INFLUENZA IMMUNIZATION CAMPAIGNS:

IS AN OUNCE OF PREVENTION WORTH A POUND OF CURE?

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A standard argument for public health care would claim efficiency gains from disease prevention. However, even where preventative technologies are more efficient, private-action may fail to exhaust external net-benefits of prevention. Furthermore, health officials may base policies on evidence failing to take externalities into account. Addressing these issues, this paper studies an influenza-immunization program expanding coverage outside the typical "target-group." Using exogenous variation in vaccine quality, I link higher vaccination to health improvements. Results indicate: (i) coverage-expansion leads to large gains for program-regions; (ii) benefits exhibit decreasing returns corresponding to a standard model of disease dynamics; (iii) substantial external benefits accrue to older-adults.

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A standard argument for public health care would claim efficiency gains from focusing on disease prevention rather than treatment of disease after the fact. However, even where prevention technologies are more efficient (i.e. "an ounce of prevention is worth a pound of cure") it can be difficult, in practice, to take complete advantage of these efficiencies. A primary issue arises when individuals do not recoup the full benefit of preventative care personally, and thus private action may fail to exhaust all external net-benefits of prevention. This feature may be further exacerbated if health coverage is offered for treatment of disease versus disease prevention, thereby distorting the relative price for preventative care and lessening the incentive to prevent illness. A secondary issue arises when individual decision-making relies on recommendations set by health authorities, which also may not account for the external benefits of preventative care. This could occur when small-scale assessments of preventative technologies fail to capture treatment spillovers in estimation, undervaluing both the private benefit of prevention and the overall benefit of large-scale preventative health measures. In this case, health authorities may set "bright line" recommendations for specific, identifiable groups well before full benefits are recouped.

This study addresses these two aspects of public health by focusing on a definitive preventative health care decision made by many each year; that of immunization against influenza, a pervasive disease linked to mortality, short-term illness, and longer-term disability and educational outcomes (WHO 2011; Almond 2006; Almond and Mazumder 2005; Thompson, et. al. 2004, 2003). Relying on standard arguments about the externality effects of preventing infectious disease, there is substantive motivation for public action. However, recommendations for receipt of influenza immunization are generally limited to specific groups and limitations, so defined, continue to be controversial. Furthermore, at the program level, since

little is known about the true impact of large-scale immunization campaigns, looming disease epidemics can lead to a broad array of policy responses.[1]

Such controversy over immunization protocol can arise when existing evidence is based on randomized assessments that, while useful for addressing efficacy of vaccines, fail to address several features salient to the decision for public action, and short of this, decisions for public health recommendations. For instance, aspects such as treatment spillovers in estimation, non-linearities in the effect of vaccination due to decreasing externality benefits, and possible heterogeneity in the effect of vaccination in a randomized versus choice-based design, may not be captured by studies assessing vaccine efficacy. Nevertheless, public policy for new and existing vaccines should rest on rigorous comparison of costs and benefits, and program evaluation of public campaigns thus requires accurate evaluation of the health and economic consequences of such programs.

By focusing on a broad-based immunization campaign targeted toward influenza, this study addresses the limitation of previous evidence by assessing the overall and external gains of immunization, and showing that these gains decline to exhaustion depending on overall immunization levels. Expanding the delivery of free vaccines beyond the traditional target group in 2000, the Ontario Universal Influenza Immunization Campaign (UIIC) was one of the first programs to offer universal vaccine coverage annually. Corresponding to the recommendations of other developed countries, policies prior to 2000 included only high-risk groups

[1] For instance, the U.K. Department of Health currently offers vaccine coverage for the standard "high-risk" group (i.e. the elderly and those with select chronic conditions) while deemphasizing the vaccine for others (http://www.dh.gov.uk/en/Publichealth/Flu/Flugeneralinformation/DH_4001688). Similarly, prior to 2008, the U.S. Advisory Committee on Immunization Practices (ACIP) set comparable policy (without national coverage) limiting recommendations to the standard target group (CDC 2007). In 2008, the ACIP expanded recommendations to include children under 18, but did not include ages 19-64 stating that "economic analysis among adults aged <65 have reported mixed results regarding influenza vaccination" (CDC 2008, 2009, 2010). Meanwhile, the threat of influenza H1N1 in 2009 led to a broad array of policy responses at the local level with some state laws or employers mandating vaccination (http://www.cdc.gov/h1n1flu/vaccination/acip.htm) and at the time, the official position of the ACIP was: "that as many people as possible receive 2009 H1N1 vaccine as quickly as possible" (http://www.cdc.gov/h1n1flu/cdcresponse.htm). Following the 2009 H1N1 pandemic response, the ACIP maintains that evidence on the cost effectiveness of the seasonal influenza vaccine for those aged <65 remains mixed, but it has adopted the policy of recommending the seasonal influenza vaccine to all groups older than 6 months (CDC 2010).

such as the elderly and those with select chronic conditions. The implications of the immunization program are twofold: it not only recommends the vaccine for all age groups, but it also fully subsidizes the cost of the vaccine and administration.

Since the UIIC was successful at delivering vaccines, it offers a useful policy experiment to evaluate the impact of expanded coverage to children and younger adults. Given that a simple before and after comparison for UIIC regions may incorrectly attribute all changes in health outcomes to the immunization campaign and even conventional difference-in-difference comparisons with non-UIIC regions may be confounded with differential trends, I instead develop an identification strategy that exploits variation in the quality of the influenza vaccine. Since this variation is based on the degree to which the vaccine relates to the influenza virus each year, it can be considered as exogenous to the decision to vaccinate. For instance, while the genetic composition of influenza is constantly changing, the composition of the vaccine is predetermined and fixed for each flu-season and across North America. This implies that if there are benefits from vaccination, UIIC regions will have more to gain when the vaccine is a good match whereas they will have little to gain when it is not. This methodology disentangles the causal impact of vaccines from alternative explanations for differences in outcomes such as advertising effects related to the program or any other associated differential trends. Furthermore, since the match of the vaccine is unknown at the time of vaccination, changes in compensatory behaviors are unlikely correlated with the match and thus cannot explain the estimated impact.[2]

This paper makes a number of contributions: (i) by using exogenous variation in the match quality of the influenza vaccine and a novel immunization campaign

[2] An advertising/encouragement effect is interesting in its own right. For instance, Hirano, Imbens, Rubin and Zhou (2000) illustrate that "positive estimates of the intention-to-treat effect need not be due to treatment itself, but rather encouragement to take the treatment." In this analysis, the authors show intent-to-treat results overstate the causal effect of the vaccine through failure of the exclusion restriction. If such an effect is not delivered through vaccination itself, but instead through an advertising effect regarding the upcoming flu-season, this has separate implications for vaccination policy, especially considering the inoculation costs associated with vaccine manufacturing, in addition to costs associated with time loss and personal discomfort.

providing vaccines to all age groups, I estimate the causal impact of a program expanding coverage outside the standard target group; (ii) by using variation in the baseline level of immunization across region, I show that health benefits are exhausted at levels corresponding to those predicted by a standard theoretical model of disease dynamics; and (iii) I provide evidence of substantial external benefits for older adults from the increased vaccination of the young.

In order to address points (i)-(iii), I use labor force survey data and provide the first large-scale evidence of the effect of vaccination on worker productivity. Further, I use a comprehensive dataset on all acute hospitalizations in Canada in order to analyze hospitalizations where respiratory disease was either the primary *or* secondary diagnosis, and examine other types of diseases to rule out misspecification. These data comprise weekly measures of health outcomes for numerous well-defined geographical areas over an eleven-year period, and allows for flexible specifications including month, season, and region fixed effects.

Estimates of the program effect for overall immunization imply a sustained 9-percentage point relative increase in vaccination for UIIC regions. This increase prevents 2 deaths per 100,000 annually and leads to a 67 percent decrease in overall influenza hospitalizations when the clinical match of the vaccine is high (a high match occurs in 1 out of every 2.2 seasons). In terms of labor force productivity, I find that during the flu-season and in a high match year, the program leads to a 22 percent decrease in work absenteeism. These results are further supported by evidence for other measures of illness. There is a 34 percent decline in the weekly surveillance rate of lab tested influenza, a 30 percent decline in bi-weekly bed illness and a 13 percent decline in consumption of over-the-counter cold and flu medications.

The large decreases in illness outcomes correspond to predictions from a standard structural model of influenza dynamics. On a theoretical basis, a vaccination rate

above 31 percent combined with a perfectly matched vaccine is predicted to prevent an influenza epidemic.[3] By using variation in the baseline level of immunization among sub-provincial regions, estimates imply that benefits are exhausted at immunization rates around 30 percent for all health outcomes studied. Furthermore, the results corroborate the large effects found for influenza hospitalizations, which were nearly eliminated in high match vaccine years.

The second stage of this paper presents evidence of large external benefits for adults over the age of 65. Since vaccination is covered for this group in all provinces since the early 1990s, coverage status is unchanged following the UIIC campaign. This feature is further reflected in relative vaccination patterns, where no difference in vaccination rates is observed across region. Given these patterns in vaccination and assuming that this age group is unaffected by the vaccination of others, there should be little additional gain for older adults in high match versus low match years following UIIC. On the other hand, a relative gain in the health of older adults indicates that this age group was positively affected by increased immunization of the young. Results support the latter case, showing significant reductions in hospitalizations, bed illness, and cold/flu medications for this older age group.

The implied aggregate benefits of the immunization campaign, including spillover benefits to older adults, are substantial relative to program costs. Considering only hospitalization and productivity losses, the impact of the vaccine campaign translates into best-case scenario cost savings of $174 million in a high match season. The expected savings (average savings multiplied by the average match rate) yields a program benefit of $124 million. Program costs, on the other hand, are much less. The campaign delivers on average 6 million more vaccinations per

[3] In a standard model of disease dynamics, vaccination reduces the average number of infections caused by an infected individual by reducing the size of the susceptible population. Given parameters regarding the infectiousness of influenza; theory predicts that average infections will fall below the rate of one (meaning, an infection less than replaces itself) at a vaccination rate greater than 31 percent (Boulier et. al. 2007; Hethcote 2000).

season. This represents $19 million in additional administration costs and an extra $14 million in vaccine costs, totaling $33 million annually.

Estimates from this study are robust to defining the clinical match rate dichotomously or as a continuous measure scaled by the proportion of unmatched influenza strains in each province and year. It is not possible to completely rule out concurrent events correlated with the effect of the vaccine match in campaign regions post-2000, but such events are unlikely. For instance, a coinciding policy directly influencing general immunity to disease could explain differences for UIIC regions in high match versus low match vaccine years. However, this is an unlikely explanation since health policies (before and after 2000) are typically directed to treatment and not preventative care. Furthermore, such a policy, being related to general immunity, would have a general effect on health. However, I find no differences for non-respiratory hospitalizations and, moreover, I find no effects on influenza related illness measures in periods other than flu season.

This paper is organized as follows; Section 1 provides background information on the influenza virus and influenza immunization, and outlines a direction for the empirical approach. Section 2 outlines the identification strategy and Section 3 describes the data and presents descriptive statistics. Section 4 presents results. First, I present a main set of results for influenza, pneumonia and worker absence. Second, I explore effects for age groups. Third, I show that these results depend on local immunization. Section 5 provides interpretation and Section 6 concludes.

1 Background

1.1 *Influenza*

Influenza (or flu) is a common respiratory virus that is contagious through droplet

spread.[4] In the U.S., influenza is estimated to be responsible for 100 million days of bed disability, 75 million days of work absenteeism, and 22 million health care provider visits per year for those aged 18 to 64 (Benson, et al. 1998). Furthermore, influenza leads to an estimated 100,000 to 300,000 hospitalizations and 20,000 to 40,000 deaths each flu-season (CDC 2010; Thompson, et al. 2003, 2004). Research has also linked influenza infection with added long-term effects. For instance, children in utero during the 1918 H1N1 influenza pandemic displayed increased rates of physical disability, and decreases in income and educational attainment in later life (Almond 2006; Almond and Mazumder 2005).

The acute effects of influenza can last from three to fourteen days, and infection risk begins prior to the onset of symptoms and continues for a number of days after recovery (CDC 2010; PHAC 2007). In addition, the virus can stay virulent on surfaces for a varying length of time. At body temperature, the virus is usually inactivated in less than a week whereas in cool dry temperatures the virus can last considerably longer (Zhang, et al. 2006). This is, in part, the reason why seasonal epidemics appear during winter months (WHO 2003).

There are many strains of the influenza virus that are genetically differentiated or typed on the basis of surface antigens, and the genetic structure of the virus is constantly changing over time through point mutations. This can lead to antigenic drift in the influenza virus and, depending on antigenic changes, the cross-immunity to the new strain that was conferred by the previously circulating virus can be minimal (PHAC 2007).

1.2 *Vaccination*

The influenza vaccine was developed in the 1940s but was only more widely used

4 Further summary information on influenza and vaccination is available from the U.S. Center for Disease Control and Prevention (http://www.cdc.gov/flu/about/disease/index.htm) or the Canadian Immunization Guide published by the Public Health Agency of Canada (http://www.phac-aspc.gc.ca/publicat/cig-gci/index-eng.php).

following early 1990s initiatives by public health organizations emphasizing the vaccine for selected high-risk groups (Fedson et al. 1995). The vaccine provides protection against influenza by triggering an antibody producing immune response to targeted strains of influenza. Because of this, protection depends on the match of the vaccine cocktail to circulating strains of influenza. For instance, in a systematic review of evidence from randomized control trials, Jefferson et al. (2007) note lower efficacy rates in studies whose timing corresponds to seasons where vaccine content is not well matched to circulating strains.

Vaccine protection usually begins within two weeks of receipt of vaccination and is sustained for six months or longer; however, if immune response is compromised (as is the case for those in low health or with weaker immune systems), then antibody levels may be below what is needed for full or sustained protection (CDC 2010). For instance, Jefferson et al. (2007) find a vaccine efficacy rate of 80 percent in healthy adults. Meanwhile, the results for children and older ages are lower: systematic review of the evidence yields an efficacy of 62 percent for children under 18 (Manzoli, et al. 2007) and an efficacy of 58 percent for adults over the age of 65 (Govaert, et al. 1994).

Due to constant genetic change in the influenza virus and the relevance of match to efficacy, the influenza vaccine is reformulated each year to account for changes in the antigenic composition of influenza strains. The World Health Organization (WHO) closely monitors circulating influenza viruses across the world and in early spring writes the annual vaccine recipe. The vaccine is constructed to target the most virulent strains in circulation and includes two subtypes of influenza A (H3N2 and H1N1) and one influenza B virus. Usually, one or two of the three virus strains in the vaccine are changed each year and the prescription is identical across the North American continent (WHO 2003).

Each year, Health Canada licenses the newly formulated inactivated influenza

vaccine for use. Once licensed, the Government of Canada, through Public Works and Government Services Canada (PWGSC), purchases influenza vaccines on behalf of the provinces and territories for distribution in late October early November.[5] The turn around period from the yearly WHO recommendation to availability of the vaccine is approximately 6 to 8 months depending on manufacturing conditions (Health Canada 2007).

1.3 *Vaccination Programs in Canada*

Provincial governments make influenza vaccine available at public health clinics and doctor's offices in accordance with provincial immunization programs.[6] Beginning in the early 1990s, all provinces developed programs covering the cost of vaccination for specific "high-risk" groups. The standard covered group included recipients less than 24 months or older than 65 years, health care support staff, residents in care homes, and those with specific chronic conditions (Gao 2004).[7] Aside from minor changes to provincial programs, and with the exception of Ontario, immunization targeting remained the same across all provinces for the next two decades.[8] The provinces have otherwise similar health care systems, per capita health expenditures, physician numbers and health resources (IHE 2008).

In July of 2000, the Government of Ontario announced the extension of vaccination coverage to all residents of the province through what it called the Universal Influenza Immunization Campaign. The campaign was only one part of a larger ten-point plan to reduce emergency room wait times (Kurji 2004). The stated objective of the program was to ease pressure on health facilities and

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[5] Administrative data from Ontario OHIP physician billings show that the majority of yearly vaccination takes place before December (Kwong and Manuel 2007). Similarly, survey data from the U.S. (the NPHS 2008) show that 91 percent of vaccinated respondents had received the current influenza vaccine by December.

[6] Government approved influenza vaccines are also available through private market contracts.

[7] Conditions include cardiac or pulmonary disease, asthma, diabetes, renal disease, liver disease, anaemia, HIV, and cancer.

[8] Quebec and New Brunswick made more recent changes to the coverage status of older adults. Quebec added 60 to 65 year olds to the standard covered group in 2001 and New Brunswick formally advertised coverage for ages over 65 in 2002 (CPA 2007, 2003). The change in New Brunswick had no measurable effect on vaccination and due to data constraints in Quebec, this province cannot be included in the analysis (hospitals in Quebec did not submit to the national hospitalization database for the full sample period).

providers, in particular emergency rooms, by decreasing the impact of influenza during the flu-season (MOHLC 2000). Even though the program targeted, by default, healthy younger individuals, it was expected that this would afford protection for high-risk groups with already high rates of vaccination through an externality effect. Secondary objectives of the program were to decrease the economic impact of influenza during flu-season and also to build infrastructure for delivery of influenza or other vaccines in the event of a pandemic (Kurji 2004). In its first year, the program cost $31 million with 6 million vaccines administered (up from 2.1 million in the previous season) (Kurji 2004).[9]

1.4 *Literature on Influenza Immunization*

The impact of influenza vaccination on respiratory infection and mortality is a key issue in developing recommendations for the use of vaccines, and is valuable information for public health agencies that are unwilling to invest in programs that do not yield adequate benefits. Previous estimates of the impact of vaccination did not support policies of immunizing younger individuals outside of certain high-risk groups. For instance, based on meta-analysis of several randomized evaluations, Demicheli (2001) claims that the benefits to vaccinating healthy adults are small and "at odds with the conclusions reported in previous meta-analysis of evidence for the effect of immunization on elderly people, which showed greater clinical effectiveness, thus supporting the present worldwide policy of vaccinating only elderly people and other high-risk groups." Further to this, more recent surveys of cost benefit analysis indicate that evidence on the efficiency of vaccinating healthy adults or children continues to be mixed with no uniform prescription on the validity of recommending vaccination for these groups (CDC 2007-2010; Nichol 2003, 2008).

[9] Overall, the total program cost is a small portion of the overall health care budget of more than $30 billion annually. Furthermore, program funding is independent of hospital and physician budgets, which are determined separately through funding formulas and negotiations with the Ontario Medical Association.

Yet evidence from these studies suffers several shortcomings that may lead to incorrect conclusions as to the benefits of vaccination, particularly as it applies to a broad based policy on immunization. First, study design in existing randomized evaluations is typically defined over one flu-season for a particular group (workers at a firm, patients of a clinic, residents of a nursing home, *et cetera*). This makes it difficult to compare results across studies and has lead to inconclusive evidence on the impact of vaccination and the associated benefits for different groups. Furthermore, from the diversity in estimates and the specificity of the chosen sample, it is then unclear how these results extrapolate to a generalized population. This is an important point when considering the fact that public campaigns are almost never designed to randomize vaccination among the population, but are instead often targeted and optional. If there is heterogeneity in the effect of vaccination then an optional public campaign may deliver different results when compared to a randomized design. Finally, since these studies typically isolate only one flu-season, they cannot adequately account for the role of the influenza vaccine match, which impacts the estimated benefits of vaccination systematically.

A second, possibly more important issue is that previous estimates are likely contaminated by treatment spillovers from the treated group to the control group. Specifically, these studies often randomize vaccination within a chosen sample and compare outcomes of treated and untreated groups. However, such methods fail to deal with external benefits for the untreated group that accrue from vaccination of the treated, which may be large if the sample is chosen from, for instance, a specific locale or workplace.[10] Furthermore, such externalities do not merely have implications for estimation, but likely drive declining returns depending on overall immunization. This can lead to diverse results depending on

[10] This difficulty has been shown in other contexts. See, for instance Philipson 2000b for a general discussion and Miguel and Kremer 2004 for a discussion within the context of intestinal helminthes and deworming interventions.

the local immunization levels and compositional characteristics of take-up.

If such externalities exist, evidence that fails to account for such spillovers will incorrectly estimate the effect of the vaccine. This is particularly a problem when establishing evidence based public health recommendations because the true impact of vaccination will always be understated if the untreated group experiences a decrease in illness due to treatment externalities (both within the experimental design and from the overall local immunization level) and thus, estimates would cause one to conclude that vaccination is less beneficial than its true measure. It may be on these grounds that other jurisdictions had developed recommendations that were far more limited in scope than the UIIC. The program, itself, was one of the first to recommend and provide the vaccine to all groups on an annual basis and, in fact a main criticism of the campaign was that it was not evidence based: estimates did not support a policy of mass immunization.

2 Identification Strategy

The purpose of the empirical work is to study the links between immunization and health by identifying the impact of vaccination delivered through a broad scope campaign. To start, the following model links underlying vaccination to health (broadly defined) with linear and homogenous effects in vaccination:[11]

$$h_{jt} = \alpha + \beta m_{jt} v_{jt} + X_{jt}\Pi + \varepsilon_{jt} \quad (1)$$

Here, h_{jt} is a health measure for region j at time t; m_{jt} reflects vaccine quality and is measured as the match rate between the vaccine and circulating influenza strains; v_{jt} is the vaccination rate; X_{jt} is a vector of controls, and ε_{jt} is the error term. Both own and external effects of vaccination are subsumed in β, which represents the total effect of changes in average vaccination, scaled by vaccine

[11] While the assumptions of linearity and homogeneity are likely too restrictive in the current context, the following is used as a baseline model to describe core estimation issues before exploring the implications of nonlinearity and heterogeneity.

quality, in region *j* at time *t*.[12]

Because β captures both the individual and external effects of vaccination, its magnitude is of interest to policy makers hoping to recoup societal benefits through increased immunization rates. However, estimation of β using variation in vaccination rates over region and time presents a number of potential challenges. For instance, while higher vaccination rates may lead to better health, it may also be the case that poorer health could lead to higher vaccination rates. This association between poor health and take-up of vaccination may mitigate the estimated relationship described by β and would bias estimates of the effect of vaccination downward.[13] Additionally, there may be other sources of selection that contribute to region-by-year variation in vaccination rates. For example, variation in incidence of other infectious diseases (colds, other respiratory viruses, *et cetera*) may be correlated with selection into vaccination and also associated with health outcomes. In this case, the positive association between vaccination and health would be mitigated by this correlated effect. Furthermore, vaccination, itself, may be associated with other behaviors that affect health. For instance, hand washing or other prevention methods may increase after receiving the vaccine. If, for instance, a higher vaccination rate is associated with increased exposure to prevention information and increased prevention behaviors, then rates of illness may be lower regardless of receipt of the shot. If such an effect is not

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[12] Here, β is a function of the individual and external effects of vaccination obtained from an individual model:

$$h_{ijt} = \alpha + \delta m_{jt} v_{ijt} + \gamma m_{jt} v_{(i)jt} + X_{ijt}\Pi + \varepsilon_{ijt}$$

In the individual model, the coefficient δ captures the individual effect of vaccination (denoted v_{ijt}) from person i's vaccination decision, and the coefficient γ captures the effect of average vaccination excluding person *i* (denoted $v_{(i)jt}$). In other words, it is the external effect of vaccination on the illness of person *i* arising from the vaccination behavior of others. The *total effect* of vaccination is recoverable when averaging the individual model over region and time.

[13] In fact, the data show that this is a probable concern. Comparing vaccinated and unvaccinated groups; the data show a counterintuitive connection between vaccination and health during the summer season where the vaccine is unlikely to causally impact health. Specifically, in the summer months where influenza is not in circulation, the rate of recent short-term illness for vaccinated individuals is 16 percent higher than that of unvaccinated individuals. This finding likely demonstrates selection into vaccination where those in poorer health or with higher infection probabilities are more likely to vaccinate, but are also more likely to experience negative health shocks.

delivered through vaccination itself, but instead through an advertising effect regarding the upcoming flu-season, this has separate implications for policy, especially considering inoculation costs associated with vaccine manufacturing, in addition to costs associated with time loss and personal discomfort.

In the present study, there are several factors that contribute to identification of the effect of a broad scope immunization program. The first factor is time-region variation in a campaign that delivers vaccines free of charge to all age groups. Here, the initiation of the campaign was unlikely motivated by higher levels of influenza in Ontario. Evidence indicates that, if anything, Ontario had marginally lower baseline surveillance rates of influenza and influenza hospitalizations. The second factor is that in different years and across provinces, there are different degrees of match between the vaccine and influenza. Furthermore, these mismatches are determined by random mutations in influenza as they relate to yearly vaccine content, which is predetermined and fixed across North America and over each year. This means that, unknown to the recipient at the time of vaccination, the vaccine may offer a high degree of protection or it may offer a marginal degree of protection. Accordingly, areas with higher levels of vaccination will experience greater benefits if the vaccine is a good match and smaller benefits when it is not.

These factors combined form the basis for disentangling other differential trends in health from the causal impact of the immunization campaign. For instance, aspects such as underlying differences in labor conditions, the supply of hospital services, and sentiment toward prevention behavior may evolve differentially over time and across region. Without considering the impact of these alternate, often unobservable, drivers of health, estimates of the value of immunization programming can be either under or over-valued depending on underlying

trends.[14] Given that results are sensitive to these underlying trends, the methodology used here explicitly controls for agnostic differences in health accruing to UIIC regions post-program and identifies the impact of immunization by using exogenous variation in vaccine quality. This suggests the following reduced form model:

$$
\begin{aligned}
y_{ajt} &= \beta_1(UIIC_p * Post_y * m_{py}) \\
&+\beta_2(UIIC_p * Post_y) + \beta_3(Post_y * m_{py}) + \beta_4(UIIC_p * m_{py}) \\
&+X_{jt}\Pi + u_{ajt}
\end{aligned} \tag{2}
$$

where y_{ajt} is an illness outcome for age group a in region j at week t; $UIIC_p$ is an indicator for regions in Ontario; $Post_y$ is an indicator for flu season-years after 2000; and m_{py} is the clinical match rate in province p in flu season-year y. The vector X_{jt} includes a set of controls for: public health expenditures on health care (hospitals, capital, physicians and other health professionals); diagnosis specific coding classification changes; the match rate in levels; and age, region, season-year and month fixed effects.[15] The variable u_{ajt} is an error term.

Inclusion of region effects captures fixed features among economic-regions, and will account for unobservable region differences that are common across all seasons and all age groups.[16] Similarly, by controlling for season and age effects, the model in (2) accounts for any fixed differences across seasons, and fixed differences across age groups. To account for any confounding differences among

[14] For instance, Groll and Thompson (2006) find that there is a small relative *increase* in surveillance counts of laboratory-confirmed influenza for Ontario compared to other provinces at the introduction of the universal program. Meanwhile, Kwong (2005), using time variation in hospital counts, finds little relative impact for influenza hospitalization for Ontario post-program. Alternatively, using a similar methodology but extending the yearly time series, Kwong et. al. (2008) find relative decreases in death, hospitalization, and emergency room visits at the introduction of the campaign. The counter-intuitive results in Groll and Thompson (2006) are likely explained by the steeper upward trend in surveillance testing in Ontario relative to the other provinces. Similarly, the results in Kwong (2005) and Kwong et. al. (2008) could suffer from differential trends in health resources that widen over time. For instance, over this period, the number of *non-respiratory* admissions declined by 1 percent in Ontario, but declined by half as much in other provinces (CIHI-HMDB).

[15] Where labor force survey data is used, the unit of analysis is at the individual-region-week level, and additional controls include education, occupation, marital status, and union status.

[16] Economic regions (ERs) refer to standard geographic areas defined at the sub-provincial level. ERs are meant to capture localized economic activity in and around major cities.

UIIC regions in the post-period, the coefficient β_2 directly captures unobservable post-period differences in illness accruing to Ontario. The model also includes careful accounting for the baseline effects of the vaccine match to allow for the possibility that, among strains of differing severity, the vaccine selection process gives rise to a direct relationship between illness outcomes and the match rate (i.e. regardless of vaccination). To account for this possibility, the model includes the vaccine match in levels, to control for the direct effect of the vaccine match on illness. Furthermore, the coefficient β_3 captures differences in the effect of the vaccine match post 2000 and hence controls for gains in the effect of the match that are common to all provinces. Finally, the coefficient β_4 captures baseline differences in the effect of the match that are different in UIIC versus non-UIIC regions. After controlling for these factors and the remaining factors in X_{jt}, the coefficient β_1 summarizes the post-period difference in the effect of the match for UIIC regions, and captures the gain in health in good match years that is explained by increased vaccination following the immunization campaign.

2.1 *Decreasing Returns*

The research design in Equation (2) can be modified to capture decreasing returns to vaccination, which necessarily occur if externality benefits decline as immunization levels rise. To address this aspect of immunization programming, I use variability in baseline average vaccination among regions. Since there is very little between-variation in the post-program immunization change for UIIC regions, post-program vaccination levels are heavily influenced by baseline vaccination differences. To assess the role that baseline immunization plays in the overall impact of the immunization campaign, the model in (2) is modified to include interactions between baseline vaccination and all innovations of *UIIC, Post,* and *m*. Expressly:

$$y_{ajt} = \beta_1[UIIC_p * Post_y * m_{py}] + \delta_1[UIIC_p * Post_y * m_{py} * (preV_j - \overline{preV})] + \text{other interactions and controls} + \upsilon_{ajt} \quad (3)$$

Here, $preV_j$ is the pre-2000 vaccination rate in region *j,* demeaned by the overall average baseline vaccination rate. The coefficient β_4 is interpreted as the program match effect at the baseline level, whereas δ_4 gives the change in the program match effect at higher baseline immunization rates and estimates the degree to which decreasing returns impact program benefits. This strategy assumes that variability in baseline vaccination is related to post-program differences in health across good match and bad match years solely through decreasing returns to immunization. Specifically, it assumes that the effect does not operate through unobservable characteristics among high and low regions that are otherwise related to future health outcomes. On the other hand, even if underlying factors related to future health outcomes are correlated with differences in baseline vaccination among regions, in order to explain results, such baseline unobservables would also need to be related to future differences in health outcomes for UIIC regions, *and* differences in the way that UIIC regions persist through future good versus bad match flu seasons. Given that future vaccine matches are difficult to predict and the campaign was largely unanticipated, the most likely explanation for UIIC regions with differing baseline starting points to have different relative post-period changes in the effect of vaccine-quality, is through decreasing returns to immunization.

2.2 *Heterogeneity*

Previous evidence on the influenza vaccine provides a biological basis for heterogeneity in the benefit of immunization (CDC 2010). Specifically, since the protection afforded by the vaccine depends on immune response; prevention of illness, conditional on exposure, is dependent on underlying health status. On the other hand, heterogeneity may also arise in the unconditional expected benefit of

infection, causing greater benefits to accrue to those who are: (i) more at-risk for virus exposure, or (ii) more at-risk for severe health costs upon infection. Since a simple model of selection would suggest that those with the largest net-gains from vaccination would be more likely to vaccinate, the results presented here likely capture a specific average effect for the type of individual within the age target induced to vaccinate when recommended to do so and coverage is provided. In particular, results may not reflect experimental estimates where vaccination is randomized. However, since these types of selection issues are likely to take place in a policy setting, this information may be of more use to policy makers than that based on random assignment of vaccine. This will be the case whenever broad policies replicating random assignment are more difficult to implement than polices involving price incentives or promotion of the vaccine. As show in the next section, there is significant and relevant heterogeneity in vaccine take-up after the campaign.

3 Data and Descriptive Statistics

The empirical analysis draws together information on health and economic outcomes, vaccination status, and the seasonal vaccine match. Table 1 contains information on the source and variable descriptions of each data set.

3.1 *Vaccination*

Health survey data from Statistics Canada is used to document the changes in influenza vaccination. Four sequential health surveys contain questions relevant to influenza vaccination in the confidential data holdings maintained by Statistics Canada's Research Data Centers. These are: the National Population Health Survey (NPHS), Cycle 2 1996/1997 and the Canadian Community Health Survey (CCHS), Cycles 1.1 (2000/2001), 2.1 (2003) and 3.1 (2005). Each survey is a national, population-based survey conducted on persons 12 years of age or older. Information includes demographic, socioeconomic and health information, and

current and previous vaccination status. In each survey, the respondent is asked: "Have you ever had a flu shot?" and if the answer is yes, respondents are asked a follow up question: "When was your last flu shot?" Along with survey timing, this information is used to determine the vaccination status of individuals in the current flu season-year, defining the season-year to be the year starting in October and continuing to September of the following year.

Figure 1 shows vaccination rates for UIIC versus non-UIIC regions by age group over time. The figure shows that vaccination increased over 1996 to 2006 for all age groups and indicates that the young have lower vaccination rates than the old over the sample time period. The figure also shows that, while baseline vaccination rates for the young are not substantially different for UIIC versus non-UIIC regions, there are significant gains at program introduction as indicated by the sustained 11-percentage point relative shift in vaccination. The same is not evident in the older age group, where there is no relative change in vaccination at the introduction of the program.

To explore differences in program impact among sub groups, Table 2 gives a summary of vaccination rates pre and post October 2000. The table shows that vaccination rates increase for all regions in the post period; with a 20.9 percentage point increase in UIIC regions and a 12.2 percentage point increase in non-UIIC regions. In relative terms, there is an 8.7 percentage point relative increase in UIIC regions following the program, solely due to the increase of 10.8 percentage points for those under 65. Figure 2 confirms these results, showing that while, on average, UIIC regions have higher baseline levels of vaccination over all age groups (and in particular for those greater than 65), the relative change post-2000 is due solely to those under 65. It is clear from these data that the impact of the program is centered on the age group that was targeted by program incentives.

To better understand the characteristics associated baseline vaccination behavior

and heterogeneity in take-up after the program, the remainder of Table 2 presents summary statistics for ages under 65 by demographic group. As shown, baseline vaccination patterns fall in line with previous research on the determinants of vaccination: females are more likely to vaccinate than males, vaccination increases with education (with the exception of those without secondary education), and decreases time spent working (Mullahy 1999). Underlying health may play a part in explaining these patterns since these factors and health characteristics are likely correlated, and it is evident from the table that there are substantial differences in baseline vaccination for different measures of health. The heterogeneity in vaccination behavior among different groups likely reflects diversity in the expected benefits versus the expected costs of immunization. For instance, those with worse self-rated health may perceive higher net-expected costs of infection relative to the cost of vaccination. Since heterogeneity along this dimension would translate into differences in the benefit of vaccination for those choosing to vaccinate compared to the randomly chosen vaccinated individual, it suggests there are important implications for the expected benefits of a program offering optional vaccine coverage. Here, benefits may be larger than those estimated from a randomized design if take-up is primarily among those who enjoy a greater benefits from vaccinating. In this case, this type of selection would deliver, as a matter of course, more "bang for the buck" than estimates from randomized designs would imply.

Focusing on heterogeneity in vaccine take-up after the universal campaign, the table shows that among those under 65, the relative increase in vaccination for UIIC regions is largest among females, those not in the labor force, and among those with lower income. The relative increase is of similar magnitude regardless of having a covered chronic condition and across the categories of self-rated health. It appears that the UIIC led to larger increases among more financially vulnerable groups, potentially ameliorating the gradient between SES measures

and preventative care for those who are not ill enough to have coverage under the former "high-risk" designation. Overall, the most apparent source of heterogeneity is among age group. Figure 2 confirms that, for those under 65, the highest degree of take-up is among the youngest and oldest groups.

3.2 *Influenza Surveillance*

In order to assess the impact of immunization on health outcomes, I first collect data on influenza surveillance. These data are used for two purposes; the first is to document different influenza strains present in each season and province, and the second is to pinpoint the period throughout the year when influenza is circulating. I define the influenza period in order to further delineate program benefits throughout the year and to demonstrate that these benefits are delivered primarily when the threat of influenza is the greatest.[17] This offers a further specification check since, in order to explain results; any alternate factor would have to differentially impact health in the influenza period *and* occur solely in UIIC regions, in weeks after October 2000, in years with a higher vaccine match.

The surveillance data comprises laboratory confirmed influenza counts available from the PHAC through its respiratory surveillance program. These data consist of weekly tests collected from appointed sentinel physicians in each surveillance region, where each test is then confirmed for presence of influenza or other respiratory disease. Surveillance data are presented graphically in Figure 3. Panel B shows the average laboratory confirmed influenza rate (percent of collected tests that are positive for influenza) and indicates the flu-season period of each year. As a matter of construction, there will be limited laboratory influenza during off-season. The same is not necessarily true for other illness measures such as hospitalizations and illness work absences, which may vary according to other

[17] The influenza period is given as the contained set of weeks starting from the first week the number of positive influenza tests is greater than 5 percent of the season total until the last week it falls below 5 percent. Results are similar to defining the influenza period as any week with positive surveillance tests.

factors related to health. Panel A of Figure 3 indicates the clinical match rate for each season. To define the clinical match rate, I use strain isolation data from the PHAC along with reports on the cross-immunity of the yearly vaccine. All influenza strains observed by the PHAC are identified as matched or not matched to the yearly vaccine by using reports on the cross immunity of circulating influenza strains published each year in the Canadian Communicable Disease Report (CCDR).[18] The match rate is calculated as the proportion of strains that are matched (i.e. have cross immunity) with the current vaccine contents. That is, using the strain-isolated sample of tests, the match rate in province p and flu season-year y is defined as:

$$(4) \quad m_{py} = \frac{\text{number of flu tests collected in } p,y \text{ that match vaccine strains in } y}{\text{total number of flu tests collected in } p,y}$$

Comparing Panel A and B, the pattern between the vaccine match and the incidence of influenza is apparent, showing higher laboratory confirmed influenza when the vaccine is mismatched.

The relationship illustrated likely operates through vaccination behavior. That is, when a matched strain appears, the vaccinated population is protected from infection, whereas when an unmatched strain appears, the vaccinated population remains susceptible. On the other hand, allowing for differing strain severity, the correlation between the match and the flu season may exist regardless of vaccination. For instance, the WHO's choice of strains is not random, but is driven by point-in-time forecasts of the future harm of circulating strains, where harm is informed by both the predicted severity of each strain and the perceived probability that each strain will appear.[19] If more probable strains are also more severe and the WHO chooses based on expected severity, then the choice will

[18] These findings correspond to reports made by the U.S. Center of Disease Control and the vaccine recipe from the WHO.
[19] For more information on selection see: http://www.cdc.gov/flu/about/qa/vaccine-selection.htm (access Jun 25, 2011) or http://www.who.int/csr/disease/influenza/influenzanetwork/vaccinerecommendations/en/index.html (access Jun 25, 2011).

more likely result in a match when the upcoming influenza strain is more severe. This would drive a relationship between the match and the severity of the flu season regardless of vaccination, and, in the case where no-one is vaccinated, what would be a "match" is more likely to occur in a more severe flu-season.

On the other hand, this process relies on accurate forecasting of strain likelihood and severity in early spring, and selection relies on known strains at that time. Meanwhile, new strain threats may occur while manufacturing is underway or after it is complete. In short, it may be difficult to operate a policy to maximize the "true" probability of future strains, since information is restricted to speculative apriori probabilities of known strains.

Because the existence of a direct relationship between the match and the flu-season is not directly testable, the empirical strategy is structured to explicitly account for this possibility. First, the base specification includes direct controls for the level effect of the vaccine match. Second, it allows for baseline differences in the impact of the match in the post period and baseline differences in the impact among UIIC regions. Consequently, this methodology disentangles the relative change in the effect of the vaccine match that accrues to UIIC regions post-adoption. Since the prescription for vaccine selection is the same across North America, the primary explanation for the change in the effect of the match in post-period UIIC regions is through increased immunization.

A final threat to identification involves the assumption that the yearly vaccine match is exogenous to the decision to vaccinate. To explore this relationship, Table 3 gives the estimated impact of the match rate on vaccination status. Results indicate that there is little relationship between the current yearly match rate and current vaccination status, both overall and within the subgroups shown. For instance, in general, the estimated effect of a 1-percentage point increase in the match rate is associated with a statistically *insignificant* 0.0015 percentage point

decrease in the likelihood of vaccination. Furthermore, last year's match rate shows little predictive power for current vaccination.

3.3 *Health Outcomes*

Data on health outcomes is gathered from hospital administrative records and monthly labor force surveys. Hospital records are obtained from the Hospital Morbidity Database (HMDB) holdings of the Canadian Institute for Health Information. The HMDB includes complete records of inpatient discharges for hospitals in Canada.[20] Each discharge abstract consists of information on patient age, sex and home postal code as well as detailed medical information including: date of hospital admittance and discharge, discharge disposition (i.e. living or deceased), and detailed diagnosis information. Each abstract reports one diagnosis labeled the most responsible diagnosis (MRD) and up to 15 co-diagnoses.

The HMDB is used to construct weekly hospitalization rates for economic regions in Canada. Each economic region (ER) is a standard geographic region defined by Statistics Canada and is made up of a group of adjacent census divisions meant to characterize regional economic activity. Focusing on ERs as opposed to census metropolitan areas (CMAs) has the advantage of covering the entire Canadian geography, both within and surrounding CMAs. Furthermore, it allows for control of fixed unobservable differences between well-defined regions, where region boundaries are set to capture localized economic activity, and likely track patterns of influenza transmission. Illness measures are assigned to each of 58 ERs based on patient postal code of residence.

Additionally, the monthly Labor Force Survey (LFS) is used to investigate effects for labor productivity. The LFS collects monthly information on the labor market and demographic variables for household members 15 years of age and older.

[20] Hospitals in Quebec and non-Winnipeg Manitoba started submitting to the HMDB after 2001 and are consequently excluded from the analysis.

Demographic characteristics include age, sex, marital status, educational attainment, and family characteristics. Labor force characteristics include employment information such as usual hours of work, and work absences in a reference week. Work absences are defined as "due to own illness".

Individual characteristics for work absences and hospitalizations are summarized in Table 4. The table indicates that work absences are more likely to occur among younger workers and among females, relative to those that do not report a work absence. Similarly, hospitalizations with a diagnosis of influenza are more likely to occur among younger age groups and among females when compared to non-respiratory admissions. Influenza hospitalizations are shorter than non-respiratory admissions, while pneumonia admissions (a common complication of influenza) are of longer duration than other admissions, lasting on average 12 days and likely reflecting respiratory infections of a more serious nature. For instance, pneumonia admissions are more likely to occur among older age groups and among residents of a residential care facility. These admissions also show a higher in-hospital death rate of 14.1 percent.

In order to explore patterns in health for different periods and over provinces, Table 5 shows weekly incidence rates for economic regions within different sub-groups. Here, the data show a visible pattern in health measures over different periods during the flu-season. For influenza, pneumonia and work absences, there are higher rates in the same weeks that that influenza surveillance rates are highest. Rates for influenza, pneumonia and work absences are also higher in seasons with a mis-match vaccine. The statistics show that for Ontario, hospital admissions are lower, while work absences are higher. Further, across all regions in the post-period, admissions decreased, while work absences rose (less so in matched seasons, however).

4 Results

4.1 *Main Results*

To investigate the patterns in illness further, I start by presenting a month-by-month comparison of the relative post-period change in illness in UIIC regions. The top panel of Figure 3 shows this comparison for flu-seasons where at least one mismatch strain is observed, while the bottom panel shows the same comparison isolating only those seasons where no mismatched strain is observed. From the top panel, it appears that there is very little relative decrease in illness for UIIC regions. The difference-in-difference estimates for each month are close to zero with a slight decline during the typical flu-season running from December to March. The small relative changes in illness are striking when considering the substantial relative increases in vaccination, and that vaccine match rates among the mismatch seasons remain relatively high at an average 52 percent. However, without further assumptions about the relative trends in illness among regions, interpretation of these results as the true impact of the immunization campaign may not provide an accurate depiction of program benefits, which may be either larger or smaller than indicated. For instance, unobservable trends in labor conditions, the supply of hospital services, or sentiment towards disease prevention are just some of the factors that may have changed differentially across UIIC and non-UIIC regions. Because of this, difference-in-difference comparisons may be a combination of the true impact and other correlated factors that change over region in the post program period.

A more compelling depiction of the impact of the immunization campaign is the comparison of estimates between the top and bottom panels of Figure 3. Compared to low-quality match years, the relative change in illness for UIIC regions in high quality match years is most favorable during the typical flu-season period. Considered separately, the estimates displayed in each panel cannot be

disentangled from alternative unobservable trends. On the other hand, to explain the difference in results *between* the two panels, any alternative factor would have to appear primarily in the December-March period, primarily in UIIC regions post-program, and primarily when the vaccine is well matched (an event that is largely unpredictable).

While these figures show suggestive patterns by vaccine quality and month, overall changes in illness can be more flexibly modeled by estimating Equation (2), which fully exploits variability in the match rate across season and province, and can be adjusted to capture differences in the timing of the flu-season year-to-year. I formalize this by estimating (2) and examining the variable of interest, UIIC*Post*M. Panel A of Table 6 displays the coefficient for UIIC*Post*M for different periods during the season. Base results show a substantial effect on influenza admissions throughout the flu-season. The largest effect occurs in the season start to peak, with a smaller effect during the season end. During the season start to peak, the coefficient on UIIC*Post*M is -2.8 per week per 100,000 and the effect is -2.4 at the season end. There is little effect in the flu off-season: the point estimate is small and insignificant. These results indicate that a good vaccine match combined with the UIIC leads to further relative decreases in hospitalizations. Using numbers for the season start to peak, results imply that relative to the average match, a high match leads to an additional gain of 0.9 less hospitalizations per week per 100,000 following the immunization campaign (the mean vaccine match rate is 71 percent). In the season end, there is a gain of 0.7 less hospitalization per week. In the influenza off-season there is no gain arising from the immunization campaign. Comparing these results to baseline average incidence indicates that the gains from a high match after UIIC adoption are large. For instance, estimates for influenza hospitalization, which has a high specificity for influenza, point to near elimination of the flu season.

Table 6 also shows results for pneumonia admissions, a frequent complication of

influenza and a common diagnosis for an influenza infection of a more serious nature. These results are in column (4) of Table 6. Effects for pneumonia are smaller relative to baseline levels but significant decreases exist for UIIC regions when the vaccine is a match. In the season start to end and relative to an average match, a perfect match averts 1.4 hospitalizations, and, again, the magnitude of the effect follows the seasonal pattern of influenza; the largest effects occur during the flu-season with little effect in the off-season. Note that this is not by construction: except through the effects of the influenza and the vaccine itself, there is little reason why the patterns for pneumonia admissions should systematically follow the surveillance patterns of laboratory influenza counts.

Work illness absences also exhibit a seasonal pattern following the typical flu season, and Column (2) confirms that the immunization program ameliorates this seasonality in work absences. In the base specification, good vaccine years post-program are associated with less work illness. Moreover, this is specific to the flu season periods of the year. In the season start to peak, there was a 0.5 percentage point decrease in worker illness. From a base of 2.7 percent this represents a 19 percent decrease when the vaccine is a perfect match and implies that relative to the average match rate, a perfect match decreases worker absences by 0.2 percentage points (7 percent relative to base).[21]

To test whether estimates are sensitive to a potential behavioral response to predicting or learning the match rate, I present results in Panel B that control for changes in circulation of other infectious disease. If individuals can accurately predict or learn the match for each season and residents of UIIC regions are even better able or more responsive to these predictions after the immunization

[21] Other health outcomes from health survey data show similar results. For instance, during flu-season, a good match vaccine decreases medications for cold/flu by 10.2 percentage points for UIIC relative to non-UIIC regions (interestingly, there is no impact, positive or negative, on the use of antibiotics). Secondly, over the full sample, there is a 3.0 percentage point fall in the rate of being in bed ill in the flu-season period. In contrast, the effect for workers is 0.54 percentage points, which is similar to the overall flu-season effect found from the LFS survey of 0.59 percentage points. Lastly, there is a 6.8 percentage point decrease in laboratory confirmed influenza rate. Full results are shown in appendix Table A1.

campaign, then it may bias results. In this case, in a bad match year, individuals can potentially compensate through other protective behaviors such as washing hands, implying that if UIIC residents are more responsive specific to the introduction of the campaign, then results will be underestimated. To assess whether this is the case, I use data on surveillance rates of other infectious disease collected by the PHAC. The diseases included are respiratory syncytial virus, parainfluenza, and adenovirus. These diseases are non-vaccine preventable respiratory viruses that are infectious through the same manner as influenza with similar symptoms. If compensatory behavior impacting influenza circulation does exist in the manner described, then this behavior will also impact circulation of other infectious disease. In order to test this, I control for disease surveillance for other infectious disease and compare results to previous estimates. Panel B shows that point estimates are somewhat larger (in absolute terms), but the difference is negligible (in magnitude and significance). These results support the supposition that individuals are unable to predict and adjust behavior according to the match rate, and to a higher degree after the immunization campaign.

4.2 *Impact on Lost Time to Illness*

Table 7 shows that the program match effect on time-spent ill is mainly due to decreased absences rather than due to shorter hours spent ill per illness. Furthermore, the decrease in the number of hospital days per 100,000 is mainly due to fewer hospitalizations since average hospital length of stay increased only marginally. There are decreases in time spent waiting in the ER before admittance to acute care, although these results are not statistically significant.[22] Lastly, there are large effects for death; relative to the average match, a perfect match after the immunization campaign delayed 0.04 deaths per week for influenza and 0.17

[22] The results for emergency room wait time are around the same magnitude (10 minute decrease) for other types of hospital admissions, possibly indicating a slackening of resource constraints across the board. Approximately 60 percent of all hospital admissions are admitted through the ER.

deaths per week from pneumonia. This represents a gain of almost 2 fewer deaths per 100,000 per season.

4.3 *Impact on Respiratory Versus Non-respiratory Admissions*

Influenza is known to cause complications for a number of diseases, such as heart, chronic respiratory, cancer, and diseases of the nervous system. To analyze the impact of the vaccine program on these diseases, I divide the admissions data into two categories: hospitalizations that contain a co-diagnosis of respiratory disease and hospitalizations that do not. Panel A in Table 8 shows results for respiratory diagnoses of any type and indicates that respiratory hospitalizations are sensitive to the post program match effect. For instance, the average rate of hospitalization for respiratory disease is 32.2 per week during the flu season and is 24.8 in off-season. Meanwhile, during the flu season, the program match effect is a decrease of 9.6 respiratory hospitalizations over and above non-UIIC regions, and the effect is small and statistically insignificant from zero in the off-season. Similar patterns emerge for heart, metal, and nervous system diseases. On the other hand, there is no effect on cancer admissions in either the flu-season or off-season, which may indicate a level of vigilance against infection that is unaffected by the UIIC. Panel B reports results for hospitalizations that do not have a contributory diagnosis of respiratory disease. Here there are no visible patterns among diseases both during flu-season and off-season: all point estimates are small relative to the mean and indistinguishable from zero. This has two implications. First, there are no observable differences in patterns of health that are not associated with the influenza or influenza complications. This further indicates that findings are not explained by a secondary factor related to general health, since such a factor, correlated with the vaccine match specific to the time and place of the introduction of the immunization program, would likely manifest in other measures of health. Conversely, the evidence shown here indicates that the impact of the program is specific to influenza and its complications and moreover,

follows the timing of elevated circulation of influenza. Secondly, there seems to be no evidence that the vaccine program decreases crowd out of other disease admissions in any statistically significant way.

4.4 *Externality Effect for Older Adults*

Figure 5 shows the program match effect over the full age distribution for combined influenza and pneumonia admissions. The decline in hospitalization for ages over 65 is substantial, rising from 10 to 50 fewer admissions (per week, per 100,000) over the older age range.[23] Moreover such decreases appear primarily during the flu-season with little effect in the off-season. These results contrast those shown for older adults in the bottom panel of Figure 5, which indicate little relative difference in vaccination for UIIC regions. If older groups are unaffected by the vaccination of others, then program benefits should follow the same pattern as relative changes in vaccination behavior. However, even where relative vaccination levels have marginally *decreased,* there are large program benefits for these older age groups. Furthermore, these large external benefits appear in spite of higher baseline immunization levels among UIIC regions (as shown in Figure 2). For instance, if there are decreasing returns to vaccination, then separate groups may experience similar increases in vaccination but expect different gains in health, given baseline levels. Since baseline vaccination levels for older adults are higher in UIIC regions, under decreasing returns, this should lead to smaller relative gains. On the other hand, estimates point to large relative gains for older adults in UIIC regions, indicating substantial external benefits from increased vaccination in younger groups (benefits that may have been even greater had baseline rates been more comparable).

Given overall results, large external benefits for older age groups are not

[23] Not only are the effects for those over 65 large in number, they are large relative to baseline incidence rates. Appendix Table A2 shows decreases of 81.0, 39.6, and 40.0 percent for influenza, pneumonia, and work absences, respectively.

surprising in this context. First, on biological grounds, older adults are less protected by vaccination due to reduced immune response (CDC 2010; Jefferson et al. 2007). This implies that even with high vaccination rates, older adults may still experience high illness rates when the influenza virus is circulating. Secondly, overall results of the UIIC program suggest that influenza epidemics are greatly diminished in high match seasons. Combining this result with the biological aspects of immunization among older adults, suggests that benefits for this group should be large. [24]

Figure 5 also indicates that young children have much to gain from the UIIC. Since underlying vaccination behavior for young children is not available in health survey data, it is not possible to disentangle the direct benefits due to immunization of young children from external benefits accruing from vaccination of older groups. However, total benefits from rollout of the UIIC are shown to be most substantial among the very young. Furthermore, relative to baseline rates, this type of hospital admission was largely eliminated among those under 10.[25]

4.5 *The UIIC and Decreasing Returns*

There is substantive reason to argue that returns to immunization decrease as immunization levels rise. For instance, previous literature indicates that, based on approximations of the transmission rate and duration rate of influenza, an infected individual mixing in a wholly unvaccinated population, would, on average, infect 1.44 others before recovery (Boulier et. al. 2007; Hethcote 2000). Using this "contact rate" within a standard model of disease dynamics implies that a vaccination rate greater than 31 percent would reduce the average infection

[24] The results for nursing home residents show further support for this argument (shown in Appendix Table A2). Vaccination rates for this population have been in excess of 90 percent since the 1990s (Clement and D'Cunha 2002; Russell 2001). Meanwhile, results show that during the flu-season, admissions of this type were nearly eliminated post-UIIC in high quality-vaccine years.
[25] These point estimates are shown in appendix Table A2. Further results using health survey data on recent bed illness and consumption of cold/flu medication support the age patterns found for work absences and hospitalizations: effects are largest for the youngest and oldest, with modest effects for those ages 25 to 64. These results are shown in appendix Table A1.

number to below one, assuming a fully protective vaccine.[26] Since an average infection rate below one will prevent an influenza epidemic (i.e. an infection less than replaces itself), it suggests that benefits from immunization beyond 31 percent would fall to zero.

The model described in Section 2.1 explores this possibility by allowing the program match effect to depend on baseline immunization levels. Results from this analysis are presented in Table 9, where Panel A shows results for the base specification and Panel B shows results allowing for the interaction of baseline immunization among region. Panel A confirms that in high match seasons, the UIIC delivers substantial additional health benefits. This is particularly among influenza hospitalizations, which has a high specificity for influenza and indicates that influenza epidemics are substantially diminished. The results in Panel B confirm the results in Panel A and further show that there are decreasing returns depending on baseline immunization starting points. Specifically, the results for UIIC*Post2000*Match show the effect at average baseline levels across region, whereas the results for the baseline interaction term indicate a decline in the impact of UIIC*Post2000*Match as baseline rates rise. The baseline rates where the program match effect would be zero are shown at the bottom of the table.[27] The numbers indicate that a region starting with vaccination rates around 25-31 percent would enjoy little additional gain from a high match vaccine under UIIC. On the other hand, based on the average starting point of 18 percent, the expected effect of the immunization program delivering a vaccine of full protective value

[26] This model is based on the Kermack and McKendrick Susceptible-Infective-Removed (SIR) model of disease epidemics. Several variations of the model are shown in: Kremer and Snyder (2006), Geoffard and Philipson (1997), Francis (1997, 2004) and Boulier, et al. (2007). Using the contact number of 1.44, the dynamics of this model imply that the average number of infections occurring from 1 infection will fall to one when at most 69 percent of the population is susceptible to influenza (i.e. 1.44*0.69=1). In other words, to prevent an epidemic, the SIR model implies that more than 31 percent of the population would need to be vaccinated (with a high match vaccine).

[27] Using the parameters in Equation (3), these rates are calculated by setting $\beta_1+\delta_1*(preV-0.182)$ equal to zero. This implies that the program match effect is zero when baseline rates equal: $\beta_1/\delta_1+ 0.182$.

should be large relative to baseline incidence rates, especially when programming leads to immunization rates in excess of 30 percent.

5 Interpretation

These results suggest that immunization leads to substantial benefits in terms of hospitalization and lost work costs. For instance, estimates indicate that 9.6 respiratory hospitalizations per 100,000 are prevented per week during the flu-season. Over the population of Ontario, this is a savings of 1,245 admissions per week. The length of the average flu-season is 9.4 weeks and the cost of an average respiratory hospitalization is $8,629 (CIHI 2008). A back of the envelope calculation indicates a savings of $101m when the match is high. At the average match rate of 71 percent, this represents a savings of $72m. For illness absences, estimates indicate a 0.6 percentage point decrease in work absences. Over the working population of Ontario, this is a savings of 47,400 work absences per week. At an average hourly wage of $18 and average absence duration of 9.1 hours this translates into $73m in savings per season for Ontario in high match years ($52m at the average match). These savings are less than programming costs, which represent an average $19m in additional administration costs and an extra $14m in vaccine costs for a total additional cost of $33m per season.

6 Conclusion

This paper illustrates the role of externality effects in immunization behavior. Principally, where externalities exist, the limitations of previous evidence to address these externalities manifests along two dimensions: (i) violation of the exclusion restriction in standard experimental design and, (ii) failure to recognize systematic differences in overall benefits depending on the level and composition of local immunization. Evidence that overlooks these aspects can lead health authorities to set immunization policies well before full benefits are recouped, and, furthermore, to neglect the implications of policies set within the context of

differing underlying immunization levels. For instance, previous literature indicates mixed evidence on the benefit of vaccinating younger adults, but largely ignores estimation spillovers and is silent on how benefits depend on local immunization levels and compositional take-up.

This paper addresses these aspects by studying a novel immunization program expanding vaccination coverage outside the standard target group. Within this context, evidence demonstrates significant overall and external gains of immunization, and shows that these gains decline to exhaustion depending on local immunization levels. First, overall benefits under UIIC are substantial, centering primarily on children and older adults. Second, there is direct evidence of external benefits for those over 65 arising from increased vaccination of younger groups. In terms of the UIIC, the gains in vaccination occurred at the most effective range possible. Overall, vaccination rose from an average of 20.9 percent to 41.4 percent, and evidence suggests that gains from further increases in vaccination would be small.

Heterogeneity in vaccine take-up is material to the interpretation of these results, and where heterogeneity exists, the implications of evidence acquired from randomized design may be limited, particularly where policy cannot easily replicate random assignment. Importantly, the nature of the UIIC program generates significant differences in take-up across age groups. This is partly by design, given previous immunization policy for older groups, but is also apparent for those under 65.

Heterogeneity of this nature has direct implications for overall expected benefits. For instance, holding the local vaccination rate constant, overall benefits may differ under scenarios where different groups are targeted and heterogeneous choice occurs within group. Specifically, immunization policies, informed by previous evidence, focused on maximizing the immunization of those over the age

of 65. The results presented here show that, even with immunization rates for older adults at levels in excess of 60 percent, there is still room for substantial gains. Recognizing the role for heterogeneity and externalities in overall immunization benefits may shed light on the effectiveness of this particular policy target. In particular, evidence indicates that the UIIC program is an effective tool to deliver benefits to older adults, demonstrating that large gains accrue from: (i) heterogeneity in the effect of immunization for younger groups, combined with (ii) further amplified external benefits delivered by younger groups. Importantly, since differences in cost effectiveness calculations between the young and the old may reflect, primarily, differences in treatment cost upon infection (which run opposite the immune protection afforded by the vaccine), ignoring external benefits delivered from young to old can severely undervalue the overall cost effectiveness of vaccination of the young.

Since the evidence presented demonstrates the important role of heterogeneity and externalities in the expected impact of immunization programs, it suggests that future research might benefit from a more explicit approach to assessing the implications of these aspects, both in terms of estimation (i.e. addressing treatment spillovers) and in overall policy design (i.e. understanding how benefits depend on the local immunization rate and compositional take-up). In particular, the UIIC program is one of expansion of recommendations and coverage outside the typical target group, which is still in use elsewhere. Furthermore, evidence presented is shown to depend on compositional take-up among younger groups, and external benefits delivered within the context of the local immunization rate. Within this policy context, results indicate that program expansion leads to substantial decreases in illness, which aside from direct and indirect benefits to individuals, delivers large relative cost savings to the publicly financed health care system.

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TABLE 1

Summary of Data Sources

Data source	Variables
Statistics Canada: NPHS Cycles 1 - 6, CCHS Cycles 1.1, 2.1, 3.1	- Vaccination status - In bed due to illness last 2 weeks - Over the counter cold/ flu medicines
Public Health Agency of Canada	- Laboratory confirmed influenza - Strain isolation of influenza subtypes
Canadian Communicable Disease Report*	- Antigenic match of influenza vaccine
Statistics Canada: Labor Force Survey	- Labour force absences
CIHI: Hospital Morbidity Database**	- Hospitalizations discharge abstracts
CIHI: National Health Expenditure Database	- Public health expenditure
CIHI: Canadian MIS Database	- Hospital bed counts
Statistics Canada: Population and Demography	- Population counts
Statistics Canada: Residential Care Facilities Survey	- Population in care facilities

Note: NPHS = National Population Health Survey, CCHS = Canadian Community Health Survey, CIHI = Canadian Institute for Health Information

* Confirmed using data from the Center for Disease Control in the U.S. and the World Health Organization

** Quebec and rural Manitoba not included

TABLE 2
Influenza Vaccination Rates by Selected Characteristic

	UIIC			non-UIIC			Relative change	Std. error
	Pre	Post	Change	Pre	Post	Change		
Full sample								
Average vacc. rate	0.208	0.417	0.209	0.170	0.291	0.122	0.087	0.023
Between ER Std. Dev.	0.021	0.032	0.017	0.018	0.031	0.019		
Average rate by age group								
Under 65	0.120	0.333	0.213	0.092	0.197	0.105	0.108	0.005
65 and over	0.609	0.737	0.128	0.521	0.645	0.124	0.004	0.029
Average rate by demographic characteristic and health status for under 65 group								
Male	0.111	0.292	0.181	0.076	0.169	0.093	0.088	0.021
Female	0.128	0.369	0.241	0.107	0.222	0.115	0.127	0.023
No secondary	0.167	0.338	0.172	0.103	0.168	0.065	0.106	0.025
Secondary graduation	0.101	0.308	0.207	0.075	0.162	0.087	0.120	0.019
Some post-secondary	0.100	0.290	0.190	0.093	0.171	0.079	0.111	0.021
Post-secondary	0.113	0.346	0.233	0.097	0.231	0.135	0.098	0.024
Income <$30K	0.130	0.350	0.220	0.101	0.186	0.085	0.135	0.021
Income $30K-$50K	0.118	0.336	0.218	0.087	0.192	0.105	0.113	0.022
Income >$50K	0.109	0.324	0.215	0.085	0.205	0.120	0.095	0.024
Full time worker	0.096	0.301	0.205	0.079	0.187	0.108	0.097	0.021
Part time worker	0.112	0.342	0.230	0.087	0.188	0.101	0.129	0.021
Not in labor force	0.187	0.448	0.262	0.149	0.263	0.114	0.147	0.023
No chronic conditions	0.085	0.267	0.182	0.061	0.143	0.082	0.100	0.020
At least one condition	0.237	0.479	0.241	0.201	0.326	0.126	0.116	0.028
SRH: excellent/very	0.095	0.302	0.207	0.072	0.174	0.102	0.105	0.023
SRH: good	0.138	0.356	0.217	0.103	0.209	0.106	0.112	0.021
SRH: fair/poor	0.256	0.455	0.199	0.213	0.304	0.091	0.107	0.024
Full sample obs.	40,012	119,294	159,306	31,824	144,774	176,598	335,904	

Notes: Statistics are calculated using the master files of the NPHS cycle 2 and CCHS cycles 1.1, 2.1, 3.1. Vaccination rates for each sub-group are shown pre and post program in UIIC and non-UIIC regions in Canada (excluding Quebec, rural Manitoba, and the Territories). Pre and post denote before and after October 2000 with the relative change in vaccination for UIIC regions displayed in the second last column (robust standard errors clustered by province shown to the right of the estimate). The between ER standard deviation calculates the standard deviation of vaccination rates between economics regions within each pre-post, UIIC-non-UIIC grouping. Chronic conditions include Asthma, Heart Disease, High Blood Pressure, Diabetes, Cancer, Emphysema/Chronic Bronchitis. SRH stands for self-rated health.

TABLE 3
Current influenza vaccination status and the clinical vaccine match rate

	Overall		By sub-group			
			Age 65+	Poor self rated health	Chronic condition	Worker
Current match	-0.0015	-0.0010	0.0068	0.0001	0.0094	0.0118
	(0.0122)	(0.0128)	(0.0147)	(0.0171)	(0.0166)	(0.0337)
Lagged match		0.0015				
		(0.0149)				
Current match*sub-group			-0.0220	-0.0002	-0.0298	0.0102
			(0.0364)	(0.0436)	(0.0283)	(0.0402)

Notes: This table reports OLS estimates of the effect of the clinical match rate on current vaccination status. Source data are from PHAC surveillance reports and the master files of NPHS cycle 2 and CCHS 1.1, 2.1, 3.1. Each set of estimates shown in Column (1) to (6) represents a separate regression. Robust standard errors are given in parentheses and are clustered by province. (* p<0.10, ** p<0.05, *** p<0.001). Column (3) to (6) include interactions of the current match with the subgroup listed in the table heading. Age 65+ is an indicator for age greater than or equal to 65. Poor self-rated health in an indicator of self rated health equal to "poor" or "fair." Chronic condition indicates the presence of one of the following chronic conditions: Asthma, Heart Disease, High Blood Pressure, Diabetes, Cancer, or Emphysema/Chronic Bronchitis. Worker indicates that the respondent worked at a job or business in the last year. All regressions are weighted by survey weight and include season fixed effects.

TABLE 4
Summary Statistics - Individual Characteristics

	Labor Force Absence		Hospital Admission		
	Absence	No absence	Flu	Pneumonia	Non-respiratory
Age	47.115	48.410	51.185	61.419	58.321
	(0.027)	(0.005)	(0.158)	(0.029)	(0.009)
Fraction male	0.2956	0.5371	0.4404	0.5349	0.5184
	(0.0011)	(0.0002)	(0.0025)	(0.0005)	(0.0002)
Duration	8.9191		6.8711	12.1870	8.8412
	(0.0249)		(0.0835)	(0.0244)	(0.0070)
Wait time in ER			4.9695	5.2511	4.8336
			(0.0565)	(0.0098)	(0.0044)
Fraction with death			0.0319	0.1407	0.0435
			(0.0009)	(0.0003)	(0.0001)
Care home resident			0.0577	0.0991	0.0379
			(0.0012)	(0.0003)	(0.0001)
Urban postal code			0.7746	0.8622	0.8678
			(0.0021)	(0.0003)	(0.0001)
Sample size	117,993	4,697,487	40,213	987,710	6,463,446

Notes: Variable means displayed with standard error of the mean given in parentheses below. Labor force data are collected from the monthly LFS where absence indicates a short-term work absence during a reference week. Hospitalization data are collected from the HMDB. Non-respiratory diagnoses include all hospitalizations that do not list a respiratory diagnosis as an MRD (most responsible diagnosis) or as a contributing diagnosis. Average duration is measured in hours for work absence and in days for hospital admissions. Wait time in ER before admission is measured in hours. Statistics are weighted by survey weights (LFS) or population cell size (HMDB).

TABLE 5
Summary Statistics - Weekly Incidence Rates for Economic Regions

	Illness work absence		Flu admissions		Pneumonia admissions	
	Mismatch	Match	Mismatch	Match	Mismatch	Match
All weeks	0.0262	0.0221	0.524	0.450	9.451	9.339
	(0.0001)	(0.0001)	(0.015)	(0.012)	(0.046)	(0.052)
Off-season weeks	0.0255	0.0217	0.245	0.266	8.805	8.715
	(0.0001)	(0.0001)	(0.006)	(0.007)	(0.043)	(0.050)
Season start to peak	0.0287	0.0238	2.280	1.572	13.359	13.204
	(0.0003)	(0.0003)	(0.102)	(0.073)	(0.187)	(0.207)
Season end	0.0289	0.0234	1.177	0.760	11.204	10.353
	(0.0003)	(0.0004)	(0.081)	(0.044)	(0.210)	(0.161)
Post program	0.0299	0.0246	0.352	0.300	9.275	9.168
	(0.0001)	(0.0002)	(0.011)	(0.012)	(0.054)	(0.067)
Pre program	0.0193	0.0193	0.823	0.599	9.756	9.509
	(0.0001)	(0.0001)	(0.036)	(0.020)	(0.085)	(0.079)
Ontario	0.0284	0.0234	0.367	0.240	8.812	8.848
	(0.0002)	(0.0002)	(0.019)	(0.012)	(0.073)	(0.081)
Not Ontario	0.0251	0.0215	0.585	0.531	9.699	9.530
	(0.0001)	(0.0001)	(0.020)	(0.015)	(0.057)	(0.065)

Notes: Labor force absence data are collected from the LFS. Illness absence indicates a short-term work absence for reasons of personal illness during a reference week within each month. Hospitalization data are collected from the HMDB. Hospitalization incidence rates are calculated per week per 100,000 for different age groups across economic regions. Statistics are displayed for flu seasons with at least one mis-matched strain and flu seasons without a mis-matched vaccine strain. The standard error of the mean is given in parentheses below. Off-season and flu season periods are defined according to flu surveillance data from the PHAC. All statistics are weighted by survey weights (LFS) or population cell size (HMDB) and all standard errors are clustered by province.

TABLE 6

The Flu Immunization Campaign, Vaccine Match and Health Outcomes

Dependant Variables:	(1) Average duration	(2) Illness work absence	(3) Flu admissions	(4) Pneumonia admissions
		Panel A: Basic Results		
Season start to peak	5.3 weeks	-0.0050 *	-2.829 **	-4.693 *
		(0.0026)	(0.750)	(2.461)
		0.0267	3.053	12.521
Season end	4.1 weeks	-0.0080 *	-2.421 **	-4.917 **
		(0.0042)	(0.661)	(1.615)
		0.0276	2.996	10.408
Off season	42.6 weeks	-0.0009	-0.006	-0.636 **
		(0.0011)	(0.032)	(0.204)
		0.0249	0.344	7.718
Panel B: Account for behavioral response to match by controlling for circulation of other infectious disease				
Season start to peak		-0.0060 **	-2.835 **	-4.726 *
		(0.0023)	(0.774)	(2.351)
Season end		-0.0079 *	-2.440 **	-4.760 **
		(0.0042)	(0.694)	(1.676)
Off season		-0.0009	-0.009	-0.607 **
		(0.0011)	(0.032)	(0.221)

Notes: This table reports estimates of the interaction of the clinical match rate, a post October 2000 dummy and a dummy for UIIC regions. Table columns report results for different health outcomes and rows report results for three different periods during the year: the flu season start to peak, the flu season end, and the flu off-season. Column (1) shows the average duration of each different period. Each estimate shown in Column (2) to (4) is a separate regression. Robust standard errors are given in parentheses and are clustered by province (* $p<0.10$, ** $p<0.05$, *** $p<0.001$). The baseline (pre October 2000) mean of the dependent variable is given below the standard error of each estimate. The dependent variables are listed in the table headings. Work absences are short-term work absences for reasons of personal illness during a reference week (source data from the LFS). Influenza admissions denote hospital admissions per 100,000, per week where influenza was either the MRD (most responsible diagnosis) or other contributing diagnosis and pneumonia admissions denote hospital admissions per 100,000, per week where pneumonia was either the MRD or other contributing diagnosis (source data from the HMDB). Regressions are weighted by survey weight (absences) or cell size (admissions). All regressions include the level effect of the match rate, month, age, season and economic-region fixed effects as well as interactions of UIICXPost, PostXMatch, and UIICXMatch. Regressions in columns (3) and (4) also control for public health expenditures on health care (hospitals, capital investments, physicians and other health professionals), and diagnosis specific coding classifications changes (ICD10 versus ICD9). Regressions in column (1) control for the same factors, and for education, marital status, sex, occupation and union status. Results in Panel B control for surveillance rates of other infectious respiratory disease (respiratory syncytial virus, parainfluenza, and adenovirus).

TABLE 7
The Influenza Immunization Campaign, Vaccine Match and Time Lost to Illness

	(1) Illness work absence		(2) Influenza admissions		(3) Pneumonia admissions	
	Flu season	Off season	Flu season	Off season	Flu season	Off season
Time lost per week[†]						
	-0.0383 *	0.0080	-15.365 **	0.765	-39.477 **	-3.366
	(0.0189)	(0.0076)	(3.596)	(0.515)	(14.378)	(4.185)
	0.1780	0.1550	23.232	2.314	124.024	94.444
Time lost per illness[†]						
	0.7634	-0.1013	3.769	-0.966	1.751	-0.041
	(1.1668)	(0.1838)	(1.473)	(1.636)	(1.321)	(0.461)
	8.9060	9.2460	7.674	6.596	9.562	10.519
Wait time in ER (hours)						
			-0.161	0.000	-0.136	-0.018
			(0.240)	(0.026)	(0.588)	0.029
			3.774	3.291	3.539	3.035
Death						
			-0.121 **	0.002	-0.560 **	-0.042
			(0.027)	(0.003)	(0.127)	(0.054)
			0.122	0.006	1.459	1.098

Notes: See Table 6 notes. Table columns report results for different health outcomes and rows report results for death and different time factors associated with illness. (* p<0.10, ** p<0.05, *** p<0.001). The baseline mean of the dependent variable is given below the standard error of each estimate. The dependent variables are listed in table headings. Time lost per illness is the average time lost conditional on illness incidence. Wait time in ER denotes the time spent in the ER before hospital admittance. Death denotes the number per 100,000, per week.
† Time lost is measured in hours in the case of work absences and in days in the case of hospital admissions.

TABLE 8
Results for Other Disease Outcomes

Dependent variable:	(1) Respiratory	(2) Heart	(3) Cancer	(4) Mental	(5) Nervous system
	Panel A: Admissions with co-diagnosis of respiratory disease				
Flu season	-9.579**	-2.756**	0.044	-1.605***	-0.212**
	(2.100)	(0.737)	(0.196)	(0.317)	(0.078)
	32.244	12.643	2.790	4.308	0.645
Off season	-1.796	-0.553	-0.021	-0.338	-0.030
	(1.354)	(0.349)	(0.124)	(0.216)	(0.020)
	24.847	10.208	2.626	3.500	0.500
	Panel B: Admissions without diagnosis of respiratory disease				
Flu season		0.280	0.474	-0.084	-0.077
		(1.185)	(0.324)	(0.543)	(0.087)
		25.342	9.264	13.347	1.045
Off season		0.725	0.209	-0.074	-0.077
		(0.457)	(0.135)	(0.325)	(0.057)
		25.469	9.627	13.293	1.060

Notes: See Table 6 notes. Panel A includes admissions with a contributory diagnosis of respiratory disease and Panel B includes admissions without a contributory respiratory diagnosis. (* p<0.10, ** p<0.05, *** p<0.001). The baseline mean of the dependent variable is given below the standard error of each estimate.

TABLE 9
Results Conditional on Baseline Vaccination Rates in each Economic Region

	(1) Illness work absence	(2) Flu admissions	(3) Pneumonia admissions
Panel A: Results for flu season weeks			
UIIC*Post2000*Match	-0.0063 **	-1.995 **	-5.140 **
	(0.0017)	(0.554)	(1.138)
Percent change in incidence rate	-23.0	-66.1	-47.1
Panel B: Results for flu season weeks conditional on baseline vaccination in each economic region			
UIIC*Post2000*Match	-0.0087 **	-1.976 **	-4.266 **
	(0.0021)	(0.491)	(0.969)
UIIC*Post2000*Match*Baseline vaccination†	0.1386 *	16.729	32.462
	(0.0649)	(10.295)	(20.471)
Baseline rate at which program effect would be zero	24.5	30.0	31.3

Notes: See Table 6 notes. Panel A reports estimates of UIIC*Post*M from Equation (2) for all weeks during influenza season. Panel B reports estimates of UIIC*Post*M and an estimate of UIIC*Post*M interacted with the demeaned baseline vaccination rate as specified in Equation (3). In Panel A, the percent change from the baseline incidence rate denotes the percent decrease from the incidence rate for each outcome pre October 2000. In Panel B, the baseline vaccination rate displayed is the implied baseline rate at which the effect of the influenza program would be zero, given a perfect vaccine match. It is calculated as the baseline average vaccination rate plus the negative ratio of the two estimates above the result.
† Baseline vaccination denotes the deviation of the rate for each region from the average baseline rate of 0.182.

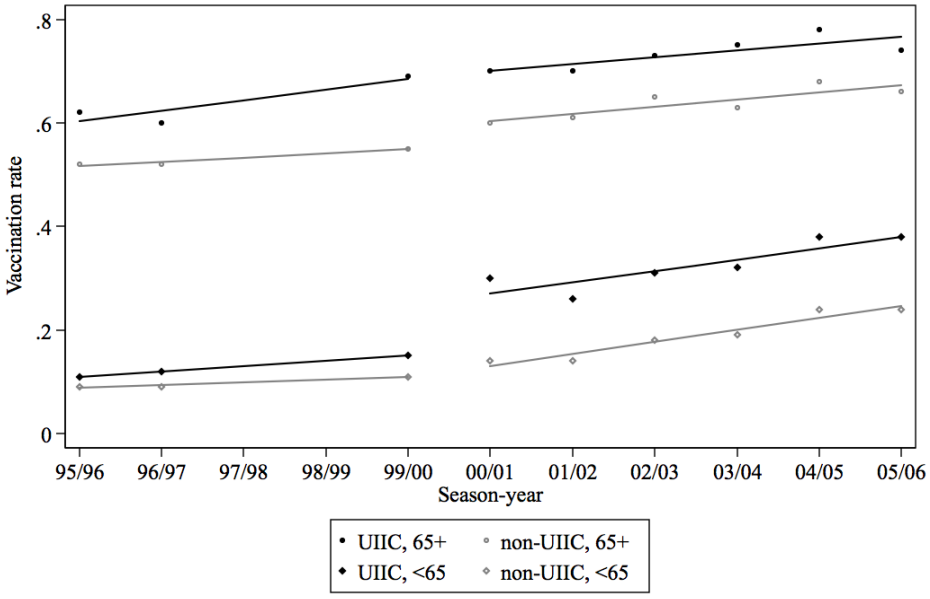

FIGURE 1
Influenza Vaccination - 1995/1996 to 2005/2006
The y-axis plots average vaccination for each flu season-year based on the master files of the National Population Health Survey Cycle 2 and the Canadian Community Health Survey Cycles 1.1, 2.1, 3.1. Solid lines show the fitted linear prediction for each age and geographic grouping.

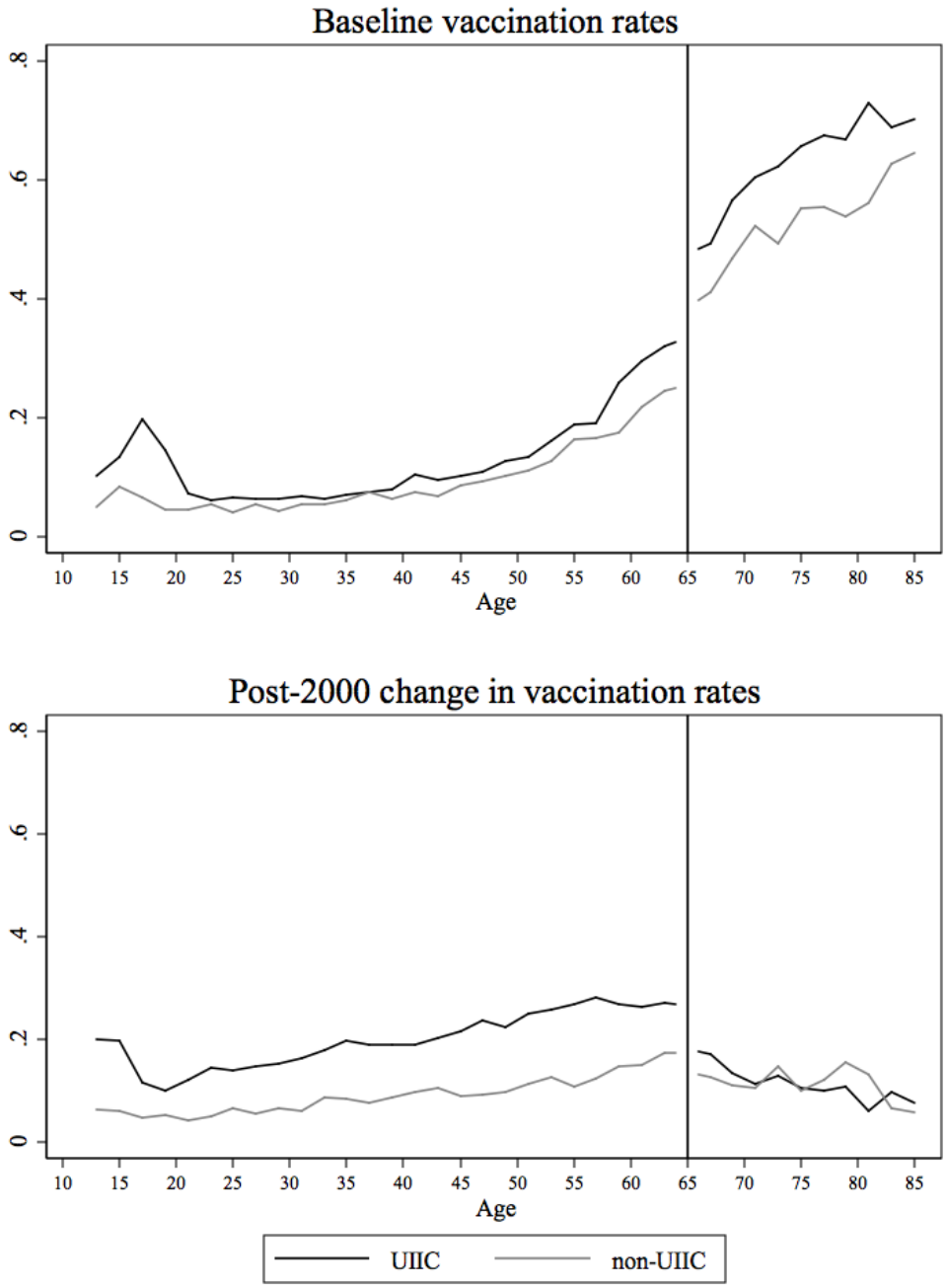

FIGURE 2
Influenza Vaccination Rates Over Age
In the top panel, the y-axis plots average vaccination for each age group pre-2000. The bottom panel shows the change in vaccination in the pre versus post period. Rates are based on data from the master files of the National Population Health Survey Cycle 2 and the Canadian Community Health Survey Cycles 1.1, 2.1, 3.1.

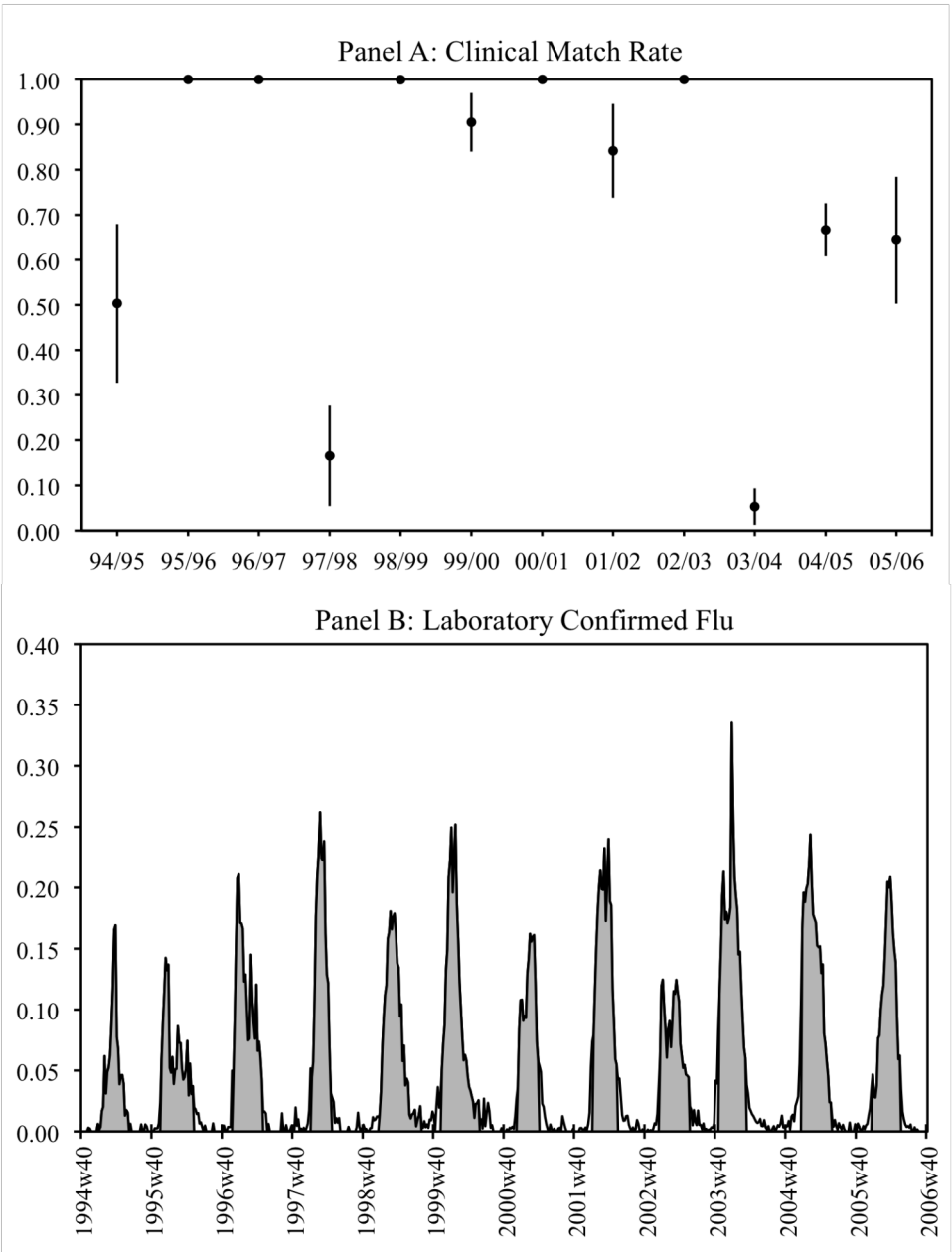

FIGURE 3
Clinical Match Rate and Infectious Disease Surveillance

In Panel A, the average clinical match rate is shown for each season with error bars indicating two standard deviations from the mean (variation is between province). The clinical match rate is calculated from the yearly Canadian Communicable Disease Report and strain isolation data from the PHAC. Panel B shows the average weekly fraction of positive influenza tests. These data are collected through the disease surveillance program of the PHAC. A tick at week 40 indicates the start of each season and the shaded area indicates the period of high flu season.

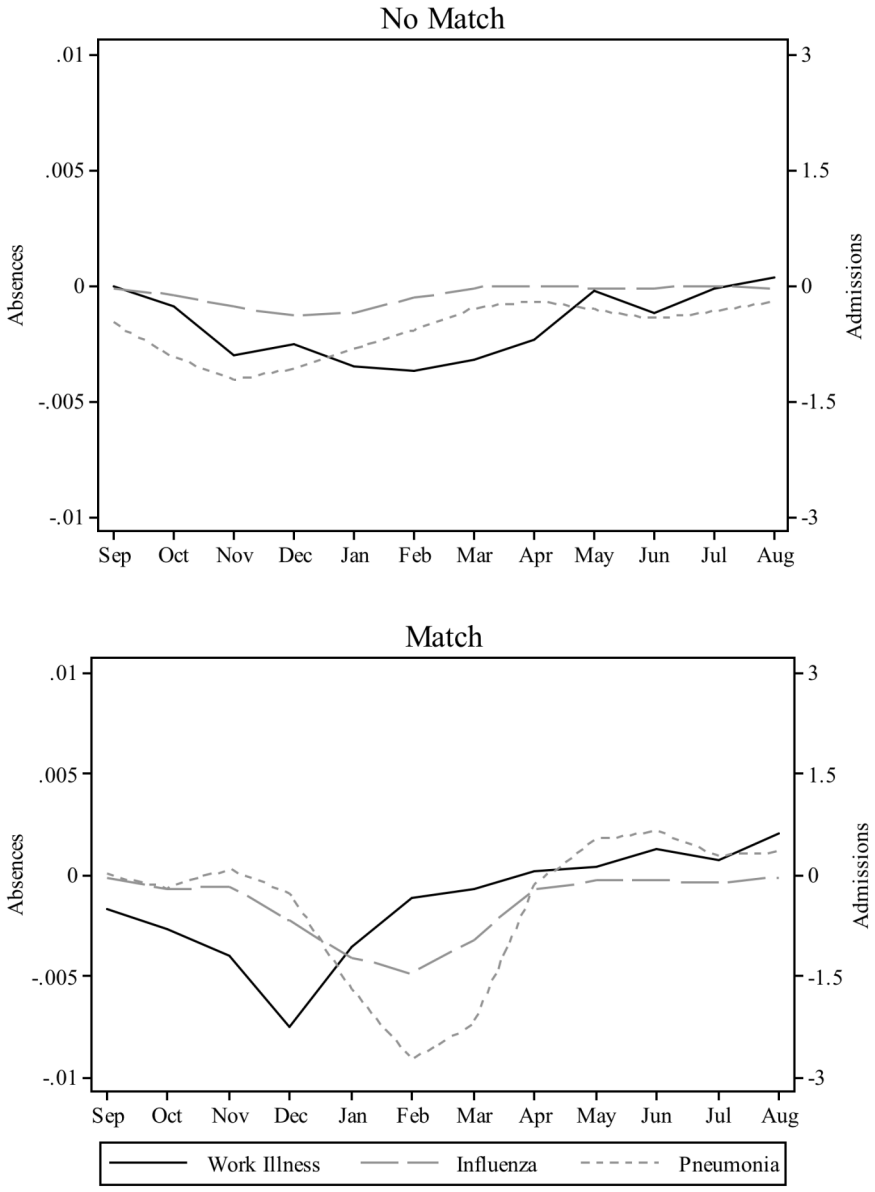

FIGURE 4
Relative Difference in Health Outcomes for UIIC Regions Post-Program

Each figure indicates monthly difference-in-difference estimates for health outcomes in UIIC regions in the post-period controlling for factors in X_{it}. The top figure compares seasons where at least one influenza strain is unmatched to the yearly vaccine, while the bottom figure compares seasons where all influenza strains are matched to the yearly vaccine. On average, the period of high flu season occurs in December-March.

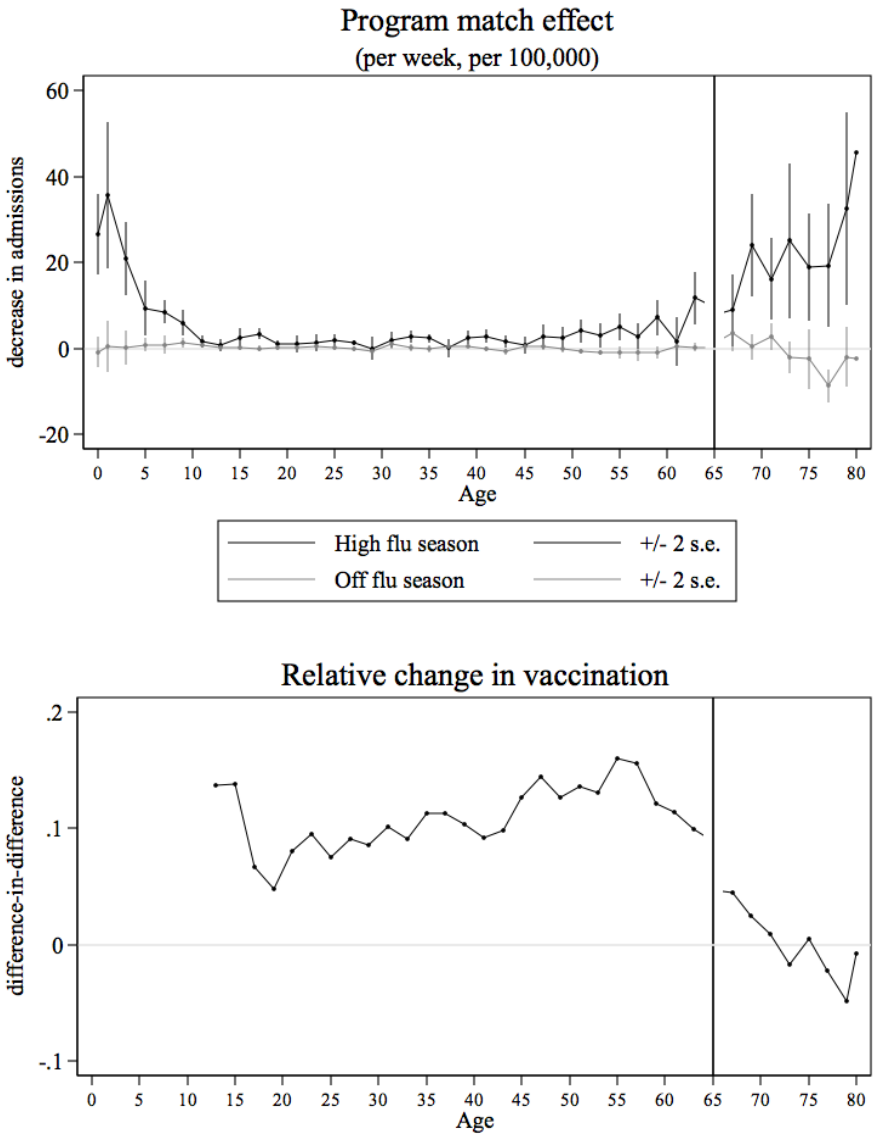

FIGURE 5
Program Match Effect for Influenza and Pneumonia Admissions

The top figure plots the age specific coefficients on the program match effect (the interaction of the clinical match rate, a post October 2000 dummy and a dummy for UIIC regions) for influenza and pneumonia admissions combined (rate per 100,000, per week). The dark solid line indicates the decline in admissions for each age group during high flu season with confidence intervals indicated by error bars for each coefficient estimate. For comparison, the grey line shows the program match effect for each age group during the off-season period. The bottom figure plots the relative change in vaccination rates post-program in UIIC regions (i.e. difference-in-difference estimates) by age group.

APPENDIX

A.1 *Table A1*

The health surveys studied include information on current health. Unlike observations in the hospitalization data, these surveys are designed to be representative of the underlying population and can be used to analyze the general impact of the UIIC program. Each respondent is asked if they spent time in bed or reduced activity due to illness in the last two weeks. Respondents are also asked detailed questions about medications taken in the last month, which can be categorized by DIN number into different medicine types. Results for these outcomes are given in Table A1.

For the full sample, there is a negative effect for both medications and bed illness. During flu-season, a good match vaccine decreases medications for cold/flu by 10.2 percentage points for UIIC relative to non-UIIC regions. As a side note, there is no impact, positive or negative, on the use of antibiotics. Overall, there is a 3.0 percentage point fall in the rate of being in bed ill. This is compared to a 6.8 percentage point decrease in laboratory confirmed influenza rate. The larger effect for lab-influenza rates may be explained by methods of testing. These lab tests are not collected through random sampling of the population but are instead collected from sentinel physicians and may have different sensitivities or specificities to true underlying influenza. Likely, there is a higher proportion of influenza incidence in this sample than in a random sample of the population. Furthermore, testing behaviors may be related to both the match rate and UIIC, which could bias the result found here.

Patterns within age groups exhibit the same patterns as for work absences and hospitalizations: effects are largest for the youngest and oldest, with modest effects for those ages 25 to 64.

Results for the sample of workers corroborates previous results from the Labour

Force Survey (LFS). There is a 0.54 percentage point decrease in recent bed illness for the sample of workers from the health surveys, which corresponds approximately to a 0.59 percentage point decrease in work absences for the same sub group using the LFS.

A.2 *Table A2*

Table A2 explores patterns among sub groups of the population. It is clear that the young and the oldest age groups have the most to gain from the vaccine program. This is true in absolute terms and relative to baseline average illness. Young children gain the most relative to baseline levels, and since this group has the highest incidence of hospitalization for influenza (next to those over 65), this translates into large savings in terms of hospital admits. For children under 5, relative to an average match, a perfect match brings a gain of 2.0 fewer hospitalizations per week per 100,000 for UIIC regions after the introduction of the vaccine campaign. There are smaller effects for middle age groups but the impact begins to increase in the elder age groups of 50 to 65. This group had a larger relative increase in vaccination of 13.9 percentage points and exhibits larger decreases in illness relative to the younger age group of 25 to 49.

TABLE A1
Results for Other Health Outcomes During Flu Season

	(1) Weekly laboratory confirmed flu rate	(2) Work absence due to illness in last week	(3) In bed due to illness in last two weeks	(4) Cold or flu medicine in last month
Panel A - Full sample				
	-0.068		-0.030 *	-0.102 *
	(0.064)		(0.017)	(0.052)
Baseline mean	0.202		0.097	0.769
Observations	1,197		72,974	18,981
Panel B - Workers				
		-0.006 **	-0.005	-0.105
		(0.002)	(0.016)	(0.066)
Baseline mean		0.027	0.097	0.737
Observations		919,830	45,220	10,143
Panel C - Age Groups				
25 and younger			-0.112 ***	-0.105
			(0.027)	(0.073)
Baseline mean			0.130	0.841
Observations			12,629	6,525
25 to 64 years			-0.010	-0.040
			(0.020)	(0.079)
Baseline mean			0.100	0.740
Observations			46,057	9,728
65 and older			-0.055 **	-0.368 **
			(0.018)	(0.156)
Baseline mean			0.061	0.697
Observations			14,288	2,728
Data Source:	PHAC	LFS	NPHS:1-3, CCHS:1.1-3.1	NPHS:1-6

Notes: See Table 6 notes. Table columns report results for different dependent variables and rows report results for different sub-groups. The regression in column (1) is for data at the province-week level, and controls include province effects instead of economic region effects. (* p<0.10, ** p<0.05, *** p<0.001). The baseline mean of the dependent variable is given below the standard error of each estimate and sample size is given below the mean.

TABLE A2
Results by Age During Flu Season

	(1) Flu admissions	(2) Pneumonia admissions	(3) Illness work absence
Less than 5 years	-6.939 **	-14.012 **	
	(1.796)	(4.674)	
	6.155	25.443	
5 to 11 years	-1.180 **	-1.228 *	
	(0.482)	(0.642)	
	1.658	3.941	
12 to 19 years[1]	-0.450 *	-1.366 **	-0.0090
	(0.196)	(0.508)	(0.0163)
	0.980	1.598	0.0250
20 to 24 years	-0.214	-1.073	-0.0179 **
	(0.154)	(0.644)	(0.0068)
	0.823	1.680	0.0330
25 to 49 years	-0.513	-1.768 **	-0.0054 **
	(0.297)	(0.389)	(0.0024)
	1.031	2.930	0.0320
50 to 64 years	-1.925 **	-4.380 **	-0.0076 ***
	(0.565)	(0.936)	(0.0015)
	2.576	9.751	0.0140
65 or more years	-11.969 **	-21.283 **	-0.0036
	(3.577)	(6.794)	(0.0066)
	14.765	53.718	0.0090
Nursing home resident	-57.648	-157.831	
	(37.779)	(104.272)	
	62.008	137.309	

Notes: See Table 6 notes. The dependent variables are listed in the table headings. The baseline mean of the dependent variable is given below the standard error of each estimate. The regressions for nursing home residents are for data at the province-week level, and controls include province effects instead of economic region effects.
[1] This age group is 15 to 19 for work absences.