The classification of tradability 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. The O*NET data is retrieved from National Center for O*NET Development (2025), while the occupational employment data come from the U.S. Bureau of Labor Statistics (2025c).

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

| | (1) High, Non-Tradable | (2) Low, Non-Tradable | (3) Low, Tradable |
|---|---|---|---|
| **Panel A: Absenteeism due to illness, CPS** | | | |
| Vaccination × Match | -0.027*** | -0.002 | 0.003 |
| | (0.009) | (0.010) | (0.011) |
| Mean of D.V. | 0.023 | 0.024 | 0.021 |
| Observations | 3,916,696 | 1,781,822 | 2,755,771 |
| **Panel B: Ln(Employment), CES** | | | |
| Vaccination × Match | 0.229** | 0.179** | 0.024 |
| | (0.101) | (0.085) | (0.102) |
| Mean of D.V. | 6.589 | 6.409 | 6.211 |
| Observations | 8,064 | 7,896 | 6,966 |
| **Panel C: Ln(Hourly Wages), CPS** | | | |
| Vaccination × Match | 0.136** | 0.060 | 0.044 |
| | (0.054) | (0.072) | (0.082) |
| Mean of D.V. | 2.529 | 2.613 | 2.731 |
| Observations | 976,182 | 392,525 | 619,776 |
| 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. Since all high-contact sectors are classified as non-tradable, the category high-contact tradable is omitted. The data on employment come from the CES; the data on wages and absenteeism come from the CPS. The unit of analysis in column two is at the state-month level, and in columns one and three at the individual-state-month level. Absenteeism is coded as one if the respondent is absent due to their own illness and zero otherwise; employment measures the number of employed workers by sector. 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. Standard errors are clustered at the state level.

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

respect to the mean). Similarly, the estimates in Appendix Table C.4 suggest that at the average match rate, a one standard deviation increase in effective vaccination in high-contact sectors increases output per worker and output per hour by 0.56 and 0.68 percent, respectively.

The impact of effective vaccination on employment and wages also appears to be more pronounced in high-contact sectors. The point estimates in Table 3 imply that at the average match rate, a one standard deviation increase in effective vaccination in high-contact sectors increases employment and wages by 0.78 and 0.46 percent, respectively.[36] However, as predicted by the implications of the model, the estimates in Table 3 show that even though the relationship between effective vaccination and labor productivity is smaller in low-contact sectors, the employment effects in low-contact non-tradable sectors are relatively large. In contrast, these effects are close to zero and not statistically significant in low-contact tradable sectors.

Sectoral spillovers may occur due to the input-output network of production or consumer responses. As shown in Section 2.3, the latter are expected to be more pronounced if households are hand-to-mouth (H2M). Since the state-level financial data are not available, I follow Cloyne et al. (2020) and exploit homeownership status as a proxy for H2M households.[37] In detail, I define two groups of states: those that have the lagged share of mortgagors and renters above and below the median (hereafter, H2M and NH2M states).[38]

Table 4 shows the impact of effective vaccination on consumption and absenteeism in H2M and NH2M states. The estimates suggest that the relationship between effective vaccination and absenteeism is similar in both groups. However, the impact of effective vaccination on restaurant consumption is three times larger in H2M states. These results provide evidence for the sectoral spillovers through the consumer demand channel.[39] Sim-

[36] Moreover, Appendix Tables C.5 and C.6 show that effective vaccination has a positive impact on hours of work and GDP in high-contact sectors.

[37] The authors find that mortgagors and renters react more strongly to income shocks, and that is why they can be classified as H2M households.

[38] The data on homeownership status is approximated from the Steven Ruggles and Williams (2025).

[39] Appendix Table C.7 shows similar findings when the lagged share of H2M and other confounders that

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

| | (1) | (2) | (3) |
|---|---|---|---|
| | Overall | H2M | NH2M |
| **Panel A: Restaurant Consumption, $ per week** | | | |
| Vaccination × Match | 0.231*** | 0.225** | 0.159 |
| | (0.080) | (0.090) | (0.129) |
| Mean of D.V. | 29.96 | 31.51 | 27.98 |
| Observations | 807,966 | 453,921 | 354,045 |
| **Panel B: Absenteeism due to illness** | | | |
| Vaccination × Match | -0.0121** | -0.0140 | -0.0105 |
| | (0.0058) | (0.0088) | (0.0085) |
| Mean of D.V. | 0.024 | 0.024 | 0.024 |
| 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. The unit of analysis is at the individual-state-month level. 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. When the dependent variable is consumption, the vaccination rate is multiplied by 100%, so that the coefficients of actual and effective vaccination reflect an increase in one percentage point. The regressions include the full set of state- and individual-level control variables described in the section 3.2. Standard errors are clustered at the state level.

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

ilar findings are presented in Table 5, which shows that the relationship between effective vaccination and labor market outcomes is also more pronounced in H2M states.

To explore whether demand chains contribute to sector spillovers, I examine hetero-

may be correlated with H2M are interacted with effective vaccination.

geneity in vaccination effects across upstream and downstream low-contact non-tradable sectors. I find that the point estimates of effective vaccination on employment are larger in sectors that tend to serve as inputs for high-contact sectors (see Appendix Table C.8).[40] These findings provide evidence that demand chains may amplify the labor market effects of influenza vaccination.

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

| | (1) High, H2M | (2) High, NH2M | (3) Low, H2M | (4) Low, NH2M |
|---|---|---|---|---|
| **Panel A: Ln(Employment)** | | | | |
| Vaccination × Match | 0.362** | 0.055 | 0.218* | 0.024 |
| | (0.154) | (0.102) | (0.108) | (0.142) |
| Mean of D.V. | 6.881 | 6.337 | 6.632 | 6.195 |
| Observations | 3,738 | 4,326 | 3,858 | 4,038 |
| **Panel B: Ln(Hourly Wages)** | | | | |
| Vaccination × Match | 0.170** | 0.063 | 0.028 | 0.141 |
| | (0.066) | (0.084) | (0.087) | (0.086) |
| Mean of D.V. | 2.571 | 2.480 | 2.655 | 2.559 |
| Observations | 523,469 | 452,713 | 221,279 | 171,246 |
| 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. The unit of analysis is individual-state-month. 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. Standard errors are clustered at the state level.

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

Finally, influenza vaccination may also directly influence consumer demand, partic-

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

ularly in high-contact sectors. Table 4 shows a positive relationship between effective vaccination and restaurant consumption. While part of this relationship appears to reflect the indirect effects driven by fluctuations in labor income, the reduced form estimates cannot disentangle to what extent restaurant consumption changes directly as a result of changes in consumer behavior, or indirectly through fluctuations in labor income. However, as discussed in Section 2.3, the propagation mechanism of influenza vaccination (i.e., through consumer demand or labor productivity) in high-contact sectors does not affect the transmission channels for sectoral spillovers.

## 4.3 Placebo Effects and Dynamics

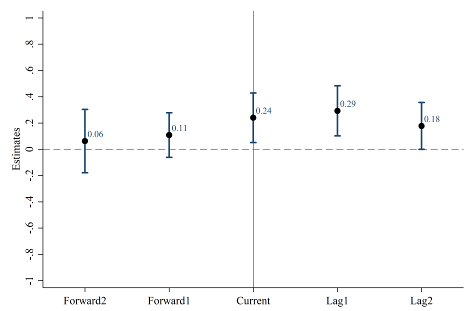
To rule out the presence of pre-trends and evaluate the persistence of the estimated effects, I estimate equation (2), which enriches the main specification with the variables that interact actual vaccination rates with match rates in prior and forward flu seasons. Figure 6 presents the estimates of equation (2) 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 lead match rates are small in magnitude and not statistically significant for high-contact and low-contact non-tradable sectors. In contrast, consistent with the results presented in Table 3, the current effective vaccination has a positive and statistically significant effect on employment in these sectors. The estimated effect appears to persist for one to two years. Furthermore, similarly to the estimates in Table 3, the current effective vaccination does not have a sizable and statistically significant effect for tradable sectors.

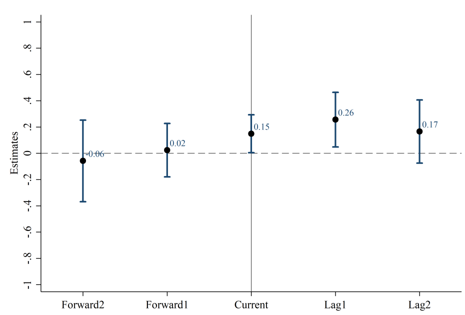
## 4.4 Heterogeneity by Geographic Area

To better understand the spatial spillovers of effective vaccination, I estimate its externality effects by the definition of the labor market. Columns one, two, and four of Table

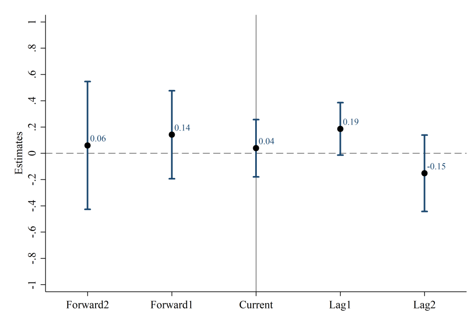
**Figure 6. Effective Vaccination and Employment by Sector: Placebo and Dynamic**




**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 90% confidence intervals are obtained with standard errors clustered at the state level.

6 present estimates based on equation (1), using variation in vaccination across states. Since data on vaccination rates at the county and MSA levels are only available for the subsample, column one presents results for the full sample, while columns two and four restrict the analysis to the subsamples for which county- and MSA-level vaccination rates are available, respectively. Columns three and five report estimates based on equation (3), which leverages within-state variation in vaccination rates.

**Table 6. Effective Vaccination and Employment: Geographic Heterogeneity**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | State | State C-Sample | County | State M-Sample | MSA |
| **Panel A: Employment** | | | | | |
| Vacc $\times$ Match | 0.117$^{***}$ | 0.188$^{***}$ | 0.100$^{**}$ | 0.273$^{***}$ | 0.146$^{**}$ |
| | (0.027) | (0.042) | (0.042) | (0.078) | (0.062) |
| Mean of D.V. | 0.752 | 0.748 | 0.748 | 0.758 | 0.758 |
| Observations | 13,508,619 | 2,593,846 | 2,593,846 | 2,374,266 | 2,374,266 |
| **Panel B: Absenteeism** | | | | | |
| Vacc $\times$ Match | -0.012$^{**}$ | -0.009 | -0.034$^{*}$ | -0.031 | -0.034 |
| | (0.006) | (0.017) | (0.019) | (0.021) | (0.029) |
| Mean of D.V. | 0.023 | 0.022 | 0.022 | 0.022 | 0.022 |
| Observations | 8,628,170 | 1,667,994 | 1,667,994 | 1,536,285 | 1,536,285 |

Notes: The data on employment and absenteeism come from the CPS. The units of analysis are at the individual-state-month and individual-local-month levels. The estimates in columns 1, 2, and 4 are obtained by estimating equation (1); full sample in column 1, sample with available county vaccination data in column 2, and sample with available MSA vaccination data in column 4. The estimates in columns 3 and 5 are obtained by estimating equation (3); in column 3, location is referred to as county, and in column 5, location is referred to as MSA. Standard errors are clustered at the state level.
$^{*}$ statistically significant at the 10% level; $^{**}$ at the 5% level, $^{***}$ at the 1% level

The results show an interesting pattern.[41] The findings suggest that the impact of

[41] The estimates in the subsamples with available vaccination data at the county and MSA levels are larger than those from the full sample. This might be because county and MSA data are available for more populous counties and MSAs, where the impact of effective vaccination may be more pronounced.

effective vaccination on employment depends on the definition of the labor market. As the geographic area of the labor market expands, the coefficients of effective vaccination become larger. When the local labor market is defined at the state level, the estimates of effective vaccination on employment are twice as large as the same estimates when the local labor market is defined at the county level. A similar pattern of results, but with a smaller absolute difference, is evident for the comparison between the estimates when the labor market is defined at the state and MSA levels. These findings suggest there are economic spillover effects from one county or MSA to another. These spillovers are absorbed by state-by-time fixed effects, which makes the estimates in columns three and five smaller compared to the estimates in columns two and four. Overall, the way different levels of aggregation can reveal externalities goes in line with the argument of Borjas (2006), who finds that the wage effect of immigration becomes larger when the area of the local labor market expands.

## 4.5 Other Results

This section presents two other sets of results: the labor market estimates for Canada and heterogeneities by season. Table 7 presents the coefficients for the Canadian setting, which are estimated using equation (4). Columns one and two show the estimates when equation (4) is estimated without any controls, while the estimates in columns three and four are obtained with the model that includes the full set of controls. First, note that there are only small differences in the estimates between the coefficients in regressions with and without controls.

The findings suggest that at the average match rate (i.e., 0.7), the UIIC appears to increase the employment-to-population rate by 0.57 percentage points. Given that the adoption of the program is associated with an 8.7 percentage point increase in actual vaccination rates, the estimates also imply that a one percentage point increase in the effective vaccination increases the employment-to-population rate in Canada by 0.09 percentage points. These findings suggest that the magnitude of the estimate of effective vaccination is comparable to the estimated impact of effective vaccination in the US.

**Table 7. Vaccination and Labor Market Outcomes: Canadian Data**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Employment Rate | LFP Rate | Employment Rate | LFP Rate |
| $\mathrm{U}IIC_p \times \mathrm{P}ost_y \times \mathrm{M}atch_{py}$ | 0.815** | 0.479 | 0.821** | 0.154 |
| | (0.294) | (0.331) | (0.281) | (0.287) |
| Mean of D.V. | 58.99 | 64.88 | 58.99 | 64.88 |
| Province FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes |
| Observations | 1,440 | 1,440 | 1,440 | 1,440 |

Notes: Based on data from Statistics Canada. The table reports triple-difference estimates from equation 4 with standard errors in parentheses. Standard errors are clustered at the province level.
$^{*}$ statistically significant at the 10% level; $^{**}$ at the 5% level, $^{***}$ at the 1% level

Next, Tables C.9 and C.10 show the differential impact of effective vaccination on labor market outcomes and absenteeism by seasons for the US and Canada. In both settings, the effects on absenteeism are larger in winter and fall, which is consistent with the fact that influenza outbreaks tend to occur more frequently during these months.[42] The impact of effective vaccination on labor market outcomes is also larger during the fall and winter, but the differences between seasonal estimates are less pronounced. These findings are consistent with the estimates in Figure 6 that show that the impact of effective vaccination persists for one to two years.

[42]Note that the measure of absenteeism for the US is an indicator variable of being absent from work due to own illness. Whereas, in Canada, the absenteeism is measured as average hours lost by workers for part of the week or a full week. The estimates for Canada suggest that effective vaccination mostly influences short-term absence. The discrepancies in the measures arise due to different questions asked by the CPS and LFS.

## 4.6 Robustness Checks

This section presents a series of robustness and specification checks.

*Sample selection.* First, I examine how sensitive the estimates are to the choice of sample. Table D.1 shows the estimates of effective vaccination for five different samples. "All" uses data from 1994 to 2022 without excluding pandemic years. "All w/o pandemic" uses data from the same period but excludes influenza seasons with H1N1 and COVID-19 pandemics. Given that the data on state-level real GDP are available after 1997, in both of these specifications, the lagged GDP growth is not included in the regressions. To examine if it affects the results, "1998-2022" uses all the data when this control variable is available. "W/o 2004/05" uses the main sample but excludes influenza season 2004/05 due to the vaccine shortage. "W/o AL and HI" excludes Alaska and Hawaii from the main sample due to the possibility of different timing of influenza seasons in these states. In all the specifications, the estimates remain statistically significant, and the point estimates range from 0.052 to 0.097.

*State trends.* Next, I examine if my findings are robust to the inclusion of state-specific trends. Table D.2 shows that the estimates are not sensitive to this specification change.

*Identification Strategy.* I also investigate whether the results are affected by 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.3 presents the estimates of the interaction between state-level vaccination rate in the flu year 2000/2001 and time-varying match rates. Under the assumption that the difference between vaccination rates across states is relatively 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.3 show that the results are robust to estimating the effects with an IV strategy. In this specification, time-varying effective vaccination is instrumented with the interaction between the time-invariant vaccination rate and time-varying match rates.

*Falsification test.* The identification strategy relies on the assumption that the difference between outcomes of high- and low-vaccinated states depends on match rates. In section 4.3 I have already shown what happens when the match rates are reassigned to their lagged and lead values. Table D.4 presents the estimates of the placebo test, where match rates are randomly reshuffled 1000 times. The results show that, in these specifications, the median impact of effective vaccination on the employment rate is negligible. The falsification test for the Canadian setting implies similar findings (see Appendix Table D.5).

*Alternative vaccination and match rates.* Lastly, I examine whether the estimates for the US and Canada are sensitive to using alternative vaccination and match measures. Appendix Table D.6 presents the findings for the US. Column one in Table D.6 replaces "strict" match in the main specification with "loose" match. Column two uses an alternative vaccine take-up described in Appendix Section A5, and column three uses alternative measures for both vaccine take-up and match rate. Table D.7 presents the estimates for Canada with the alternative match rates discussed in Section 3.1. The findings suggest that the coefficients for both the US and Canada remain largely unaffected when these alternative measures are used.

## 4.7 Discussion

This paper investigates the causal effects of influenza vaccination on labor market outcomes by leveraging variation in random match rates and geographic variation across different levels of aggregation in the US and Canada. I find that influenza vaccination has sizable effects on employment and wages. The findings suggest that asymmetric health effects across sectors and subsequent sectoral spillovers contribute to the magnitude of the relationship between effective vaccination and labor market outcomes. As Guerrieri et al. (2022) argue, due to sectoral spillovers, there is a difference between a 100 percent decrease in output in half of the sectors and a 50 percent decrease in output in the whole economy. Given that this study is the first to examine sectoral spillovers from influenza vaccination, it is important to compare 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 if workers cannot be easily substituted (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 in high-contact sectors reduces absenteeism by 0.03 percentage points and increases output per hour by 0.16 percent, which implies that the elasticity of output per worker to absenteeism is -0.13. This estimate is slightly larger than those from the previous studies, which may be due to the fact that 60-80% of workers may continue working while being ill but experience lower productivity (Blanchet Zumofen et al., 2023).

Another important elasticity to consider is the elasticity of employment to labor productivity. Most studies examining labor productivity shocks focus on those driven by technological advancements. Due to displacement effects, these studies often find no or negative effects of technology adoption on employment (Autor and Salomons, 2018; Acemoglu and Restrepo, 2018; Acemoglu and Restrepo, 2020). Moreover, as per Gali (1999), an increase in labor productivity may lead to lower employment if aggregate demand does not adjust accordingly. However, since influenza vaccination does not induce displacement effects, my findings are more comparable to studies examining the impact of worker training on employment (Naval et al., 2020; OECD, 2004). [43]

[43] Naval et al. (2020) find that an increase in on-the-job training increases both employment and labor

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 in 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, with spending on restaurants being 1.15-1.3 times more affected than the average spending (Baker and Yannelis, 2017). Importantly, H2M households, who are more likely to be employed in high-contact sectors, tend to be more responsive to income changes (Kaplan and Violante, 2014; Baker and Yannelis, 2017).[44] This paper finds that a one percentage point increase in effective vaccination increases employment-to-population rate and wages by 0.09 percentage points (0.15% with respect to the mean) and 0.1 percent, respectively, while restaurant consumption increases by 0.23 US dollars (0.77% 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 among healthier individuals, while indirect effects stem from income changes. Comparing the estimate of an increase in restaurant consumption to the elasticity of consumption to income suggests that the direct effects are relatively large.[45]

Finally, to analyze spillover effects from high-contact sectors to low-contact non-tradable sectors, I consider the elasticity of employment to consumption. Mian and Sufi (2014) find that the elasticity of non-tradable employment to consumption is around 0.48.

productivity, but the authors do not explicitly discuss the elasticity of employment to labor productivity. Moreover, the effect of influenza vaccination on employment in high-contact sectors may also come through an increase in consumer demand. However, since the reduced form estimates cannot disentangle the relative importance of these channels, it is difficult to compare the effect of vaccination on employment with the elasticity of employment to labor productivity.

[44]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).

[45]Moreover, I also show that effective vaccination has a positive impact on hours of work and hourly wages, which may contribute to the increase in consumption.

My findings suggest that a one percentage point increase in effective vaccination is associated with a 0.17 percent increase in employment in low-contact non-tradable sectors. 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 the input-output structure of production. The data on non-tradable consumption are not available at the state-by-month level. However, given the effect of vaccination on restaurant consumption, the estimates are broadly consistent with the elasticity in Mian and Sufi (2014).

# 5 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 effective vaccination on employment and wages. Specifically, the results suggest that at the average match rate, a one standard deviation increase in effective vaccination increases the employment-to-population rate by 0.3 percentage points. The effects appear to be homogeneous across demographic groups, but there is substantial heterogeneity across sectors. The relationship between effective vaccination and labor market outcomes is stronger within high-contact non-tradable sectors. Furthermore, effective vaccination has a positive impact on employment in low-contact non-tradable sectors, while this impact is small in low-contact tradable sectors.

This sectoral heterogeneity provides suggestive evidence for the channels through which effective 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 consumer 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 demand for goods and services. Moreover, this study provides evidence that labor productivity shocks in directly affected sectors may lead to demand fluctuations in sectors that are not directly affected.

# References


**Abo-Zaid, Salem M and Xuguang Simon Sheng**, "Health shocks in a general equilibrium model," *Available at SSRN 3611404*, 2020.

**Acemoglu, Daron and Pascual Restrepo**, "The race between man and machine: Implications of technology for growth, factor shares, and employment," *American economic review*, 2018, *108* (6), 1488–1542.

_ **and** _ , "Robots and jobs: Evidence from US labor markets," *Journal of political economy*, 2020, *128* (6), 2188–2244.

_ **and Simon Johnson**, "Disease and development: the effect of life expectancy on economic growth," *Journal of political Economy*, 2007, *115* (6), 925–985.

_ **and** _ , "Disease and development: a reply to Bloom, Canning, and Fink," *Journal of Political Economy*, 2014, *122* (6), 1367–1375.

**Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh**, "Inequality in the impact of the coronavirus shock: Evidence from real time surveys," *Journal of Public economics*, 2020, *189*, 104245.

**Allen, Steven G**, "How much does absenteeism cost?," *Journal of Human Resources*, 1983, pp. 379–393.

**Almond, Douglas**, "Is the 1918 influenza pandemic over? Long-term effects of in utero influenza exposure in the post-1940 US population," *Journal of political Economy*, 2006, *114* (4), 672–712.

_ **and Bhashkar Mazumder**, "The 1918 influenza pandemic and subsequent health outcomes: an analysis of SIPP data," *American Economic Review*, 2005, *95* (2), 258–262.

**Alon, Titan, Sena Coskun, Matthias Doepke, David Koll, and Michèle Tertilt**, "From mancession to shecession: Women's employment in regular and pandemic recessions," *NBER Macroeconomics Annual*, 2022, *36* (1), 83–151.

**Aum, Sangmin, Sang Yoon Tim Lee, and Yongseok Shin**, "COVID-19 doesn't need lockdowns to destroy jobs: The effect of local outbreaks in Korea," *Labour Economics*, 2021, *70*, 101993.

**Autor, David and Anna Salomons**, "Is automation labor-displacing? Productivity growth, employment, and the labor share," Technical Report, National Bureau of Economic Research 2018.

**Autor, David H, Lawrence F Katz, and Melissa S Kearney**, "Trends in US wage inequality: Revising the revisionists," *The Review of economics and statistics*, 2008, *90* (2), 300–323.

**Baird, Sarah, Joan Hamory Hicks, Michael Kremer, and Edward Miguel**, "Worms at work: Long-run impacts of a child health investment," *The quarterly journal of economics*, 2016, *131* (4), 1637–1680.

**Baker, Scott R and Constantine Yannelis**, "Income changes and consumption: Evidence from the 2013 federal government shutdown," *Review of Economic Dynamics*, 2017, *23*, 99–124.

**Baqaee, David and Emmanuel Farhi**, "Supply and demand in disaggregated Keynesian economies with an application to the Covid-19 crisis," *American Economic Review*, 2022, *112* (5), 1397–1436.

**Barofsky, Jeremy, Tobenna D Anekwe, and Claire Chase**, "Malaria eradication and economic outcomes in sub-Saharan Africa: evidence from Uganda," *Journal of health economics*, 2015, *44*, 118–136.

**Beraldi, Francesco and Cedomir Malgieri**, "Fiscal Multipliers and Phillips Curves with a Consumption Network," Technical Report, Working paper 2024.

**Blanchard, Olivier Jean**, "A traditional interpretation of macroeconomic fluctuations," *The American Economic Review*, 1989, pp. 1146–1164.

**Bleakley, Hoyt**, "Disease and development: evidence from hookworm eradication in the American South," *The quarterly journal of economics*, 2007, *122* (1), 73–117.

**Bloom, David E, David Canning, Rainer Kotschy, Klaus Prettner, and Johannes J Schünemann**, "Health and economic growth: reconciling the micro and macro evidence," Technical Report, National Bureau of Economic Research 2019.

**_ , Jeffrey D Sachs, Paul Collier, and Christopher Udry**, "Geography, demography, and economic growth in Africa," *Brookings papers on economic activity*, 1998, *1998* (2), 207–295.

**Bluedorn, John, Francesca Caselli, Niels-Jakob Hansen, Ippei Shibata, and Marina M Tavares**, "Gender and employment in the COVID-19 recession: Cross-country evidence on "she-cessions"," *Labour Economics*, 2023, *81*, 102308.

**Borjas, George J**, "Native internal migration and the labor market impact of immigration," *Journal of Human resources*, 2006, *41* (2), 221–258.

**Borusyak, Kirill and Peter Hull**, "Nonrandom exposure to exogenous shocks," *Econometrica*, 2023, *91* (6), 2155–2185.

**Bronchetti, Erin Todd, David B Huffman, and Ellen Magenheim**, "Attention, intentions, and follow-through in preventive health behavior: Field experimental evidence on flu vaccination," *Journal of Economic Behavior & Organization*, 2015, *116*, 270–291.

**Bütikofer, Aline and Kjell G Salvanes**, "Disease control and inequality reduction: Evidence from a tuberculosis testing and vaccination campaign," *The Review of Economic Studies*, 2020, *87* (5), 2087–2125.

**Centers for Disease Control and Prevention**, "Behavioral Risk Factor Surveillance System (BRFSS)," 2025. [Accessed July 2025].

_ , "Morbidity and Mortality Weekly Report (MMWR)," 2025. [Accessed July 2025].

**Cloyne, James, Clodomiro Ferreira, and Paolo Surico**, "Monetary policy when households have debt: new evidence on the transmission mechanism," *The Review of Economic Studies*, 2020, *87* (1), 102–129.

**Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber**, "Labor markets during the COVID-19 crisis: A preliminary view," Technical Report, National Bureau of economic research 2020.

**East, Chloe N, Annie L Hines, Philip Luck, Hani Mansour, and Andrea Velásquez**, "The labor market effects of immigration enforcement," *Journal of Labor Economics*, 2023, *41* (4), 957–996.

**Environment and Climate Change Canada**, "Canadian Climate Summary — Environment and Climate Change Canada," Government of Canada 2025. [Accessed August 2025].

**Faggio, Giulia and Henry Overman**, "The effect of public sector employment on local labour markets," *Journal of urban economics*, 2014, *79*, 91–107.

**Flood, Matthew Sobek Daniel Backman Grace Cooper Julia A. Rivera Drew Stephanie Richards Renae Rodgers Jonathan Schroeder Steven Ruggles Sarah and Kari C.W. Williams**, "IPUMS USA: Version 16.0 [dataset]," Minneapolis, MN: IPUMS 2025. [Accessed July 2025].

**Gali, Jordi**, "Technology, employment, and the business cycle: do technology shocks explain aggregate fluctuations?," *American economic review*, 1999, *89* (1), 249–271.

**Gallup, John Luke and Jeffrey D Sachs**, "The economic burden of malaria," *CID Working Paper Series*, 2000.

**Ganong, Peter and Pascal Noel**, "Consumer spending during unemployment: Positive and normative implications," *American economic review*, 2019, *109* (7), 2383–2424.

**Gathmann, Christina, Ines Helm, and Uta Schönberg**, "Spillover effects of mass layoffs," *Journal of the European Economic Association*, 2020, *18* (1), 427–468.

**Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning**, "Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages?," *American Economic Review*, 2022, *112* (5), 1437–1474.

**Hansen, Casper Worm and Lars Lønstrup**, "The rise in life expectancy and economic growth in the 20th century," *The Economic Journal*, 2015, *125* (584), 838–852.

**Hong, Sok Chul**, "Malaria and economic productivity: a longitudinal analysis of the American case," *The Journal of Economic History*, 2011, *71* (3), 654–671.

**Kaplan, Greg and Giovanni L Violante**, "A model of the consumption response to fiscal stimulus payments," *Econometrica*, 2014, *82* (4), 1199–1239.

**Kelly, Elaine**, "The scourge of Asian Flu: In utero exposure to pandemic influenza and the development of a cohort of British children," *Journal of Human resources*, 2011, *46* (4), 669–694.

**King, Renae Rodgers Steven Ruggles J. Robert Warren Daniel Backman Annie Chen Grace Cooper Stephanie Richards Megan Schouweiler Sarah Flood Miriam and Michael Westberry**, "IPUMS CPS: Version 12.0 [dataset]," Minneapolis, MN: IPUMS 2024. [Accessed July 2025].

**Koopmanschap, Marc A, Frans FH Rutten, B Martin Van Ineveld, and Leona Van Roijen**, "The friction cost method for measuring indirect costs of disease," *Journal of health economics*, 1995, *14* (2), 171–189.

**Lin, Ming-Jen and Elaine M Liu**, "Does in utero exposure to illness matter? The 1918 influenza epidemic in Taiwan as a natural experiment," *Journal of health economics*, 2014, *37*, 152–163.

**Lucas, Adrienne M**, "Malaria eradication and educational attainment: evidence from Paraguay and Sri Lanka," *American Economic Journal: Applied Economics*, 2010, *2* (2), 46–71.

**Mian, Atif and Amir Sufi**, "What explains the 2007–2009 drop in employment?," *Econometrica*, 2014, *82* (6), 2197–2223.

**Miguel, Edward and Michael Kremer**, "Worms: identifying impacts on education and health in the presence of treatment externalities," *Econometrica*, 2004, *72* (1), 159–217.

**Miller, Raegen T, Richard J Murnane, and John B Willett**, "Do worker absences affect productivity? The case of teachers," *International Labour Review*, 2008, *147* (1), 71–89.

**Montenovo, Laura, Xuan Jiang, Felipe Lozano-Rojas, Ian Schmutte, Kosali Simon, Bruce A Weinberg, and Coady Wing**, "Determinants of disparities in early COVID-19 job losses," *Demography*, 2022, *59* (3), 827–855.

**Moretti, Enrico**, "Local multipliers," *American Economic Review*, 2010, *100* (2), 373–377.

**National Center for O*NET Development**, "O*NET Database version 20.1," U.S. Department of Labor, Employment and Training Administration 2025. [Accessed July 2025].

**Naval, Joaquín, José I Silva, and Javier Vázquez-Grenno**, "Employment effects of on-the-job human capital acquisition," *Labour Economics*, 2020, *67*, 101937.

**NOAA National Centers for Environmental Information**, "Climate at a Glance: Statewide Time Series," `https://www.ncei.noaa.gov/pub/data/cirs/climdiv/` 2025. [Accessed July 2025].

**OECD**, "OECD Employment Outlook 2004," *OECD Publishing, Paris*, 2004.

**Ozier, Owen**, "Exploiting externalities to estimate the long-term effects of early childhood deworming," *American Economic Journal: Applied Economics*, 2018, *10* (3), 235–262.

**Pauly, Mark V, Sean Nicholson, Judy Xu, Dan Polsky, Patricia M Danzon, James F Murray, and Marc L Berger**, "A general model of the impact of absenteeism on employers and employees," *Health economics*, 2002, *11* (3), 221–231.

**Public Health Agency of Canada**, "FluWatch: Canada's influenza surveillance system," Government of Canada 2010. Archived at the Wayback Machine.

**Rondinella, Sandro and Damiano B Silipo**, "The effects of chronic migraine on labour productivity: Evidence from Italy," *Labour*, 2023, *37* (1), 1–32.

**Sachs, Jeffrey and Pia Malaney**, "The economic and social burden of malaria," *Nature*, 2002, *415* (6872), 680–685.

**Sacks, Daniel W and Justin R Sydnor**, "Preferences, Beliefs, and Demand for the Flu Vaccine," Technical Report, National Bureau of Economic Research 2025.

**Sarma, Nayantara, Edith Patouillard, Richard E Cibulskis, and Jean-Louis Arcand**, "The economic burden of malaria: revisiting the evidence," *The American journal of tropical medicine and hygiene*, 2019, *101* (6), 1405.

**Schwandt, Hannes**, “The lasting legacy of seasonal influenza: In-utero exposure and labor market outcomes,” *Available at SSRN 3098159*, 2018.

**Shastry, Gauri Kartini and David N Weil**, “How much of cross-country income variation is explained by health?,” *Journal of the European Economic Association*, 2003, *1* (2-3), 387–396.

**Spence, Michael and Sandile Hlatshwayo**, “The evolving structure of the American economy and the employment challenge,” *Comparative Economic Studies*, 2012, *54*, 703–738.

**Statistics Canada**, “Table: 14-10-0287-01 (formerly CANSIM 282-0087): Labour force characteristics, monthly, seasonally adjusted and trend-cycle,” `https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1410028701` 2025. [Accessed July 2025].

_ , “Table 17-10-0005-01: Population estimates on July 1st, by age and sex,” Government of Canada 2025. [Accessed July 2025].

_ , “Table 36-10-0312-01: Gross domestic product (GDP), expenditure-based, provincial economic accounts, annual, 1981 - 2010 (x 1,000,000),” Government of Canada 2025. [Accessed July 2025].

**Strauss, John and Duncan Thomas**, “Health, nutrition, and economic development,” *Journal of economic literature*, 1998, *36* (2), 766–817.

**U.S. Bureau of Economic Analysis**, “SAGDP1 State Annual Gross Domestic Product (GDP) Summary,” `https://apps.bea.gov/itable/?ReqID=70` 2025. [Accessed July 2025].

**U.S. Bureau of Labor Statistics**, “Job Openings and Labor Turnover Survey (JOLTS),” `https://www.bls.gov/jlt/data.htm` 2025. [Accessed July 2025].

—, "Local Area Unemployment Statistics (LAUS)," https://www.bls.gov/lau/ 2025. [Accessed July 2025].

—, "Occupational Employment and Wage Statistics (OEWS)," U.S. Department of Labor 2025. [Accessed July 2025].

—, "State and Area Employment, Hours, and Earnings (SAE)," 2025. [Accessed July 2025].

**U.S. Census Bureau**, "Vintage Population Estimates — Annual County, State, and National Data," https://www2.census.gov/programs-surveys/popest/datasets/ 2025. [Accessed July 2025].

**Ward, Courtney J**, "Influenza vaccination campaigns: is an ounce of prevention worth a pound of cure?," *American Economic Journal: Applied Economics*, 2014, *6* (1), 38–72.

**White, Corey**, "Measuring social and externality benefits of influenza vaccination," *Journal of Human Resources*, 2021, *56* (3), 749–785.

**Zhang, Wei, Huiying Sun, Simon Woodcock, and Aslam H Anis**, "Valuing productivity loss due to absenteeism: firm-level evidence from a Canadian linked employer-employee survey," *Health economics review*, 2017, *7*, 1–14.

**Zivin, Joshua Graff, Matthew Neidell, Nicholas J Sanders, and Gregor Singer**, "When externalities collide: Influenza and pollution," *American Economic Journal: Applied Economics*, 2023, *15* (2), 320–351.

**Zumofen, Marie-Hélène Blanchet, Jeff Frimpter, and Svenn Alexander Hansen**, "Impact of influenza and influenza-like illness on work productivity outcomes: a systematic literature review," *Pharmacoeconomics*, 2023, *41* (3), 253–273.

# Online Appendix

## Appendix A: Details on Calculating Actual Vaccination Rates

The data on state-year-level vaccination rates come from the BRFSS. The exact format of the question on the vaccination status slightly 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?”. Due to a 12-month recall on the vaccination status, the exact timing of the distribution of the vaccine is unknown, particularly for the answers given 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).

For the main specification, I use all the data and classify the answers according to the following example. Suppose that respondents answered these questions in 1999 and 2000. I use data between September to December 1999 and between January and August 2000 to calculate the vaccination rate for the 1999/2000 flu year. In the alternative specification, to avoid ambiguity, I omit the answers between September and December.

## 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-to-Population Rate | 0.621 | 0.046 |
| LFP rate | 0.657 | 0.042 |
| Openings Rate | 0.031 | 0.006 |
| Hiring Rate | 0.039 | 0.007 |
| Layoff Rate | 0.015 | 0.004 |
| Quits Rate | 0.020 | 0.005 |
| Share 0-14 | 0.199 | 0.018 |
| Share 15-24 | 0.142 | 0.010 |
| Share 25-44 | 0.268 | 0.017 |
| Share 45-64 | 0.256 | 0.020 |
| Share +65 | 0.135 | 0.020 |
| Observations | 8,400 | 8,400 |

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) |
|---|---|---|---|---|---|---|---|
| | | | | Match Rate | | | |
| L.Match | 0.0739 | 0.0481 | | | | | |
| | (0.2473) | (0.2345) | | | | | |
| L.Employment ratio | | | -4.1796 | -6.0138 | | | |
| | | | (2.9482) | (4.9808) | | | |
| L.LFP Ratio | | | | | -3.9344 | 6.6238 | |
| | | | | | (4.6342) | (16.9162) | |
| Trend | | 0.0138 | | -0.0091 | | 0.0331 | 0.0141 |
| | | (0.0146) | | (0.0260) | | (0.0507) | (0.0139) |
| Observations | 17 | 17 | 17 | 17 | 17 | 17 | 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 2000 to 2017 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) |
|---|---|---|---|---|
| | Actual Vaccination Rate | | | |
| Match | 0.0016 | -0.0087 | 0.0401 | 0.0643 |
| | (0.0022) | (0.0210) | (0.0511) | (0.0564) |
| Match $\times$ Baseline Vacc. | | 0.0315 | | |
| | | (0.0632) | | |
| Match $\times$ Baseline Empl. | | | -0.0590 | |
| | | | (0.0779) | |
| Match $\times$ Baseline LFP | | | | -0.0922 |
| | | | | (0.0827) |
| Trend | $0.0061^{***}$ | $0.0061^{***}$ | $0.0061^{***}$ | $0.0061^{***}$ |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Observations | 850 | 850 | 850 | 850 |

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) High, Non-Tradable | (2) Low, Non-Tradable | (3) Low, Tradable |
|---|---|---|---|
| **Panel A: Ln(Output per worker)** | | | |
| Vaccination × Match | 0.164* | 0.079 | -0.366 |
| | (0.087) | (0.082) | (0.248) |
| Mean of D.V | 4.205 | 4.948 | 5.082 |
| Observations | 1,920 | 1,880 | 1,626 |
| **Panel B: Ln(Output per hour)** | | | |
| Vaccination × Match | 0.202** | -0.224 | -0.084 |
| | (0.084) | (0.262) | (0.448) |
| Mean of D.V | -0.360 | 0.815 | 1.279 |
| Observations | 1,312 | 960 | 1,472 |

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. Standard errors are clustered at the state level.

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

**Table C.5.** **Effective Vaccination and Hours Worked Last Week**

| | (1) | (2) | (3) |
|---|---|---|---|
| | Hours Worked Last Week | | |
| | High, Non-Tradable | Low, Non-Tradable | Low, Tradable |
| Vaccination | 0.031** | -0.016 | -0.014 |
| | (0.014) | (0.012) | (0.011) |
| Mean of D.V. | 37.19 | 38.34 | 41.19 |
| Observations | 4,723,458 | 2,053,509 | 2,895,952 |

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. Standard errors are clustered at the state level.

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

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

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Ln(GDP) | | | |
| | Total | HNT | LNT | LT |
| Vaccination $\times$ Match | 0.133 | 0.358** | 0.218** | -0.216 |
| | (0.116) | (0.159) | (0.103) | (0.247) |
| Mean of D.V. | 12.22 | 10.78 | 11.30 | 11.20 |
| Observations | 2,000 | 1,996 | 2,000 | 1,928 |

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.Standard errors are clustered at the state level.

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

**Table C.7. Effective Vaccination and Restaurant Consumption: Interactions with Demographic Characteristics**

| | (1)<br>Restaurant Consumption | (2)<br>Restaurant Consumption |
|---|---|---|
| Vaccination × Match | 0.196 | -0.024 |
| | (0.121) | (0.188) |
| Vaccination × Match × H2M | 0.490** | 0.843*** |
| | (0.185) | (0.258) |
| Vaccination × Match × White | 0.034 | 0.034 |
| | (0.070) | (0.072) |
| Vaccination × Match × Share 65+ | -1.015*** | -1.129*** |
| | (0.363) | (0.339) |
| Vaccination × Match × Bachelor | | 0.392 |
| | | (0.244) |
| Mean of D.V. | 29.96 | 29.96 |
| Observations | 807,966 | 807,966 |

Notes: Based on data 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 and lagged shares of H2M, White, population above 65, and those with a bachelor's degree. The table presents the estimates of effective vaccination interacted with these shares. Standard errors are clustered at the state level.

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

**Table C.8.** **Effective Vaccination and Input-Output Network**

| | (1) | (2) |
|---|---|---|
| | Ln(Employment) | |
| | Downstream | Upstream |
| Vaccination × Match | 0.231 | 0.116* |
| | (0.158) | (0.069) |
| Mean of D.V | 4.993 | 6.051 |
| Observations | 7,896 | 8,400 |

Notes: Based on data from the CES. The estimates are obtained with a two-way fixed effects OLS model. The table presents the estimates for upstream and downstream low-contact non-tradable sectors. The regressions include the full set of state- and individual-level control variables described in the section 3.2. Standard errors are clustered at the state level.

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

**Table C.9.** **Effective Vaccination and Labor Market Outcomes by Seasons: US Setting**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Absenteeism | | Employment | | Ln(Wages) | |
| | F+W | S+S | F+W | S+S | F+W | S+S |
| Vaccination × Match | -0.017 | -0.006 | 0.141*** | 0.092*** | 0.111* | 0.074 |
| | (0.011) | (0.011) | (0.030) | (0.029) | (0.061) | (0.058) |
| Mean of D.V. | 0.026 | 0.022 | 0.763 | 0.759 | 2.612 | 2.599 |
| Observations | 4,297,642 | 4,330,528 | 6,695,531 | 6,813,088 | 999,691 | 1,006,824 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: Based on data 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. F+W denotes winter and fall months, while S+S denotes spring and summer months. Standard errors are clustered at the state level.

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

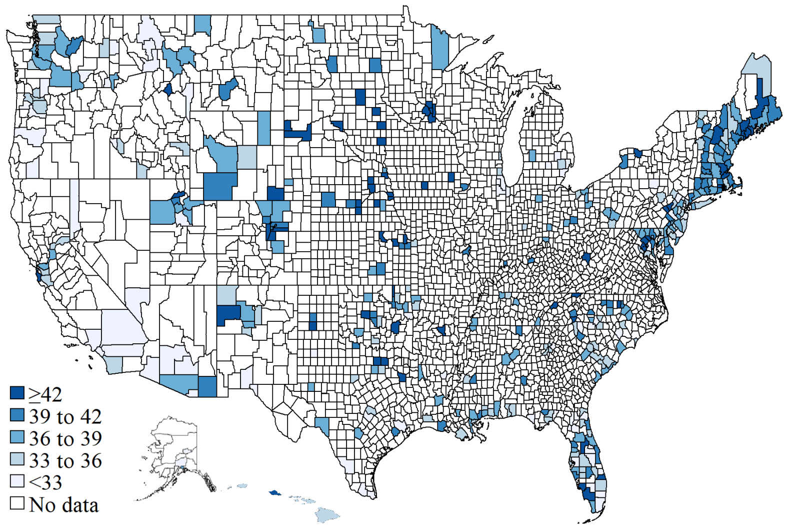
**Table C.10. Effective Vaccination and Labor Market Outcomes by Seasons: Canadian Setting**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | P.Absenteeism | | F.Absenteeism | | Employment | |
| | F+W | S+S | F+W | S+S | F+W | S+S |
| $\mathrm{U}IIC_p \times \mathrm{P}ost_y \times \mathrm{M}atch_{py}$ | -0.021$^{*}$ | -0.005 | 0.011 | 0.010 | 0.894$^{**}$ | 0.734$^{**}$ |
| | (0.011) | (0.015) | (0.054) | (0.034) | (0.279) | (0.319) |
| Mean of D.V. | 0.273 | 0.221 | 0.609 | 0.575 | 58.97 | 59.02 |
| Observations | 720 | 720 | 720 | 720 | 720 | 720 |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province FE | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: Based on data from Statistics Canada. The dependent variables in columns 1 and 2, 3 and 4, 5 and 6 are average part-week lost hours per worker, average full-week lost hours per worker, and employment, respectively. 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. F+W denotes winter and fall months, while S+S denotes spring and summer months. Standard errors are clustered at the state level.

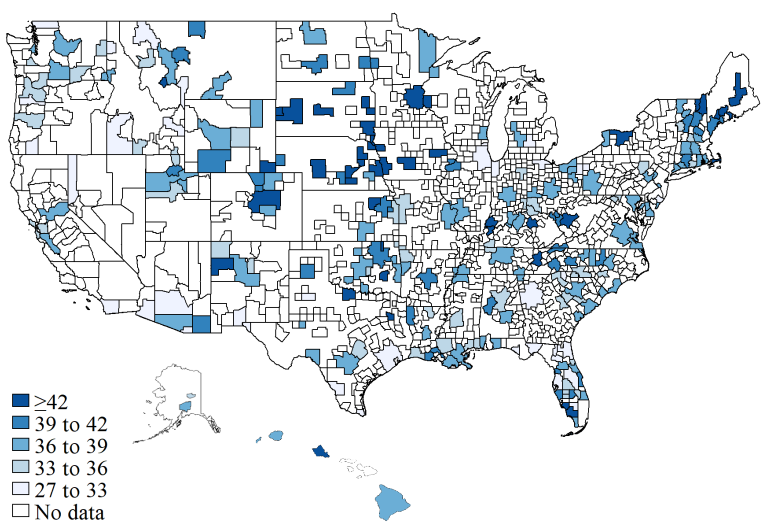
$^{*}$ statistically significant at the 10% level; $^{**}$ at the 5% level, $^{***}$ at the 1% level

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




Note: Based on the data from BRFSS SMART from 2003/04 to 2010/11. The sample size is reduced due to a change in the MSA administrative division and the absence of the interview month variables in BRFSS SMART after 2010.

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




Note: Based on the data from BRFSS SMART from 2003/04 to 2010/11. The sample size is reduced due to a change in the MSA administrative division and the absence of the interview month variables in BRFSS SMART after 2010.

## Appendix D: Robustness Checks

**Table D.1. Effective Vaccination and Employment: Alternative Samples**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Employment-to-Population Rate | | | | |
| | All | All w/o pandemics | 1998-2022 | W/o 2004/05 | With AL and HI |
| Vaccination × Match | 0.064*** | 0.052** | 0.058*** | 0.091*** | 0.097*** |
| | (0.020) | (0.021) | (0.020) | (0.028) | (0.029) |
| Vaccination | -0.000 | 0.013 | -0.008 | -0.000 | 0.016 |
| | (0.024) | (0.025) | (0.021) | (0.033) | (0.033) |
| Observations | 17,394 | 14,994 | 14,400 | 7,800 | 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 rate. The regressions in columns 3-5 include the full set of state-level control variables described in the section 3.2, and the regressions in columns 1-2 exclude lagged GDP growth. Column 1 presents findings by using data from 1994 to 2022; column 2 replicates column 2 but excludes pandemic years 2008/2009, 2009/2010, 2019/2020, and 2020/2021. Column 3 presents the findings for the years since the data on lagged GDP growth are available. Column 4 drops the years with vaccine shortage from the sample used in the main analysis, and column 5 excludes Alaska and Hawaii from the original sample. Standard errors are clustered at the state level.

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

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

| | (1) | (2) |
|---|---|---|
| | Employment-to-Population Rate | |
| Vaccination × Match | 0.089*** | 0.060*** |
| | (0.028) | (0.019) |
| Vaccination | 0.011 | -0.015 |
| | (0.032) | (0.026) |
| Mean of D.V. | 0.621 | 0.621 |
| State FE | Yes | Yes |
| Time FE | Yes | Yes |
| State Trends | No | Yes |
| Observations | 8,400 | 8,400 |

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 rate. Standard errors are clustered at the state level.

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

**Table D.3. Effective Vaccination and Labor Market Outcomes: Alternative Identification Strategy**

| | (1) Employment Rate | (2) LFP Rate |
|---|---|---|
| **Panel A: Reduced Form** | | |
| Vaccination × Match | 0.0804** | 0.0161 |
| | (0.0332) | (0.0300) |
| Mean of D.V. | 0.621 | 0.657 |
| Observations | 8,400 | 8,400 |
| **Panel B: IV** | | |
| Vaccination × Match | 0.0872** | 0.0174 |
| | (0.0360) | (0.0320) |
| Mean of D.V. | 0.621 | 0.657 |
| Observations | 8,400 | 8,400 |

Notes: The data come from the LAUS. The dependent variables are employment-to-population rate, 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. Standard errors are clustered at the state level.

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

**Table D.4. Effective Vaccination and Labor Market Outcomes: Placebo Test for the US**

| | (1) Employment rate | (2) LFP rate |
|---|---|---|
| Vaccination $\times$ Match | -0.010 | -0.006 |
| | (0.061) | ( 0.037) |
| Mean of D.V. | 0.621 | 0.657 |
| Observations | 8,400 | 8,400 |

Notes: Based on data from the LAUS. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are employment-to-population rate, 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.5. Effective Vaccination and Labor Market Outcomes: Placebo Test for Canada**

| | (1) Employment rate | (2) LFP rate |
|---|---|---|
| $\mathrm{U}IIC_p \times \mathrm{P}ost_y \times \mathrm{M}atch_{py}$ | -0.037 | -0.028 |
| | (0.817) | (0.572) |
| Mean of D.V. | 58.99 | 64.88 |
| Observations | 1,400 | 1,400 |

Notes: Based on data from Statistics Canada. The estimates are obtained with a two-way fixed effects OLS model. The dependent variables are employment-to-population rate, and labor force participation. The match rates are shuffled 1000 times. The regressions include the full set of control variables. The table reports the median of the estimated coefficients and the standard deviation of the estimated coefficients (in parenthesis).

**Table D.6. Effective Vaccination and Employment: Alternative Match and Vaccination Rates for the US**

| | (1) | (2) | (3) |
|---|---|---|---|
| | Employment-to-Population Rate | | |
| Vaccination × Match | 0.100*** | 0.095*** | 0.102*** |
| | (0.036) | (0.026) | (0.035) |
| Observations | 8,400 | 8,400 | 8,400 |
| Mean | 0.621 | 0.621 | 0.621 |

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 rate. The regression in column 1 replaces the match rate in the main specification by the match rate based on reduced titers, column 2 replaces the vaccination rate by the one based only on January and August, and column 3 replaces both the match rate and vaccination rate by their alternatives. Standard errors are clustered at the state level.

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

**Table D.7. Effective Vaccination and Employment: Alternative Match Rates for Canada**

| | (1) | (2) | (3) |
|---|---|---|---|
| | Employment Rate | | |
| | Reduced titers | Adjusted Match | Regional Match |
| $\mathrm{U}IIC_p \times \mathrm{P}ost_y \times \mathrm{M}atch_{py}$ | 0.680* | 0.540* | 0.666** |
| | (0.316) | (0.252) | (0.236) |
| Mean of D.V. | 58.99 | 58.99 | 59.05 |
| Province FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Observations | 1,440 | 1,440 | 1,416 |

Notes: Based on data from Statistics Canada. The table reports triple-difference estimates from equation 4 with standard errors in parentheses. Column 1 uses the match rate based on reduced titers; column 2 uses the adjusted match rate; column 3 uses the regional match rate. Standard errors are clustered at the province level.

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

## Appendix E: Derivations

Suppose now that in period zero each state faces a different labor productivity shock in sector $H$, which causes workers' labor productivity in sector $H$ to go to $1 - \delta_s$.

***Real Wage Rigidity in both sectors***

In this case, prices in sector $H$ become smaller than the marginal productivity of labor, implying that firms in sector $H$ would stop hiring. As shown in Guerrieri et al. (2022), if sector $H$ is completely shut down and sector $L$ is non-tradable, then the demand for its goods in period zero is equal to:[46]

$$Y_{Ls0} = \mu \times 0 + (1 - \mu\phi) \times (1 - \phi)$$

Following Guerrieri et al. (2022), it can be shown that a labor productivity shock that induces the firms in sector $H$ to stop hiring, would decrease employment in sector $L$ if the following condition holds:

$$(1 - \mu\phi)(1 - \phi)^{\frac{\sigma-\epsilon}{\epsilon-1}} < 1$$

which has a similar interpretation to the condition derived for the labor supply shock. Under real wage rigidity, a labor productivity shock in sector $H$ would decrease employment in sector $L$ if sectors are complementary enough, which is captured by $(1 - \phi)^{\frac{\sigma-\epsilon}{\epsilon-1}}$, and if the share of financially constrained households increases, which is captured by $(1 - \mu\phi)$

***No Nominal or Real Wage Rigidity***

Wages in sector $H$ are set according to the following profit maximization equation: $\Pi_{Hs0} = P_{Hs0}(1-\delta_s)n_{Hs0} - W_{Hs0}n_{Hs0}$, which implies that in a new equilibrium: $W_{Hs} = P_{Hs}(1 - \delta_s)$.

[46]In the case of a linear production function, the employment in sector A would go to zero independently of the size of a productivity shock. Hence, in this case, the effect in tradable and non-tradable sectors would be the same unless some states do not experience any labor productivity shock.

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

$$(1-\delta_s)\phi = \phi\left(\frac{P_{Hs0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{P_{Hso}}{P_{s0}}(1-\delta_s)+(1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right) \quad (5)$$

$$(1-\phi) = (1-\phi)[\left(\frac{P_{Ls0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{P_{Hs0}}{P_{s0}}(1-\delta_s)+(1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right)] \quad (6)$$

$$P_{s0} = \left(\phi P_{Hs0}^{1-\epsilon}+(1-\phi)P_{Ls0}^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}$$

Combining equations (5) and (6) gives: $(1-\delta_s) = (\frac{P_{Hs0}}{P_{Ls0}})^{-\epsilon}$, which implies that $P_{Hs0} = P_{Ls0}(1-\delta_s)^{-\frac{1}{\epsilon}}$ and $P_{s0} = P_{Ls0}[\phi(1-\delta_s)^{1-\frac{1}{\epsilon}}+(1-\phi)]^{\frac{1}{1-\epsilon}}$. Plugging this into equation (5) gives:

$$P_{Ls0} = \left[\frac{1-\mu\phi\frac{(1-\delta_s)^{1-\frac{1}{\epsilon}}}{\phi(1-\delta_s)^{1-\frac{1}{\epsilon}}+(1-\phi)}}{(1-\mu\phi)(\phi(1-\delta_s)^{1-\frac{1}{\epsilon}}+(1-\phi))^{\frac{\epsilon-\sigma}{1-\epsilon}}}\right]^{-\frac{1}{\sigma}}$$

Hence $P_{Ls0} = W_{Ls0} < 1$ if

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

Which after taking logarithms, implies that:

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

Hence, under flexible prices and wages in both sectors, a labor productivity shock in sector $H$ translates into a decrease in wages and prices in sector $L$ 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 $L$ is tradable, then prices and wages in this sector in all the states would change by the same amount, satisfying the following system of equations:

$$(1-\delta_s)\phi = \phi\left(\frac{P_{Hs0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{P_{Hso}}{P_{s0}}(1-\delta_s)+(1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right)$$

$$N(1-\phi) = (1-\phi)\sum_{s=1}^{n}[\left(\frac{P_{L0}}{P_{s0}}\right)^{-\epsilon}\left(\mu\phi\frac{P_{Hso}}{P_{s0}}(1-\delta_s)+(1-\mu\phi)\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}\right)]$$

$$P_{s0} = \left(\phi P_{Hs0}^{1-\epsilon}+(1-\phi)P_{L0}^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}$$

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

Finally, consider the case when prices in sector $H$ are allowed to increase as a result of a labor productivity shock, but wages are downward rigid in both sectors.

From the profit maximization: $n_{Hs0} = 1$ if $P_{Hs0} \geq \frac{W_{Hs0}}{1-\delta}$ and $n_{Hs0} = 0$ if $P_{Hs0} < \frac{W_{Hs0}}{1-\delta}$

If $n_{Hs0} = 1$ and both sectors are non-tradable, then the market clearing conditions would be:

$$\phi(1-\delta) = \phi\left(\frac{P_{Hs0}}{P_{s0}}\right)^{-\epsilon}\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma} \tag{7}$$

$$Y_{Ls0} = (1-\phi)\left(\frac{P_{Ls0}}{P_{s0}}\right)^{-\epsilon}\left(\frac{P_{s0}}{P_{s1}}\right)^{-\sigma}, \tag{8}$$

where $P_{s0} = (\phi P_{Hs0}^{1-\epsilon}+1-\phi)^{\frac{1}{1-\epsilon}}$ and $P_{s1} = 1$.

Plugging these values into equation (7) and considering that the price in sector $H$ has to be greater than one to clear the market, it can be noticed that if $\epsilon < 1$, $P_{Hs0} \geq \frac{W_{Hs0}}{1-\delta}$ if $\sigma > \epsilon$.

Combining equations (7) and (8) and using $n_{Ls0} = \frac{Y_{Ls0}}{1-\phi}$, $n_{Ls0}$ can be rewritten as:

$$n_{Ls0} = (1-\delta)\left(\frac{P_{Hs0}}{P_{Ls0}}\right)^{\epsilon} = (\phi P_{Hs0}^{1-\epsilon}+1-\phi)^{\frac{\epsilon-\sigma}{1-\epsilon}},$$

which given that $P_{Hs0} > 1$ and assuming $\epsilon < 1$ would be less than one if $\sigma > \epsilon$.

Hence, a labor productivity shock that increases prices in sector $H$ would lead to a decrease in employment in sector $L$ if the intertemporal elasticity of substitution is larger than the elasticity of substitution between goods. Again, the sectoral spillovers would occur only if sector $L$ is non-tradable.