Just the Flu? The Labor Market Spillovers of Influenza Vaccination

Oleksandra Cheipesh*

December 30, 2025

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Abstract

This study estimates the spillover effects of influenza vaccination on labor markets. To identify the causal impact of flu vaccines, I employ a difference-in-differences design based on plausibly exogenous variation in vaccine quality and local vaccination rates in the United States. I show that influenza vaccination not only reduces illness but also generates substantial gains in employment and wages. My analysis suggests that the main mechanisms are an increase in labor productivity in high-contact sectors and demand spillovers across sectors. By developing a general-equilibrium model and testing its predictions in the data, I show that these spillovers are driven by the input–output structure of production and changes in consumers' earnings. To probe the external validity of these results, I study a change in vaccination policy in Canada. Together, these findings provide the first causal evidence that influenza vaccination yields sizable economic benefits, highlighting the importance of both direct and indirect channels.

Keywords: Influenza Vaccination, Employment, Labor Productivity, Sectoral Spillovers

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*Oleksandra Cheipesh: ocheipes@eco.uc3m.es, Universidad Carlos III de Madrid (UC3M). I am grateful to Warn N. Lekfuangfu, Jan Stuhler, Costas Meghir, Yarine Fawaz, Iván Werning, David Green, Felix Wellschmied, Joseph Altonji, Francesco Beraldi, Matilde Machado, Daniel I. Rees, Pascual Restrepo, Johannes Schneider, Jesse Schreger, Carlo Galli, Morteza Ghomi, Nazarii Salish, Jon Piqueras, Emircan Yurdagul, Pedro Mira, and participants at Yale University, UC3M, UCL, HHES, ENTER, SAEe, EEA, and CINCH Academy for their comments and suggestions. I am also thankful to Corey White for providing the match rate calculator and data. This project received funding from the Ministry of Science, Innovation and Universities (FPI grant).

1 Introduction

Seasonal influenza poses significant public health risks around the world. According to the World Health Organization (WHO), it infects roughly one billion people each year and causes three to five million severe cases. While a growing body of evidence documents that influenza vaccination reduces illness (Ward, 2014; White, 2021; Graff Zivin et al., 2023), no studies have investigated its spillover effects on employment and wages. In light of the ongoing public debate over the benefits of vaccination, it is increasingly important to assess the broader economic consequences of immunization programs. Using two distinct settings in the US and Canada, this paper provides the first causal evidence that influenza vaccination generates sizable labor market gains. These findings suggest that vaccination can be viewed not only as a public health intervention but also as a labor market policy.

To address the identification challenge that vaccine take-up is often endogenously determined, I use a difference-in-differences design that exploits plausibly exogenous variation in vaccine quality (hereafter, the *vaccine match rate*) and local-level vaccine take-up. The match rate is measured as the degree to which the viruses in the vaccine resemble those in circulation. Experts must decide on vaccine composition in advance, and a mismatch may occur because of unpredictable mutations in influenza viruses.[1] These fluctuations provide a plausibly exogenous source of variation over time. For the main analysis, I follow White (2021) and construct a measure of effective vaccination by interacting year-to-year variation in the match rate with state-by-year vaccine take-up across 50 states from 2001 to 2016. Data on vaccine take-up come from the Behavioral Risk Factor Surveillance System (BRFSS), and data on match rates come from influenza surveillance reports.

Conditional on vaccine take-up, variation in the vaccine match rate generates exogenous variation in *effective vaccination* that allows me to provide a causal estimate of the effect of flu vaccines on labor market outcomes. Intuitively, this difference-in-differences design relies on comparing the differences in outcomes between states with high and low vaccine take-up

[1] To examine whether the vaccine match is as good as random, I test whether it can be predicted by a linear trend, its lag, and lags of labor market outcomes. I find no evidence that these variables are correlated with the vaccine match.

rates across flu seasons with different vaccine matches. In other words, when the flu vaccine works well, the gap in outcomes between states with 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 whether states have a high or low share of vaccinated individuals. To complement the main analysis, I also combine vaccine match data with vaccination rates at the county and metropolitan statistical area (MSA) levels, as well as a change in vaccination policy in Canada, described in greater detail below. The main outcomes of interest are employment, wages, and labor market turnover.[2]

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, particularly for those without paid sick leave or the self-employed. For firms, this 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.[3] 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.

Building on the two-sector, general-equilibrium model of Guerrieri et al. (2022), I outline a theoretical framework that examines how effective vaccination propagates across sectors and generates spillovers. The model features an open economy with a finite number of geographic states, in which one sector is directly hit by a state-specific shock to labor supply, labor productivity, or consumer demand. This assumption is motivated by evidence that flu incidence is substantially higher in sectors that rely heavily on face-to-face interactions, commonly referred to as high-contact sectors (Houštecká et al., 2021). Thus, in these sectors, vaccination may reduce absenteeism and increase on-the-job productivity more than in their low-contact counterparts. Lower flu incidence may also reduce the fear of infection, disproportionately boosting

[2]These data come from the Current Population Survey (CPS) and other surveys conducted by the Bureau of Labor Statistics (BLS). When aggregate state-level data are used, the unit of analysis is the state-month level, whereas when CPS data are used, the unit of analysis is the individual–state–month level.

[3]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).

consumption in high-contact sectors.[4]

The model yields three main predictions. First, regardless of the propagation 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, they should be less affected by fluctuations in local demand. Second, changes in local demand may be driven by both consumer and producer responses. Third, consumer responses are amplified if households spend most of their additional income (commonly referred to as hand-to-mouth households), while producer responses primarily affect upstream sectors. The intuition is as follows. If households in the directly affected sector are hand-to-mouth (H2M), then an increase in their labor income, induced by higher employment or wages, translates into greater spending on goods and services across a variety of sectors, not just the directly affected one. On the other hand, if one sector faces a positive 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 examine how sectoral shocks propagate through the economy. My causal estimates show that effective vaccination has a large positive impact on employment and wages. At the average match rate, a one standard deviation increase in vaccination (five percentage points) increases the employment-to-population ratio and wages by 0.3 percentage points and 0.4 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 impact of effective vaccination on labor market outcomes is rather homogeneous across demographic groups. In contrast, I find that workers in high-contact sectors experience larger gains in employment and wages. The results also suggest that in these sectors, effective vaccination reduces absenteeism, increases output per worker, and leads to

[4]Consumption in high-contact sectors is often a group activity, and if one member of a group is unwilling to participate, others may choose to stay home as well.

higher consumption. These findings provide suggestive evidence that increased labor productivity and consumer demand are the two main channels through which effective vaccination influences employment and wages.

Furthermore, I find strong support for the predictions of the model regarding sectoral spillovers. I show that effective vaccination also 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 states with a higher share of H2M households. I also find suggestive evidence for the input-output channel. Specifically, using input–output matrices, I show that the relationship between effective vaccination and employment is stronger in low-contact non-tradable sectors that are more likely to serve as intermediate inputs to high-contact sectors.

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 area-specific vaccination rates and include state-by-time fixed effects when estimating outcomes at the county or MSA levels.[6] In other words, I compare the estimates obtained using between-state variation to those obtained using 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 in line with expectations because positive demand externalities of vaccination may spread to neighboring counties or metropolitan areas, which are absorbed by state-by-time fixed effects. Intuitively, if vaccination increases employment and output in one area, some of these gains may spill over to nearby counties or MSAs through commuting flows, cross-area consumption, and business linkages. State-level regressions capture the full effect, while within-state estimates net out

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

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

these cross-border spillovers and produce smaller coefficients.

Lastly, to provide evidence on the external validity of my findings, I exploit the Universal Influenza Immunization Program (UIIP) in Ontario. In July 2000, Ontario began subsidizing influenza vaccines for all residents, which increased flu vaccination coverage in the province by eight percentage points (Ward, 2014). Using a triple-difference design that exploits the introduction of the UIIP 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, due to multiple channels through which effective vaccination impacts labor market outcomes, it generates sizable gains in employment and wages. 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 the data and the 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 include at most 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 exogenous variation in effective vaccination.

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 parasitic 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.,

[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.

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 relationships 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 extend beyond health benefits could 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 the 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 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., 2023; Alon et al., 2022; Coibion et al., 2020; Montenovo et al., 2022; Adams-Prassl et al., 2020; Abo-Zaid and Sheng, 2020; Baylis et al., 2022). 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.

In this section, I propose a model to provide formal intuition for sectoral spillovers. I assume that the directly affected sector is high-contact (H) and non-tradable, and that the sector that is not directly affected is low-contact (L) and can be either non-tradable or tradable. The assumption of asymmetric exposure is motivated by evidence that influenza incidence is substantially higher in high-contact sectors (Houštecká et al., 2021). Consequently, in these sectors, vaccination may reduce absenteeism and boost on-the-job productivity more than in their low-contact counterparts. High-contact sectors may also see larger demand increases when flu incidence falls because consumption in these sectors might be more affected by fear of getting

[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.

sick and by stronger network effects. For example, dining out is often a group activity, so if one member of a group becomes more willing to participate, others might be more likely to join as well.[10]

I begin by analyzing the case in which the low-contact sector is tradable and focus on the setting where influenza vaccination affects labor supply in the high-contact sector under nominal wage rigidity. To do so, I extend the model in Guerrieri et al. (2022) and incorporate an open-economy setting, following Mian and Sufi (2014). The other two mechanisms and implications under alternative assumptions are also briefly discussed in this section and in Appendix Section A5.

To analyze the implications of the Guerrieri et al. (2022) model in an open economy, I assume 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 ϵ and a constant inter-temporal elasticity of substitution σ.

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

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

The shipment costs are equal to zero. I begin by 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 across states. Households face the following budget constraint:

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

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_{ist} are bond holdings and i_{st} is a nominal interest rate. Furthermore, a random share μ of workers do not have access to credit (i.e., $a_{ist} \geq 0$).

Labor is supplied inelastically, and the production technology in each sector j is linear:

[10] The tradability assumption reflects the fact that all high-contact sectors are classified as non-tradable, whereas low-contact sectors can be either tradable or non-tradable.

$Y_{jst} = N_{jst}$. A share ϕ of agents works in sector H, and a share $1-\phi$ works in sector L. There is no labor mobility between states or sectors. Non-tradable goods can be sold only within a state. However, firms in the tradable sector split the national demand (the sum of state-level demands) evenly, which implies that $Y_{Hst} = C_{Hst}$ and $Y_{Lst} = \frac{\sum_{s=1}^{n} C_{Lst}}{n}$, where n is the number of states. Firms are competitive, meaning that, in equilibrium, $W_{jst} = P_{jst}$. Without loss of generality, in the steady state, prices and wages in both sectors are normalized to one.[11]

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 of actual to potential output, where actual output is derived from the market-clearing condition and 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 of 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, they split total demand equally across all

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

states, which 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 the ratio of actual to 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 equally across the country, and the larger n is, the less employment in sector L depends on the labor-supply shock in sector H within its own 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.

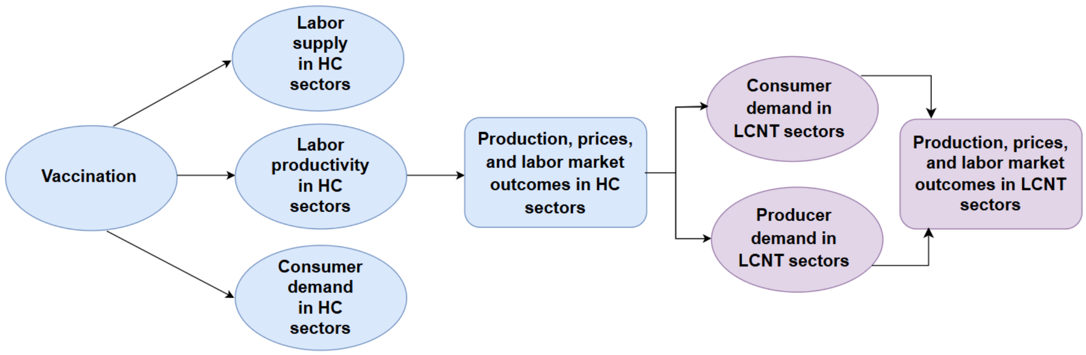
Additionally, as shown in Guerrieri et al. (2022), the transmission of aggregate supply shocks may be exacerbated if sector L serves as an intermediate input for sector H. This is because if production in sector H falls, the firms in this sector would decrease the demand for the intermediate inputs.

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 as follows. First, state-specific shocks generate spillovers through fluctuations in local demand and thus affect non-tradable sectors in the affected states more than their tradable counterparts. Second, as illustrated in Figure 1, local demand spillovers may propagate through both producer and consumer responses. Third, spillovers to consumer demand may occur through changes in relative prices between goods and in the labor income of the directly affected workers, while producer responses occur due to the input–output structure of production. Finally, consumer responses are amplified if households are H2M, while producer responses affect upstream sectors.

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 the 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.[12]

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 area, and county.[13] 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).[14] Following White (2021), to assign vaccine match rates, I redefine years as "flu-years" running from July through June.[15] This redefinition is

[12]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 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.

[13]Here, time refers to influenza season.

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

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

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.[16] BRFSS is a health-related telephone survey that, among other questions, provides information on 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 at the county and MSA levels, I utilize data from the BRFSS Selected Metropolitan/Micropolitan Area Risk Trends (SMART), which are available from 2004 to 2012 for a subset of counties and MSAs.[17]

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.[18] 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 across counties and MSAs for all states.

US Outcomes. Data on labor market outcomes come from multiple sources. State-level data on the employment-to-population ratio and labor force participation rate come from the U.S. Bureau of Labor Statistics (2025b).[19] 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

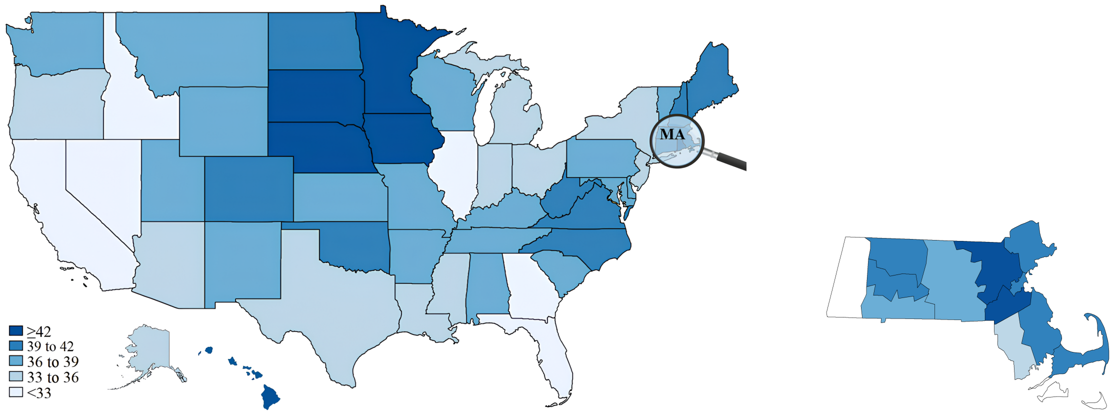
[16] These data can be accessed at Centers for Disease Control and Prevention (2025a).

[17] 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.

[18] 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.

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

Figure 2. Geographical Variation in Vaccination Rates



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

Notes: Based on data from the Behavioral Risk Factor Surveillance System (BRFSS) and BRFSS Selected Metropolitan/Micropolitan Area Risk Trends (SMART). Panel A map shows the average vaccination rates by state from 2000/01 to 2016/17. Panel B shows the average vaccination rates by county for Massachusetts from 2003/2004 to 2010/2011.

layoff rates.[20] 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.[21]

The individual-level data come from the Current Population Survey (CPS).[22] The variables of interest are employment, the natural logarithm of inflation-adjusted hourly wages, absenteeism due to illness (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 respondents usually work at their job.[23]

Absenteeism is used as a proxy for labor productivity. Given that the CPS interviews only full-time workers about their reasons for working part-time or being absent from work, the

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

[21]When these datasets are used, the unit of analysis is at the state-by-month level. Employment data for certain industries are unavailable for some states. Hence, when the CES data are used, the sample excludes some states.

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

[23]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.

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.[24]

Restaurant consumption serves as a proxy for consumer demand. These data are available only through 2015, and the spending is top-coded at 250$.[25] Lastly, I 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.

US controls. To address potential confounders, I collect data on temperature, precipitation, population shares, and lagged growth of Gross Domestic Product (GDP).[26]

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 2005/06 flu seasons.[27] The data on the employment-to-population ratio and LFP rate at the province-by-month level come from the Statistics Canada (2025a).

To derive the flu-year vaccine match in Canada, I use data on influenza activity from the 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.[28] The province-level match rates are used for robustness analysis. Lastly, I

[24]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.

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

[26]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+.

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

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

obtain data on the same control variables as in the US setting.[29]

3.2 Empirical Strategy

To overcome the identification challenge that vaccine take-up is often endogenously determined, I employ a difference-in-differences design that exploits plausibly exogenous variation in the match rate. Following White (2021), I construct a measure of effective vaccination by interacting state-by-year vaccine take-up with match rates. Figure 3 presents the evolution of vaccine take-up and match rates and illustrates the intuition behind this identification strategy.

Panel A of Figure 3 shows variation in vaccine match rates and actual vaccination rates over time. The latter are presented for groups of states that, in a given flu year, have actual vaccination rates in the bottom and top quartiles (hereafter, low- and high-vaccinated 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.[30] The vaccine match appears to be random over time, with no discernible pattern.[31]

To examine this more formally, I test whether match rates can be predicted by their own lags, lags of labor market outcomes, or a linear time trend. I find no evidence that any of these variables predict match rates (see Appendix Table C.2). Similarly, Appendix Table C.3 shows that the relationship between vaccination rates and match rates is small and not statistically significant, suggesting that individual vaccination decisions are not affected by match rates. Moreover, I find no evidence that states with higher baseline vaccination rates, employment-to-population ratios, or labor-force participation rates respond differently to match rates.

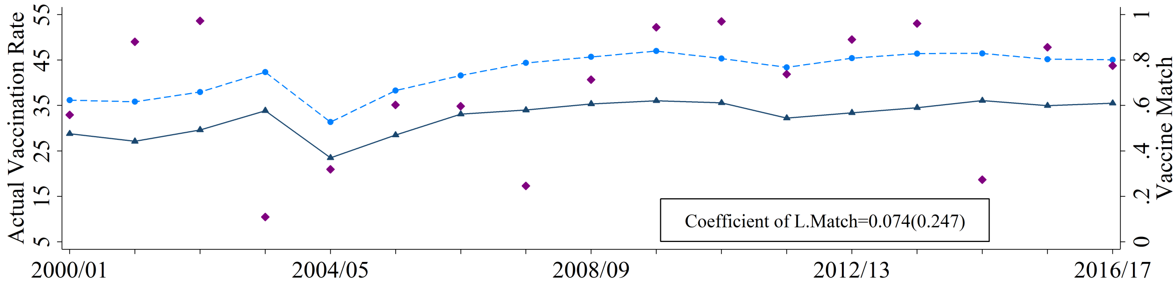
Panel B of Figure 3 presents the evolution of the effective vaccination rate for high- and low-vaccinated states. By construction, the gap in effective vaccination between these states increases when the vaccine match is high and is almost negligible when the vaccine match is low. The identification strategy thus examines how differences in effective vaccination between high- and low-vaccinated states relate to differences in outcomes across these states.

[29] 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).

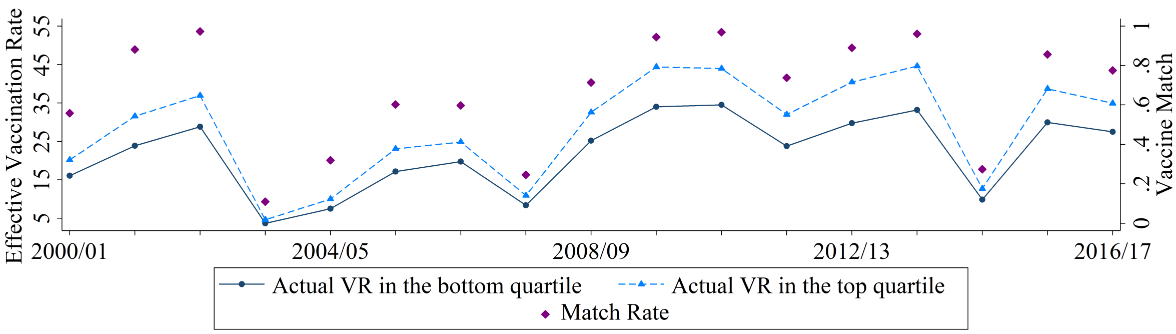
[30] Furthermore, there is no evidence suggesting that vaccination coverage was higher during seasons with elevated flu activity, such as the H1N1 pandemic.

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

Figure 3. Actual and Effective Vaccination Rates Over Time



Panel A: Actual Vaccination Rates

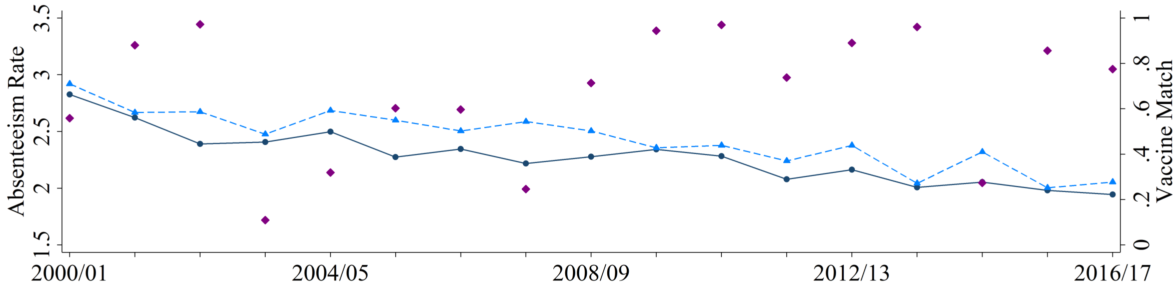


Panel B: Effective Vaccination Rates

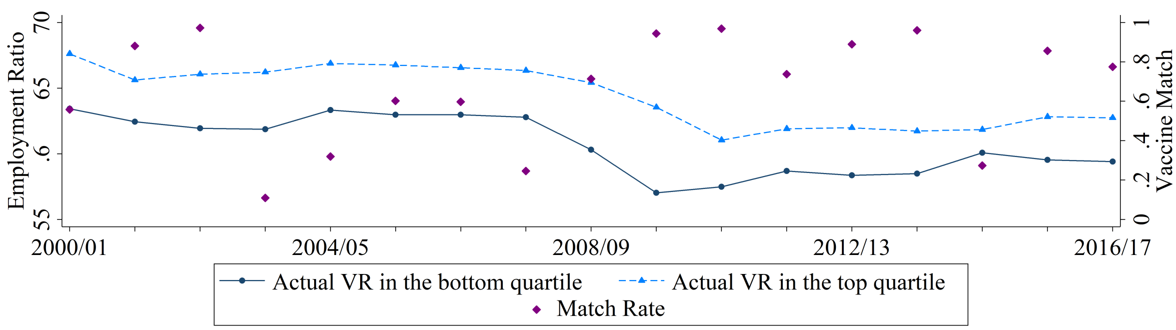
Notes: Based on data from the Behavioral Risk Factor Surveillance System (BRFSS). The graph shows the actual and effective vaccination rates from 2000/01 to 2016/17.

To examine this pattern visually, Panels A and B of Figure 4 present the evolution of absenteeism and the employment-to-population ratio for high- and low-vaccinated states, while Panels C and D show how the gap in these outcomes between the two groups varies with match rates. Figure 4 shows that states with greater vaccination coverage generally experience higher absenteeism. However, in years when the vaccine match rate is close to one, this gap narrows. This reflects that high-vaccinated states experience larger declines in absenteeism than their counterparts in seasons when the vaccine works well. When the vaccine performs poorly, differences in vaccination coverage have little effect on the predetermined gaps in absenteeism. A similar pattern emerges for employment: states with higher vaccination coverage tend to have higher employment-to-population ratios, and this advantage becomes larger as

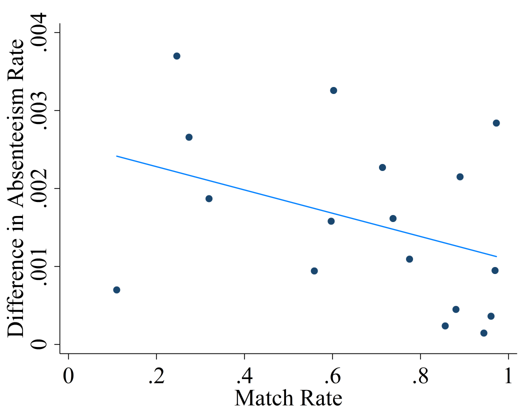
Figure 4. **Absenteeism and Employment in Low- and High-Vaccinated States**



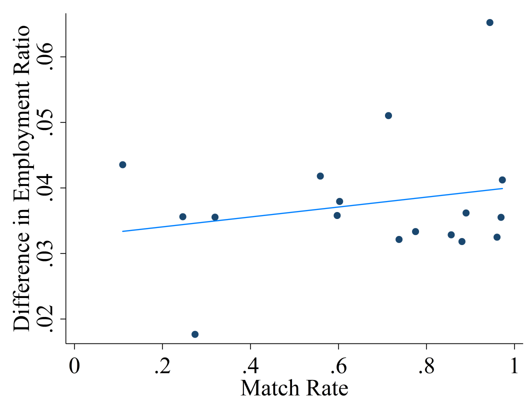
Panel A: Absenteeism



Panel B: Employment



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



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

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

the vaccine match rate increases. Overall, these patterns provide the first evidence that effective vaccination is negatively associated with absenteeism and positively associated with the employment-to-population ratio.

To causally estimate the impact of flu vaccines on labor market outcomes, I estimate equation (1) as follows:

$$Y_{smt} = \beta_0 + \beta_1(V_{st} \times MR_t) + \beta_2 V_{st} + \beta_3 X_{smt} + \delta_{mt} + \gamma_s + \epsilon_{smt} \tag{1}$$

where Y_{smt} is the outcome variable in state s, month m, and flu-year t.[32] 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 shares of five age groups, and lagged GDP growth. The vector γ_s denotes state fixed effects, and δ_{mt} are month-by-year fixed effects. These variables absorb state-specific time-invariant components and common time shocks.

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 regressor 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 identifies the causal effect of influenza vaccination.[33]

Next, to evaluate the validity of the treatment and 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 rate to equation (1) and estimate the following model:

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

[32]When the CPS data are 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 equation (1). Moreover, when the outcome denotes output per worker or output per hour, the dependent variable is at the state-quarter level.

[33]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, measured by the effective vaccination.

In this equation, the interactions $V_{st} \times MR_{t+2}$ and $V_{st} \times MR_{t+1}$ serve as a falsification test and 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 $V_{st} \times MR_{t-2}$ evaluate the persistence of the effects.

Next, 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 characteristics, and the vectors ϕ_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 Program (UIIP), which aimed to provide 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 and absenteeism.

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

where Y_{pmt} denotes outcome in province p, month m, and flu-year t. $UIIP_p$ 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. The 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 ξ_p are time and province fixed effects, respectively. Note that in this setting, the term $\text{UIIP}_p \times \text{Post}_t$ accounts for unobservable post-period differences in outcomes in Ontario, for example, any other labor market policies or events that coincided with the introduction of UIIP. In contrast, the term $\text{UIIP}_p \times MR_t$ controls for any differential effects of match rates in Ontario that are common in the pre- and post-period.[34]

Table 1. Effective Vaccination and Labor Market Outcomes

	Employment Ratio		LFP Rate	
	(1)	(2)	(3)	(4)
Vaccination × Match	0.112***	0.089***	0.030	0.023
	(0.033)	(0.028)	(0.021)	(0.019)
Vaccination	-0.010	0.011	0.057*	0.052*
	(0.032)	(0.032)	(0.030)	(0.030)
Mean of D.V.	62.08	62.08	65.71	65.71
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	8,400	8,400	8,400	8,400

Notes: OLS estimates of equation (1) based on data from the Local Area Unemployment Statistics (LAUS). The unit of analysis is the state-month level. The dependent variables are the employment-to-population ratio and the labor force participation rate. The regressions in columns (2) and (4) include the full set of state-level control variables described in 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 Results

4.1 Main Results

Table 1 shows the estimated effects of influenza vaccination on the employment-to-population ratio and the labor force participation rate. Columns one and three control only for state and time fixed effects, while columns two 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 state-level actual vaccination rates are endogenous: states with higher vaccination rates tend to have higher labor force participation rates.

[34]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 $\text{Post}_t \times MR_{pt}$.

Table 2. Effective Vaccination and Labor Market Turnovers

	Opening Rate	Hiring Rate	Quit Rate	Layoff Rate
	(1)	(2)	(3)	(4)
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.	3.123	3.897	2.021	1.490
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	8,400	8,400	8,400	8,400

Notes: OLS estimates of equation (1) based on data from the Job Openings and Labor Turnover Survey (JOLTS). The unit of analysis is at the state-month level. The dependent variables are the opening, hiring, quit, and layoff rates. The regressions include the full set of state-level control variables described in 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

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 two, a one percentage point increase in effective vaccination increases the employment-to-population ratio by 0.09 percentage points. This suggests that in an average match season (i.e., when the match rate is 0.68), a one standard deviation increase in actual vaccination (five percentage points) leads to a 0.3 percentage point increase in the employment-to-population ratio.[35] Given the low cost of one additional flushot (roughly 100$), this finding suggests that the cost-per-job of this public health intervention is around 1700$.[36]

The magnitude of this effect appears to be surprisingly large but not implausible, considering the multiple mechanisms through which effective vaccination may affect employment. Section 4.6 discusses the plausibility of these estimates in greater detail. On the other hand, the impact of effective vaccination on labor force participation is smaller in magnitude and not sta-

[35] 5 percentage point increase in vaccination × 0.68 average match rate × 0.09 coefficient = 0.3 percentage points.

[36] This is because the estimate of 0.09 implies that in an average match season, for every 17 vaccinated individuals, one additional person is employed ($\frac{1}{0.09 \times 0.67}$.

tistically 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 impact on hiring and job opening rates, but it does not appear to affect 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.

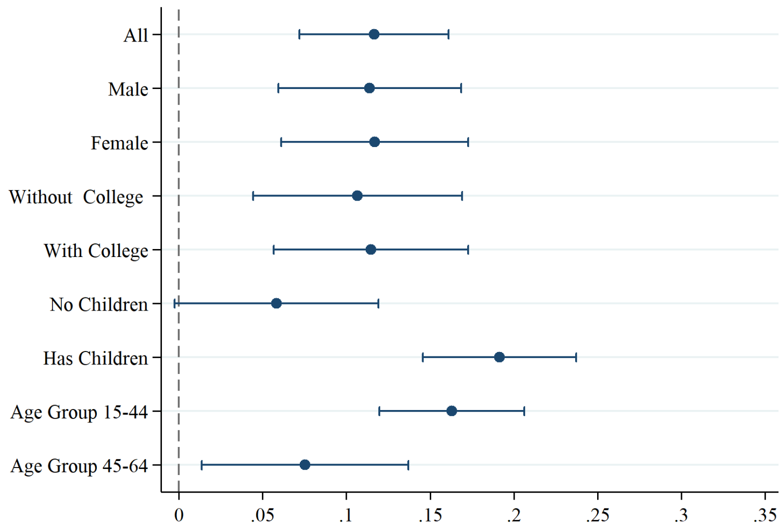
Next, I turn to the CPS data to examine the heterogeneous impact of effective vaccination on employment and wages across demographic characteristics. Figures 5a and 5b show that the relationship between effective vaccination and labor market outcomes is rather homogeneous across demographic groups, with some minor exceptions. Particularly, the estimates of effective influenza vaccination on employment are larger for those who are younger or those who have children. Note also that the estimates presented in Figure 5b suggest that, at the average match rate, a one-standard-deviation increase in actual vaccination increases hourly wages by 0.4 percent.

4.2 Mechanisms

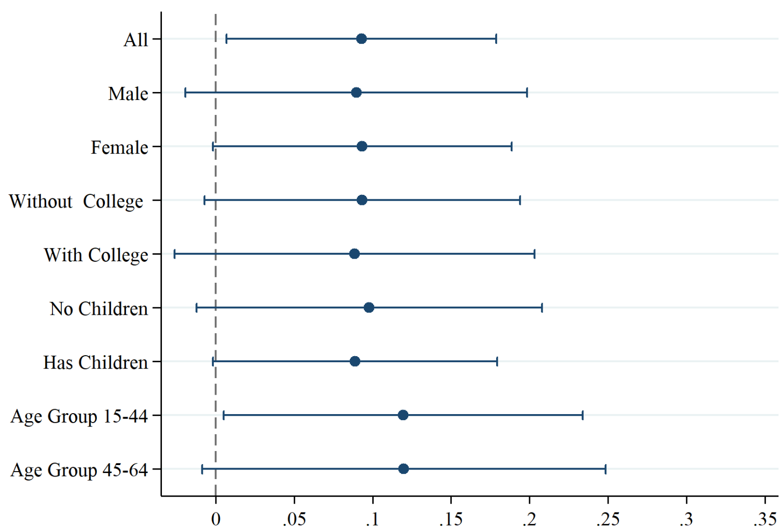
As discussed above, effective vaccination may affect labor market outcomes through three channels: labor supply, labor productivity, and consumer demand. The results presented in Section 4.1 provide evidence that employment effects are driven by labor demand factors, suggesting that vaccination affects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

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



Panel A: Employment



Panel B: Hourly Wages

Notes: OLS estimates of equation (1) based on data from the Current Population Survey (CPS). The unit of analysis is at the individual-state-month level. 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 clustered at the state level. Because employment is measured as a binary indicator (rather than as a percentage rate), and wages are expressed in logs, I scale all estimates by 100 to improve readability.

on labor productivity is heterogeneous across sectors. I then evaluate the spillovers on labor market outcomes. Due to the higher incidence of influenza in high-contact sectors (Houštecká et al., 2021), the direct impact of effective vaccination is expected to be more pronounced in these 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.[37]

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 actual vaccination reduces absenteeism in high-contact sectors by 0.1 percentage point (a 5% decrease with 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 actual vaccination in high-contact sectors increases output per worker and output per hour by 0.56 and 0.68 percent, respectively.

Consistent with the productivity gains, the effects on employment and wages are also concentrated in high-contact sectors.[38] However, as predicted by 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 gains in low-contact non-tradable sectors are relatively large. In contrast, the employment effects are close to zero and not statistically significant in low-contact tradable sectors. These findings provide the first evidence for the

[37]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 Hlatshwayo and Spence (2014), 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 are retrieved from National Center for O*NET Development (2025), while the occupational employment data come from the U.S. Bureau of Labor Statistics (2025c).

[38]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.

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

	High-contact Non-tradable	Low-contact Non-tradable	Low-contact Tradable
	(1)	(2)	(3)
Panel A: Absenteeism due to illness, CPS			
Vaccination $\times$ Match	-0.027***	-0.002	0.003
	(0.009)	(0.010)	(0.011)
Mean of D.V.	2.343	2.360	2.111
Observations	3,916,696	1,781,822	2,755,771
Panel B: Ln(Employment), CES			
Vaccination $\times$ 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 $\times$ 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: OLS estimates of equation (1). Column (1) shows the estimates for high-contact non-tradable sectors, column (2) for low-contact non-tradable sectors, 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 Current Employment Statistics (CES); the data on wages and absenteeism come from the Current Population Survey (CPS). The unit of analysis in Panel B is the state-month level, and in Panels A and C 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 regressions include the full set of state- and individual-level control variables described in Section 3.2. Standard errors are clustered at the state level. Because absenteeism is measured as a binary indicator (rather than a percentage rate), and wages as well as employment are expressed in logs, I scale all estimates and the mean of absenteeism by 100 to improve readability.
* statistically significant at the 10% level; ** at the 5% level; *** at the 1% level.

demand spillovers across sectors.

As discussed in Section 2.3, these spillovers may arise through the input–output network of production or through consumer responses, with the latter being amplified by a larger share of H2M households. Since state-level financial data are not available, I follow Cloyne et al. (2020) and use homeownership status as a proxy for H2M households.[39] Specifically, I define two groups of states: those with the lagged share of mortgagors and renters above and below the median (hereafter, H2M and NH2M states).[40]

Table 4. **Estimated Effects of Vaccination on Consumption and Absenteeism by H2M status**

	Overall	H2M	NH2M
	(1)	(2)	(3)
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	-0.012**	-0.014	-0.011
	(0.006)	(0.009)	(0.009)
Mean of D.V.	2.361	2.351	2.371
Observations	8,499,256	4,512,469	3,986,787
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Notes: OLS estimates of equation (1). The data on the share of homeowners by state come from the American Community Survey (ACS), and the data on restaurant consumption and absenteeism come from the Current Population Survey (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. Because absenteeism is measured as a binary indicator (rather than as a percentage rate), I scale its estimate and mean by 100 to improve readability. The regressions include the full set of state- and individual-level control variables described in 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 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

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

[40]The data on homeownership status are approximated from Steven Ruggles and Williams (2025).

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.[41] Similar 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 sectoral spillovers, I examine heterogeneity in vaccination effects across upstream and downstream low-contact non-tradable sectors. By using input-output matrices, I find that the point estimates of effective vaccination on employment are larger in sectors that tend to serve as inputs to high-contact sectors (see Appendix Table C.8).[42] These findings suggest that demand chains may amplify the labor market effects of influenza vaccination.

Finally, influenza vaccination may also directly influence consumer demand, particularly 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, low-contact non-tradable, and low-contact tradable

[41] Appendix Table C.7 shows similar findings when the lagged share of H2M and other confounders that may be correlated with H2M are interacted with effective vaccination.

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

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

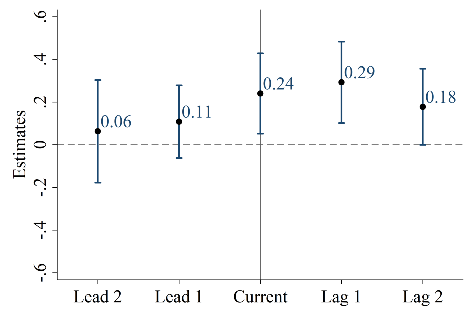
	Non-tradable			
	High-contact		Low-contact	
	H2M	NH2M	H2M	NH2M
	(1)	(2)	(3)	(4)
Panel A: Ln(Employment)				
Vaccination × Match	0.362**	0.055	0.218*	0.024
	(0.154)	(0.102)	(0.108)	(0.142)
Mean of D.V.	6.881	6.337	6.632	6.195
Observations	3,738	4,326	3,858	4,038
Panel B: Ln(Hourly Wages)				
Vaccination × 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: OLS estimates of equation (1). The data on employment and wages come from the Current Employment Statistics (CES) and the Current Population Survey (CPS), respectively; the data on the share of home-owners by state come from the American Community Survey (ACS). Columns 1 and 3 (2 and 4) show the results when the share of homeowners is below (above) the median. The regressions include the full set of state- and individual-level control variables described in Section 3.2. Because wages and employment are expressed in logs, I scale the estimates by 100 to improve readability. Standard errors are clustered at the state level.
* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

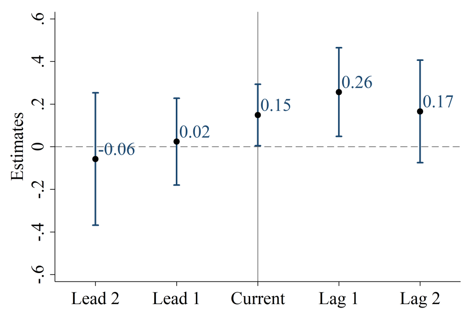
sectors.

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.

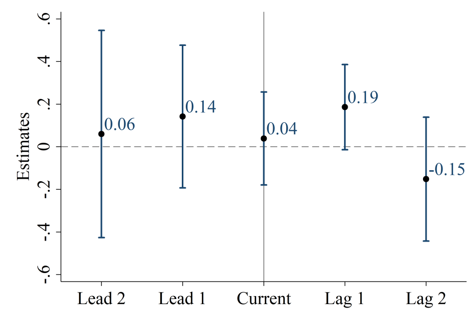
Figure 6. Effective Vaccination and Employment by Sector: Placebo and Dynamics



Panel A: High-contact non-tradable



Panel B: Low-contact non-tradable



Panel C: Low-contact tradable

Notes: OLS estimates of equation (2) based on data from Current Employment Statistics (CES). The regressions include the full set of state control variables described in Section 3.2. Because employment is expressed in logs, I scale the estimates by 100 to improve readability. The 90% confidence intervals are obtained with standard errors clustered at the state level.

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 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.

The results show an interesting pattern.[43] The findings suggest that the impact of effective

[43]The estimates in the subsamples with available vaccination data at the county and MSA levels are larger than

Table 6. Effective Vaccination and Employment: Geographic Heterogeneity

	State	State C-Sample	County	State M-Sample	MSA
	(1)	(2)	(3)	(4)	(5)
Panel A: Employment					
Vacc × 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.	75.23	74.80	74.80	75.83	75.83
Observations	13,508,619	2,593,846	2,593,846	2,374,266	2,374,266
Panel B: Absenteeism					
Vacc × 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.	2.263	2.179	2.179	2.237	2.237
Observations	8,628,170	1,667,994	1,667,994	1,536,285	1,536,285

Notes: Based on data from the Current Population Survey (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. Because employment and absenteeism are measured as binary indicators (rather than as percentage rates), I scale all estimates and means by 100 to improve readability. Standard errors are clustered at the state level.
* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

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 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 that 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. Intuitively, if vaccination boosts employment in a given area, part of these gains can diffuse to neighboring counties or MSAs through commuting patterns, cross-area consumption, and business linkages. As a result, state-level regressions capture both the direct and spillover ef-

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.

fects, whereas within-state specifications subtract these cross-border spillovers and therefore yield smaller coefficients.[44]

4.5 External Validity of the Findings and Seasonal Patterns

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 UIIP appears to increase the employment-to-population ratio 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 ratio 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.

Next, Appendix Tables C.9 and C.10 show the differential impact of effective vaccination on labor market outcomes and absenteeism across 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.[45] The impact of effective vaccination on labor market outcomes is also larger during the fall and winter, although the differences across seasons 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.

[44]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.

[45]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.

Table 7. Vaccination and Labor Market Outcomes: Canadian Data

	Employment Ratio		LFP Rate	
	(1)	(2)	(3)	(4)
$\mathrm{U}IIP_p \times \mathrm{P}ost_y \times \mathrm{M}atch_{py}$	0.815**	0.821**	0.479	0.154
	(0.294)	(0.281)	(0.331)	(0.287)
Mean of D.V.	58.99	58.99	64.88	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 clustered at the province level in parentheses.
* statistically significant at the 10% level; ** at the 5% level, *** at the 1% level

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. Across all specifications, the estimates remain statistically significant, and the point estimates range from 0.052 to 0.097.

State trends. Next, I examine whether 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 control 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 estimates of the interaction between the state-level vaccination rate in the 2000/01 flu season and time-varying match rates. Under the assumption that differences in vaccination rates across states remain relatively constant over time, this identification strategy should yield estimates of comparable magnitude to those in the main specification. The findings indicate that the estimates are robust to using a time-invariant measure of vaccination instead of controlling for actual vaccination rates. Furthermore, Panel B of Table D.3 shows that the results are robust to an IV strategy, in which 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 in outcomes between 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-to-population ratio is negligible. The falsification test for the Canadian setting yields 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

By leveraging time variation in random match rates and geographic variation in vaccination rates across different levels of aggregation in the US and Canada, this paper investigates the causal effects of influenza vaccination on labor market outcomes. 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. To do so, I focus on four different relationships.

First, I begin by reconciling the health and labor productivity impact of effective vaccination. I find that a one percentage point increase in effective vaccination decreases absenteeism in high-contact sectors by 0.03 percentage points (1.25% with respect to the mean) and increases output per worker by 0.16 percent. While both effects are large, a decrease in absenteeism alone is unlikely to drive such large increases in output per worker. This suggests that effective vaccination impacts not only absenteeism but also productivity at work.

Most employees (60-80%) keep working while being ill but experience lower productivity (Blanchet Zumofen et al., 2023). Moreover, recent medical literature argues that, similar to COVID-19, influenza might have long-term negative health effects, lasting for at least six months after a flu episode. The studies find that up to 30 percent of people infected with the flu may develop long-lasting symptoms, including fatigue, abnormal breathing, headache, and other pain. To examine this channel, I study the impact of effective vaccination on physical health. Table C.11 suggests that a one percentage point increase in effective vaccination decreases the number of days during which physical health is not good by 0.016 (0.4% with respect to the mean). Similarly, in a year in which the vaccine match is one, being vaccinated (i.e., individual vaccination, not state-level) decreases bad physical health days by 0.28 (7% with respect to the mean). These findings provide suggestive evidence that flu might cause long-lasting health problems, the severity of which might be reduced by the vaccines. These estimates, together with the evidence that there are peer effects from changes in labor productivity (Moretti, 2010), imply that even though the relationship between effective vaccination and labor productivity is large, it is not implausible.

Second, since labor productivity is affected only in high-contact sectors, I compare the output per worker estimates with the employment gains in these sectors. Most studies that examine 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 pollution or worker training on employment. Both pollution and worker training might affect employment through changes in labor productivity. A growing body of literature shows that pollution reduces labor productivity (Zivin and Neidell, 2012; Hill et al., 2024). A recent study also finds that pollution substantially decreases earnings and employment (Borgschulte et al., 2024). Furthermore, Naval et al. (2020) find that an increase in on-the-job training leads to a large increase in employment and labor productivity.[46]

Third, since I argue that spillovers occur due to changes in consumer demand, I analyze how my findings relate to the previously estimated elasticities of consumption to employment and income. Other 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 with respect 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

[46]Moreover, as argued below, the impact of effective vaccination on employment in high-contact sectors may also operate 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 these estimates with those studied by other papers.

changes (Kaplan and Violante, 2014; Baker and Yannelis, 2017).[47]

This paper finds that a one percentage point increase in effective vaccination increases the employment-to-population ratio 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 with respect to income suggests that the direct effects are relatively large.[48]

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

[47]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).

[48]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.

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 differences between high- and low-vaccinated states when the vaccine match is high, with differences between high- and low-vaccinated states when the vaccine match is low.

The findings provide evidence of a large 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 ratio by 0.3 percentage points and wages by 0.4 percent. 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 that effective vaccination affects labor market outcomes through both direct and indirect channels. The direct channels operate via enhanced labor productivity and increased consumer demand in high-contact sectors, which, in turn, generate demand spillovers across 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. Apart from my findings specific to influenza vaccination, the paper also provides more general evidence on how sectoral shocks can propagate through the economy.

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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**

	Mean (1)	St. Dev. (2)
Employment Ratio	62.08	4.61
LFP rate	65.71	4.23
Openings Rate	3.12	0.64
Hiring Rate	3.90	0.74
Layoff Rate	1.49	0.38
Quits Rate	2.02	0.48
Share 0-14	19.90	1.76
Share 15-24	14.18	0.98
Share 25-44	26.79	1.74
Share 45-64	25.65	2.01
Share +65	13.49	2.03
Observations	8,400	8,400

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

Table C.2. Match Rates Predictions

	Match Rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.Match	0.074	0.048					
	(0.247)	(0.235)					
L.Employment ratio			-4.180	-6.014			
			(2.948)	(4.981)			
L.LFP Ratio					-3.934	6.624	
					(4.634)	(16.916)	
Trend		0.014		-0.009		0.033	0.014
		(0.015)		(0.026)		(0.051)	(0.014)
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 the 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

	Actual Vaccination Rate			
	(1)	(2)	(3)	(4)
Match	0.002	-0.009	0.040	0.064
	(0.002)	(0.021)	(0.051)	(0.056)
Match × Baseline Vacc.		0.032		
		(0.063)		
Match × Baseline Empl.			-0.059	
			(0.078)	
Match × Baseline LFP				-0.092
				(0.083)
Trend	0.006***	0.006***	0.006***	0.006***
	(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 the 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 the 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**

	High-contact Non-tradable	Low-contact Non-tradable	Low-contact Tradable
	(1)	(2)	(3)
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: Panel A uses quarterly data starting in 2005; Panel B uses quarterly data starting in 2007. Data on output come from the BEA, and data on the number of employees and hours come from the CES. Estimates are obtained with a two-way fixed-effects OLS model. The regressions include the full set of state-level controls described in Section 3.2. Because dependent variables are expressed in logs, I scale all estimates by 100 to improve readability. 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**

	High-contact Non-tradable	Low-contact Non-tradable	Low-contact Tradable
	(1)	(2)	(3)
Vaccination × Match	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: OLS estimates of equation (1) based on data from the CPS. The regressions include the full set of state- and individual-level control variables described in 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

	Total	High-contact Non-tradable	Low-contact Non-tradable	Low-contact Tradable
	(1)	(2)	(3)	(4)
Vaccination × 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: The analysis uses quarterly data starting in 2005. Sectoral GDP data are from the BEA. Estimates are obtained using a two-way fixed-effects OLS model. The regressions include the full set of state-level control variables described in Section 3.2. Because the dependent variable is expressed in logs, I scale all estimates by 100 to improve readability. 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

	Restaurant Consumption	
	(1)	(2)
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: OLS estimates of equation (1) based on data from the CPS. The regressions include the full set of state- and individual-level control variables described in Section 3.2 and lagged shares of H2M, White population, 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

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

Notes: OLS estimates of equation (1) based on data from the CES. The table presents the estimates for upstream and downstream low-contact non-tradable sectors. The regressions include the full set of state-level control variables described in Section 3.2. Because the dependent variable is expressed in logs, I scale all estimates by 100 to improve readability. 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

	Absenteeism		Employment		Ln(Wages)	
	F+W	S+S	F+W	S+S	F+W	S+S
	(1)	(2)	(3)	(4)	(5)	(6)
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)
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: OLS estimates of equation (1) based on data from the CPS. The regressions include the full set of state- and individual-level control variables described in Section 3.2. F+W denotes winter and fall months, while S+S denotes spring and summer months. Because dependent variables are either binary or expressed in logs, I scale all estimates by 100 to improve readability. 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**

	P.Absenteeism		F.Absenteeism		Employment	
	F+W	S+S	F+W	S+S	F+W	S+S
	(1)	(2)	(3)	(4)	(5)	(6)
$UIIP_p \times Post_y \times Match_{py}$	-0.021*	-0.005	0.011	0.010	0.894**	0.734**
	(0.011)	(0.015)	(0.054)	(0.034)	(0.279)	(0.319)
Observations	720	720	720	720	720	720
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes

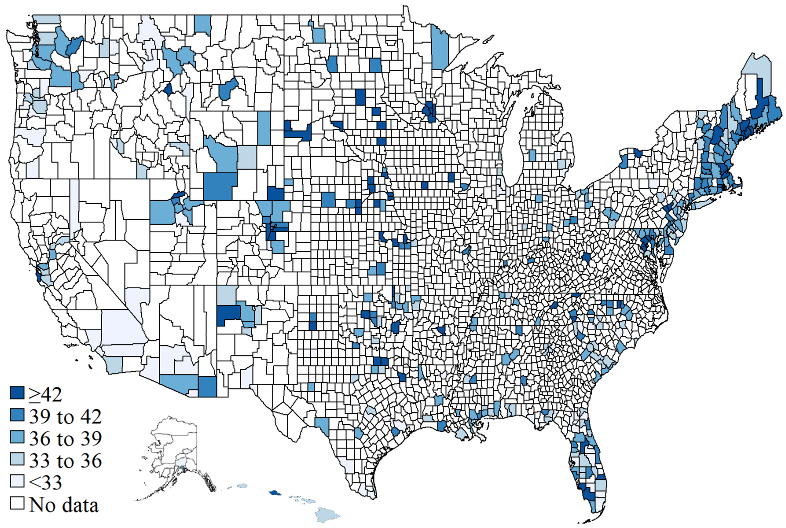
Notes: OLS estimates of equation (4) based on data from Statistics Canada. The dependent variables in columns 1 and 2, 3 and 4, 5 and 6 are average part-week lost hours per worker, average full-week lost hours per worker, and employment, respectively. The regressions include the full set of province-level control variables described in 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.11. **Effective Vaccination and Physical Health**

	Days of bad health	
	(1)	(2)
Vaccination × Match	-0.016**	-0.014**
	(0.007)	(0.007)
Vaccination	0.013*	0.010
	(0.007)	(0.007)
Vaccinated × Match		-0.279***
		(0.026)
Vaccinated		0.838***
		(0.018)
State FE	Yes	Yes
Time FE	Yes	Yes
Mean of D.V.	3.725	3.723
Observations	5,044,304	4,865,128

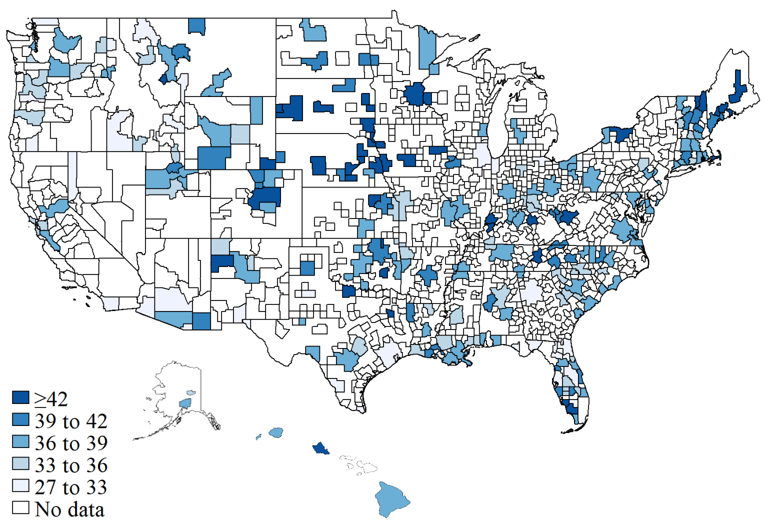
Notes: Based on data from the BRFSS. The dependent variable is the number of days in a month during which physical health is not good. Vaccination denotes the state-level vaccination rate, while vaccinated denotes individual vaccination status. The regressions include the full set of state- and individual-level control variables described in Section 3.2. Standard errors are clustered at the state level. All the regressions are weighted with the sample weights.
* 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 data from the 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 data from the 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 Ratio: Alternative Samples

	All	All w/o pandemics	1998-2022	W/o 2004/05	With AL and HI
	(1)	(2)	(3)	(4)	(5)
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: OLS estimates of equation (1) based on data from the LAUS. The dependent variable is the employment-to-population ratio. The regressions in columns 3-5 include the full set of state-level control variables described in 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 main sample, and column 5 excludes Alaska and Hawaii from the main 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

	Employment Ratio	
	(1)	(2)
Vaccination × Match	0.089***	0.060***
	(0.028)	(0.019)
Vaccination	0.011	-0.015
	(0.032)	(0.026)
State FE	Yes	Yes
Time FE	Yes	Yes
State Trends	No	Yes
Observations	8,400	8,400

Notes: Based on data from the LAUS. The dependent variable is the employment-to-population ratio. 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**

	Employment Ratio (1)	LFP Rate (2)
Panel A: Reduced Form		
Vaccination × Match	0.0804**	0.0161
	(0.0332)	(0.0300)
Observations	8,400	8,400
Panel B: IV		
Vaccination × Match	0.0872**	0.0174
	(0.0360)	(0.0320)
Observations	8,400	8,400

Notes: Based on data from the LAUS. The dependent variables are the employment-to-population ratio, and the labor force participation rate. The regressions include the full set of state-level control variables described in 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**

	Employment Ratio (1)	LFP rate (2)
Vaccination × Match	-0.010	-0.006
	(0.061)	(0.037)
Observations	8,400	8,400

Notes: OLS estimates of equation (1) based on data from the LAUS. The dependent variables are the employment-to-population ratio and labor force participation. The match rates are shuffled 1000 times. The regressions include the full set of state-level control variables described in 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**

	Employment Ratio (1)	LFP Rate (2)
$UIIP_p \times Post_y \times Match_{py}$	-0.037	-0.028
	(0.817)	(0.572)
Observations	1,400	1,400

Notes: OLS estimates of equation (4) based on data from Statistics Canada. The dependent variables are the employment-to-population ratio and the labor force participation rate. 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**

	Employment Ratio		
	(1)	(2)	(3)
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: OLS estimates of equation (1) based on data from the LAUS. The dependent variable is the employment-to-population ratio. The regression in column 1 replaces the match rate in the main specification with the match rate based on reduced titers, column 2 replaces the vaccination rate with the one calculated only between January and August, and column 3 replaces both the match rate and vaccination rate with 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**

	Employment Ratio		
	Reduced Titers	Adjusted Match	Regional Match
	(1)	(2)	(3)
$UIIP_p \times Post_y \times Match_{py}$	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:[49]

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

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: $W_{Hs} = P_{Hs}(1-\delta_s)$.

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

[49] 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.

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

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

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

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.