HEDG
HEALTH, ECONOMETRICS AND DATA GROUP
THE UNIVERSITY of York

WP 15/19

# Learning to trust flu shots: quasi-experimental evidence on the role of learning in influenza vaccination decisions from the 2009 influenza A/H1N1 (swine flu) pandemic

Jürgen Maurer & Katherine M. Harris

September 2015

http://www.york.ac.uk/economics/postgrad/herc/hedg/wps/

# Learning to trust flu shots: Quasi-experimental evidence on the role of learning in influenza vaccination decisions from the 2009 influenza A/H1N1 (Swine flu) pandemic

Jürgen Maurer[1] (University of Lausanne and RAND Corporation)

and

Katherine M. Harris (IMPAQ International and RAND Corporation)

May 2015

[1] Corresponding author: Jürgen Maurer, Institute of Health Economics and Management (IEMS) and Department of Economics (DEEP), University of Lausanne, Internef, Dorigny, 1015 Lausanne, Switzerland. Email: jurgen.maurer@unil.ch. The survey data used in this study was collected under contract with GlaxoSmithKline (GSK). GSK had no role in the design, management, analysis, or interpretation of these data, and had no role in the preparation, review, or approval of the manuscript. The opinions expressed here are solely those of the authors and do not represent those of the University of Lausanne, IMPAQ International, the RAND Corporation or GSK. The authors have no conflicts of interest to declare and have no financial disclosures. The authors should like to thank seminar participants at the RAND Corporation, University of Zurich, University of Rotterdam, University of Tilburg, DIW Berlin, IEMS Lausanne, the Health Economics Section of the German Economic Association, the Empirical Health Economics Workshop in Munich, the Health Economics Workshop in Grindelwald, the Economics of Disease Workshop in Darmstadt as well as Jerôme Adda, Mark Dusheiko, Simona Grassi, Peter Haan, Rafael Lalive, Martin Salm, and Joachim Winter for useful comments and suggestions that greatly improved the paper. All errors are our own responsibility.

**Abstract**

This paper studies consumer learning in influenza vaccination decisions, i.e., potential causal effects of past experiences of being vaccinated on current use of influenza vaccine. Existing structural models of demand usually identify consumer learning parametrically based on functional form assumptions within dynamic forward-looking Bayesian demand models. To the best of our knowledge, we are the first to explore the potential role of consumer learning in pharmaceutical demand within a reduced form instrumental variable framework. The emergence of a new virus strain (influenza A H1N1/09) during the 2009 influenza pandemic resulted in the use of two different influenza vaccines each recommended for distinct population subgroups. We used these exogenous inputs to vaccination decisions to construct instrumental variables for the effect of past influenza vaccination experiences on the demand model for pandemic vaccine. We find large causal effects of seasonal vaccination on pandemic vaccination with changes in perceived vaccination safety being an important pathway. Our results suggest an important role of learning in vaccination decisions. Our findings further highlight that expanding uptake of seasonal vaccination is an important component of pandemic preparedness.

*Keywords: Pharmaceutical demand, influenza vaccination, consumer learning, preventive care use, pandemic preparedness, instrumental variable estimation*

*JEL codes: I10, I11, I18*

"One must learn by doing the thing, for though you think you know it, you have no certainty until you try" (Sophocles 406 BC)

## I. Introduction

Consumer learning describes a process in which personal consumption experiences or exposure to external information result in new insights, attitudes and beliefs regarding uncertain product characteristics, such as the benefits and risks of specific pharmaceuticals. The newly acquired knowledge, attitudes and beliefs with regard to these product characteristics in turn provide the basis for future demand behavior, leading to a process of feedback between product experiences on the one hand and product demand on the other. Demand decisions may therefore not only affect the instantaneous consumption utility of individuals, but also provide valuable learning experiences that affect future product demand. Such a dynamic process may shape consumers' knowledge, attitudes and beliefs toward different products and lead to persistence in product demand over time. Marketing research has shown that consumer learning can explain key stylized facts of dynamic product demand such as "brand loyalty" or the long-run impact of advertising (Ching, Erdem and Keane (2013)).

Consumers are often uncertain about the benefits and safety of pharmaceutical products, including vaccines, and consumer learning may thus be an important factor in determining pharmaceutical demand. In addition, learning may also explain why pharmaceutical demand is often rather heterogeneous across consumers, but highly persistent within consumers over time. For example, consumer demand for seasonal influenza vaccination displays both a strong association with vaccination-related attitudes and beliefs (Lindley et al. (2006)) as well as strong persistence over time (Parente et al. (2005), de la Mata (2011)). Similar patterns are

also observed when new, but similar pharmaceutical products enter the market as in the case of H1N1 (Swine flu) influenza vaccine during the 2009 influenza pandemic: Vaccination-related attitudes and beliefs were significantly associated with pandemic vaccine acceptance (Liao et al. (2011) and the use of seasonal influenza vaccine emerged as one of the strongest predictor of pandemic vaccine use and pandemic vaccination-related attitudes (Harris et al. (2010)). These findings suggest considerable scope for consumer learning in shaping individuals' knowledge, attitudes and beliefs concerning pharmaceutical products as well as the dynamics of pharmaceutical demand. Over and above any immediate improvements in medication use, current pharmaceutical policies may therefore also yield large long-run benefits by determining future drug use patterns. For example, expanding regular uptake of influenza vaccine may not only improve population health in the short run, but also enhance public health preparedness for future emergencies thanks to the dynamic impact of learning.

In order to assess the importance of learning in product demand empirically, one needs to disentangle it from other unmeasured factors that may directly affect both past and future demands such as preferences or access to the product (unobserved heterogeneity). In contrast to learning, which represents a causal mechanism linking past consumption experiences and current demand behavior, unobserved heterogeneity captures the potential role of unmeasured factors, such as individual differences in the valuation of product attributes, risk aversion, procrastination and other personality traits or effective product prices that may affect past and future demand. As a result, unobserved heterogeneity can generate time persistence in individual consumption decisions even in the absence of learning and thus makes individual consumption histories endogenous in a model of current vaccine demand. Empirical studies of learning in consumer demand must therefore isolate the effects of learning from those of unobserved heterogeneity in order to estimate the causal effect of past consumption

experiences on future demand. This situation is similar to the issue of distinguishing heterogeneity and state dependence, which often occurs in dynamic models in applied microeconomics (see, e.g., Heckman (1981) and Keane (1997) for a broader discussion).

The typical approach for studying consumer learning in demand analysis is to develop dynamic structural models of demand under uncertainty that parametrically specify the entire choice environment of consumers including their preferences, sources of information, learning processes and choice behavior (Ching et al. (2013)). These models are normally solved using dynamic programming techniques and structural parameters are recovered using simulation estimation. Several prominent studies in health economics have adopted some version of this structural approach to analyze learning of consumers or physicians in pharmaceutical markets (Chan and Hamilton (2006), Chan et al. (2013), Ching (2010a), Ching (2010b), Ching and Ishihara (2010, 2012), Chintagunta et al. (2009), Chintagunta et al. (2012), Coscelli and Shum (2004), Crawford and Shum (2005), Dickstein (2014), Fernandez (2013), Ferreyra and Kosenok (2011), Kalra et al. (2011), Lim and Ching (2012)). These studies suggest that learning may play a key role in explaining pharmaceutical consumption over time, highlighting a potentially large impact of product certainty on the dynamic pattern of demand for pharmaceuticals. Main advantages of this structural approach are that one can recover "deep" economic and behavioral parameters that can be used in welfare assessments, counterfactual analyses and policy simulations as well as to compare the predictive performance of competing theories (Reiss and Wolak (2007)). As a result, structural learning models have improved our understanding of key aspects of dynamic consumer demand such as "brand loyalty" or the long-run effects of "advertising" or "detailing" (Ching et al. (2013)).

Despite their significant contributions to our understanding of dynamic consumer demand, there are also some remaining challenges for structural learning models, especially with regard to identification. Specifically, "there is no nonparametric method to sort out the relative importance of heterogeneity and state dependence in generating persistence [and] inferences about the relative and absolute importance of heterogeneity and state dependence are conditional on functional form assumptions" (Keane (1997), p. 311). Hence, the "deep" economic and behavioral parameters of structural learning models are only "parametrically" identified within the context of an assumed model structure. As a result, the identification of learning in structural models crucially hinges on an appropriate specification of the entire dynamic choice behavior and environment of consumers and may otherwise be misleading in case of misspecification. Importantly, distinguishing learning from other mechanisms that may yield similar demand patterns in terms of state dependence and persistence is often challenging in practice, especially in the context of very rich and complex behavioral models (Ching et al. (2013)).

The present paper complements previous structural analyses of consumer learning in pharmaceutical demand by providing quasi-experimental evidence on the causal relationship between past product use and future acceptance of closely related pharmaceutical products, which we interpret as evidence for learning. Specifically, we analyze the relationship between past experiences with seasonal influenza vaccination and acceptance of a newly introduced pandemic influenza vaccine during the 2009 influenza A/H1N1 (Swine flu) pandemic in the United States. In order to distinguish the effects of learning from those of unobserved heterogeneity, we use an instrumental variable (IV) approach to estimate the causal effect of previous use of seasonal influenza vaccine on pandemic vaccine uptake and pandemic vaccination-related attitudes. Our IV approach exploits a unique feature of the 2009 influenza

pandemic, specifically, the introduction of a new pandemic vaccine whose target indications differed from those of regular seasonal influenza vaccination. Reflecting early epidemiological evidence on differences in health risks associated with the two virus strains, the new pandemic vaccine was mainly targeted toward young adults and middle-aged persons with certain chronic conditions, while the use of seasonal vaccine prior and during the 2009 H1N1 pandemic was primarily targeted toward older adults and other persons at elevated risk of complications from seasonal influenza. These differences in U.S. government's vaccination targeting based on exogenous risk characteristics of the respective influenza viruses allows us to construct IVs for previous seasonal vaccination experiences in a demand model for pandemic vaccination and corresponding econometric models for pandemic vaccination-related attitudes. This identification strategy is based on the assumption that conditional on actual and self-reported perceptions of coverage by a government vaccination recommendation for pandemic influenza and other individual characteristics, actual and perceived coverage by a government vaccination recommendation for seasonal influenza only affects pandemic vaccination through its association with previous seasonal vaccination experiences, thus capturing consumer learning. Given common concerns about vaccination safety, we also aim to explore the potential role of consumer learning for producing more favorable pandemic vaccination-related attitudes, especially regarding vaccine safety.

Our results support the hypothesis of consumer learning in influenza vaccination decisions. Specifically, we find large and statistically significant causal effects of previous influenza vaccination experiences on the demand for pandemic vaccination as well as on pandemic vaccination-related attitudes. Regular seasonal influenza vaccination efforts thus appear to have a "double benefit." Beyond mitigating the immediate health and economic cost of influenza, vaccination efforts also increase individuals' willingness to get vaccinated in the

future and thus enhance preparedness for future influenza epidemics. Consistent with the hypothesis of consumer learning, we also find that previous experiences with seasonal vaccination significantly improve attitudes toward pandemic vaccination, especially with regard to perceived vaccination safety.

## II. Background: Influenza and the 2009 H1N1 pandemic in the United States

Influenza is a common, but potentially serious respiratory disease that affects people of all ages. Depending on their severity, annual outbreaks can result in as many as 610,660 life-years lost; 3 million hospital days; 31 million outpatient visits; and 44 million days of productivity lost. Overall, the average immediate economic burden of influenza totals USD 87.1 billion per year in the United States alone (Molinari et al. (2007)). The U.S. Centers for Disease Control and Prevention (CDC) estimated that between 1976 and 2007 influenza-related mortality in the United States ranged from 3,349 in 1986-87 to 48,614 in 2003-04 (Thompson et al. (2010)). Beyond these immediate effects on society and the economy, influenza epidemics can also have considerable long-term consequences. There is evidence that exposure to influenza virus in-utero causes higher rates of cardiovascular disease and physical disability, lower levels of education. and lower life-time incomes compared to those not exposed (Almond and Mazumder (2005), Almond (2006), Mazumder et al. (2010)). Preventing influenza and its adverse health and economic consequences is therefore an important priority in U.S. public health policy (U.S. Department of Health and Human Services (2013)).

Occasionally, sustained community-level influenza outbreaks occur on a global scale (World Health Organization (WHO) (2009)). These outbreaks are commonly referred to as influenza pandemics and typically involve the widespread circulation of a novel influenza virus to

which human immunity is limited. Historically, influenza pandemics occurred every 10 to 50 years (WHO (2009)), with the "Russian Flu" (1889–90), the "Spanish Flu" (1918–20), the "Asian Flu" (1957–58), the "Hong Kong Flu" (1968–69), the "Russian Flu" (1977-78) and the "2009 H1N1 Flu" (2009-2010) being "recent" examples. The CDC predicts that a future influenza pandemic in the United States could lead to as many as 89,000 to 207,000 deaths; 314,000 to 734,000 hospitalizations; 18 to 42 million outpatient visits; and 20 to 47 million additional illnesses, with medical cost and lost earnings alone amounting to USD 71.3 to 166.5 billion (Meltzer et al. (1999)). Likewise, the U.S. Congressional Budget Office (CBO) estimated that a new pandemic influenza outbreak may lower U.S. GDP by 1 to 4.25 percent (CBO (2006)).

The 2009 influenza A/H1N1 pandemic or "Swine flu pandemic" started in Mexico in early 2009. The first U.S. cases of novel 2009 H1N1 influenza were detected in April 2009 in California (CDC (2009b)), and the virus spread quickly across the rest of the United States (CDC (2010b). In late April 2009, the U.S. government declared the H1N1 outbreak a public health emergency before World Health Organization (WHO) declared the outbreak a global pandemic in June 2009. Virus activity and H1N1 influenza-related hospitalizations in the United States peaked in late September and early October 2009, about four months earlier in the season than usual peaks in virus activity of influenza. For the period between April 2009 and April 2010, the CDC estimated that the pandemic caused roughly 43 to 89 million influenza cases, 195,000 to 403,000 hospitalizations and 8,870 to 18,300 deaths in the United States (CDC (2010c)). Its overall impact in terms of morbidity and mortality was thus comparable to that of previous non-pandemic influenza seasons, even if the pandemic H1N1 virus more commonly affected younger persons than previous influenza seasons (Belongia et al., 2010). In August 2010, the WHO declared the global H1N1 pandemic over.

Influenza vaccination is a highly effective tool for preventing influenza outbreaks (Cox and Subbarao (1999), CDC (2010a), Ward (2014)). As a result, public health authorities throughout the world devote considerable resources to ensure the feasibility of fast and safe development, manufacturing and stockpiling of influenza vaccine (U.S. Department of Health and Human Services (2010), WHO (2013)). Yet, even when armed with highly developed technical and logistic capabilities, public health preparedness for influenza outbreaks crucially depends on public willingness to get vaccinated for influenza. Despite unprecedented outreach and communication efforts of public health officials and other stakeholders and substantial media attention to the 2009 H1N1 pandemic, only around two in five U.S. adults were vaccinated for seasonal influenza and one in five U.S. adults were vaccinated for H1N1 influenza, respectively (Harris et al. (2010), CDC (2011)). The relatively low uptake rate of H1N1 vaccination is particularly noteworthy, as the future incidence and severity of the pandemic was not well understood during the time in which H1N1 vaccine was widely available to the general public and vaccination was seen as a key policy measure to prevent a potential third wave of H1N1 infections (Kilbourne (2006), Lee et al. (2010)). Specifically, while the public perceived H1N1 influenza as a more serious disease than seasonal influenza, there was also more widespread public skepticism regarding the safety of H1N1 vaccination relative to that of seasonal vaccination (Maurer et al. (2010a)), despite comparable safety profiles of the two vaccines (CDC (2009a)).

Compared to typical seasonal influenza outbreaks, H1N1 pandemic influenza was more severe in young and less severe in older adults. Based on early epidemiological evidence of an unusual concentration of H1N1 influenza-related hospitalization among younger adults, the Advisory Committee on Immunization Practices (ACIP) at the CDC—the only U.S.

government entity making vaccination recommendations—released distinct vaccination recommendations for seasonal and pandemic influenza (CDC (2009c), CDC (2009d)). As in previous years, seasonal influenza vaccination continued to be mainly targeted toward older persons and their personal contacts, whereas pandemic vaccination efforts tended to be more directed toward younger persons. Table 1 summarizes the ACIP 2009-2010 vaccination recommendations for seasonal and 2009 H1N1 pandemic vaccination in detail. As usual, these vaccination recommendations were based on individuals' health characteristics such as age or the existence chronic conditions, individuals' activity patterns such as being in regular contact with children or older persons as well as individuals' occupational risks, notably whether or not individuals work as healthcare professionals. ACIP specifically recommended seasonal vaccination for children aged six months to 18 years, adults aged 50 years and older; persons with specific high-risk health conditions; pregnant women; healthcare workers; close contacts of children under the age of five, of high-risk individuals or of persons aged 50 years and older. By contrast, pandemic vaccination was specially recommended vaccination for children aged six months to 18 years, young adults aged 18-24 years; adults aged 18-64 years with a high-risk health condition; pregnant women; healthcare workers; and close contacts of infants under the age of six months. The emergence of the novel H1N1 virus thus resulted in new vaccination targeting for H1N1 influenza that did not include important subgroups traditionally recommended for seasonal influenza vaccination such as older adults. While the traditional vaccination recommendations for seasonal influenza encouraged the past and contemporaneous use of seasonal vaccine thereby ensuring instrument relevance in our empirical analysis, they were clearly distinct from corresponding recommendations for the use of pandemic vaccine and thus provide credible (conditional) exclusion restrictions for our IV analyses. This exclusion of individuals traditionally recommended for seasonal vaccination from the corresponding recommendations for pandemic vaccine is also different

from any previous expansions of seasonal vaccination recommendations, which continued to recommend seasonal influenza vaccination for traditional recommendation groups and did therefore not yield the type of exclusion restriction available in the pandemic context considered here. In addition to the above differences in health, activity and occupational risk factors and corresponding vaccination targeting by the federal government, seasonal influenza vaccination became available much earlier than pandemic vaccination. Pandemic vaccine was produced later than seasonal vaccine, as the development and production of seasonal vaccine had already begun prior to the H1N1 outbreak. The sudden outbreak of H1N1 in April 2009 thus required the development and production of a separate pandemic vaccine for protection against the H1N1 virus strain, as this strain could not be included in the regular seasonal influenza vaccine any more. Reflecting the different time frames of the development and production of seasonal and pandemic vaccine, seasonal vaccine administration started in August 2009 and the seasonal vaccine was widely available from September 2009, whereas pandemic vaccine became only available in October 2009 and was only widely available without restrictions starting from December 2009 (CDC (undated)). Given the otherwise large similarities in the development and production processes for seasonal and pandemic vaccines, both vaccinations showed similar safety profiles (CDC (2009a)), even if the public appeared to have less favorable views of pandemic vaccination safety compared to the perceived safety of seasonal vaccination (Maurer et al. (2010a)).

Beyond differences in the timing of the development and production of seasonal and pandemic vaccine, the location of vaccine delivery also differed between the two types of vaccinations (Uscher-Pines et al. (2011)). While seasonal vaccination was mainly distributed via the usual vaccination providers such as physician offices, health clinics, the work place or drug stores, pandemic vaccines were more commonly distributed through specialized

influenza vaccination clinics run by local health departments, especially during the early phases of vaccine roll-out. Moreover, due to initial supply shortages, the pandemic vaccine was at first only distributed to persons who were covered by one of the aforementioned government vaccination recommendation for pandemic vaccine and only later (December 2009) made widely available to the general public.

## III. An illustrative model of pandemic vaccine demand with consumer learning

We first illustrate some of key issues in individuals' vaccination decisions based on a simple model for the demand of pandemic vaccination. This model integrates learning in vaccination decisions for pandemic influenza by introducing previous experience with seasonal influenza vaccination as preference shifters in the demand for pandemic vaccine. Specifically, we assume that individuals make their decision about whether or not to get vaccinated for H1N1 pandemic influenza $Vax_{H1N1}^{i*}$ by maximizing their subjective expected utility $\mathrm{U}_{\mathrm{H1N1}}^{\mathrm{i}}$ of pandemic vaccination such that

$$\mathrm{Vax}_{\mathrm{H1N1}}^{\mathrm{i}*} = \underset{\mathrm{Vax}_{\mathrm{H1N1}}^{\mathrm{i}} \in \{0,1\}}{\operatorname{argmax}} \; \mathrm{U}_{\mathrm{H1N1}}^{\mathrm{i}}\left(\mathrm{Vax}_{\mathrm{H1N1}}^{\mathrm{i}}, \mathrm{D}^{\mathrm{i}}, \mathrm{H}_{\mathrm{H1N1}}^{\mathrm{i}}, \mathrm{Z}_{\mathrm{H1N1}}^{\mathrm{i}}, \mathrm{I}_{\mathrm{H1N1}}^{\mathrm{i}}, \mathrm{Vax}_{\mathrm{S}}^{\mathrm{i}*}, \varepsilon_{\mathrm{H1N1}}^{\mathrm{i}}\right) \qquad (1)$$

Individual i's subjective expected utility $U_{H1N1}^{i}$ of H1N1 pandemic vaccination depends on her demographic characteristics $D^{i}$, H1N1 influenza-specific health risk factors $H_{H1N1}^{i}$, H1N1 influenza-specific activity or occupational risk factors $Z_{H1N1}^{i}$, her subjective information set concerning her government recommendation status for pandemic vaccination $I_{H1N1}^{i}$ as well as her previous experience with seasonal vaccination $Vax_{S}^{i*}$ capturing potential effects of consumer learning. $\varepsilon_{H1N1}^{i}$ denotes remaining unobserved factors that affect individual preferences for H1N1 vaccination, such as risk aversion or individual preferences for health.

Decisions regarding regular seasonal influenza vaccination, in turn, are made by maximizing the subjective expected utility $U_S^i$ of seasonal vaccination, i.e.,

$$Vax_S^{i*} = \underset{Vax_S^i \in \{0,1\}}{\operatorname{argmax}} \; U_S^i\left(Vax_S^i, D^i, H_S^i, Z_S^i, I_S^i, \varepsilon_S^i\right) \qquad (2)$$

whereby the subjective expected utility $U_S^i$ of seasonal vaccination is assumed to depend on demographic characteristics $D^i$, seasonal influenza specific health-risk factors $H_S^i$, seasonal influenza-specific activity or occupational risk factors $Z_S^i$, and individual i's subjective information set concerning seasonal influenza vaccination $I_S^i$. As before, $\varepsilon_S^i$ denotes remaining unobserved factors that affect individual preferences for seasonal influenza vaccination, which – in this case – also includes any potential learning from prior influenza vaccination decisions. We will therefore only estimate reduced form equations for (2).

Our main object of interest is the potential causal effect of seasonal influenza vaccination experiences on the use of pandemic vaccination, i.e., the role of $Vax_S^{i*}$ in individual i's vaccination decision for H1N1 pandemic influenza $Vax_{H1N1}^{i*}$ as summarized in (1). Given the different morbidity and mortality risks associated with pandemic influenza compared to seasonal influenza during the 2009 pandemic, the pandemic vaccination decision is assumed to depend on the pandemic influenza-specific health-risk factors $H_{H1N1}^i$, the pandemic influenza-specific activity and occupational risk criteria $Z_{H1N1}^i$, as well as the pandemic influenza-specific information set $I_{H1N1}^i$, whereas the decision to get vaccinated for seasonal influenza only depends on seasonal influenza-specific health-risk factors $H_S^i$, seasonal

influenza-specific activity and occupational risk criteria $Z_S^i$, as well as an individual's seasonal influenza-specific information set $I_S^i$.

Our illustrative model highlights the potential use of seasonal influenza-specific risk factors and perceived government recommendation status for seasonal influenza vaccination as exclusion restrictions in a structural equation for pandemic vaccine use based on (1). Specifically, conditional on all health, activity and occupation-specific risk factors for pandemic influenza, perceived coverage by a pandemic vaccination recommendation and other demographic controls, the corresponding risk factor and belief measures for seasonal influenza should have no direct effect on the uptake of pandemic vaccine (instrument validity). At the same time, the above decision criteria imply that risk factors and belief measures for seasonal influenza will affect the previous use of seasonal influenza (instrument relevance), and may also indirectly affect pandemic vaccine use if past experiences with seasonal vaccination have a causal effect on pandemic vaccine uptake as implied by hypotheses of consumer learning.

## IV. Methods

### *IV.A. Data source*

Between March 4th and March 24th, 2010, we fielded a self-designed 36-item survey to adult members of a nationally representative online panel of U.S. households managed by Knowledge Networks, Inc., Menlo Park, CA (KN). KN uses a probability-based sampling scheme that combines random digit dialing with address-based sampling to recruit panelists. If a sampled household does not have Internet access at the time of recruitment, KN provides WebTV or a laptop computer and free monthly Internet access in return for participation in the panel (KN (2010)). To ensure a sufficient representation of older adults and ethnic

diversity, we oversampled adults age 65 and older, African Americans, and Hispanic participants.

Our survey started with an introductory text that highlighted the topic of the survey (influenza vaccination and related experiences), provided some background information about influenza, notably the existence of two distinct vaccines for seasonal and 2009 H1N1 influenza or "Swine flu" during the 2009 influenza A/H1N1 pandemic, and disclosed the sponsor of the data collection (GlaxoSmithKline). Moreover, the introduction clearly indicated that responding the survey was completely voluntary. The RAND Corporation's institutional review board also approved the full content of our survey. 73.5 percent of sampled panelists responded to our survey, yielding an overall sample of 4,040 respondents. After deleting observations with missing information on any survey item used in our analysis (112 deletions), we obtained a final analytical sample of 3,928 respondents.

Table 2 presents both unweighted and weighted means of selected sample characteristics. The weighted estimates are computed using poststratification weights derived from the Current Population Survey that adjust for known selection probabilities; sample stratification; and non-response to panel recruitment and panel attrition (KN (2009)). Reflecting our stratified sampling design, the sample has good coverage of older adults and ethnic minorities, while the weighted means largely match the corresponding means in the U.S. adult population.

*IV.B Measures*

Since our survey was specifically designed to study influenza vaccination, it contains detailed information on individuals' risk characteristics as well as influenza vaccination-related knowledge, attitudes, beliefs and behaviors. The following section briefly summarizes

corresponding measures for our outcomes and explanatory variables of interest, the construction of IVs that address potential confounding of the relationship between pandemic vaccine uptake and seasonal vaccination experiences as well as other control variables used in our causal model for pandemic vaccine uptake and the first-stage regressions for seasonal vaccination experiences, respectively.

1. *Outcome measures*

Our main outcome of interest—pandemic vaccine uptake—was assessed based on the survey question "Have you received a **H1N1/Swine flu** vaccine this flu season" (bold and underlined text in the original survey instrument). In order to explore the role of perceived safety of pandemic vaccine for the relationship between pandemic and seasonal vaccine uptake, we also estimated additional models using "perceived value" and "perceived safety" of pandemic vaccine as dependent variables. Respondents were classified as perceiving pandemic vaccination as "valuable" or "safe" if they indicated that they "strongly agree" or "agree" (as opposed to "neutral", "disagree" or "strongly disagree") with the statements: "Being vaccinated against **H1N1/Swine flu** is worth the time and expense" and "Being vaccinated against **H1N1/Swine flu** is safe" (bold and underlined text in the original survey instrument)..

2. *Main explanatory variable of interest*

Uptake of seasonal vaccination during the 2009 H1N1 pandemic was used as our main measure for capturing learning from previous seasonal influenza vaccination experiences. Uptake of seasonal vaccination during the 2009 H1N1 pandemic was assessed based on a survey item of the form: "Did you get a **seasonal flu** vaccine this past flu season (August 2009 to March 2010)?" (bold and underlined text in the original survey instrument). We also used "regular seasonal vaccine use" as an alternative measure for previous experiences with

influenza vaccination in the statistical models for pandemic vaccination-related outcomes as robustness check. To this end, we categorized respondents as regular vaccine users if their response to the question: "How often do you get a **seasonal flu** vaccine?" (bold and underlined text in the original survey instrument) was either "every year" or "most years" (as opposed to "some years", "rarely" or "never").

3. *Socio-economic control variables*

In order to control for the potential impact of socio-demographic variables on the uptake of pandemic vaccination, we also obtained several socio-demographic characteristics of the respondents from our own survey or from the regularly updated KN panelists profile questionnaire. Specifically, our statistical models incorporated information on respondents' sex, race and ethnicity, marital status, presence of a child, income, education, employment status, health insurance status and urbanity of the community of residence.

4. *Health and occupational risk factors and perceived coverage by government vaccination recommendations*

In order to capture individual differences in the risk of infection with the pandemic virus, we employed a series of survey questions about respondents' health and demographic characteristics that directly mirrored those used in the federal government's ACIP vaccination recommendations for pandemic vaccination the 2009-2010 influenza season summarized in Table 1. Following ACIP's assessment of relevant health and occupational risk factors for adults, the model for pandemic vaccine uptake included direct controls for being aged 18-24 years; aged 18-64 years with a high-risk health condition; pregnant; a healthcare worker; or a close contact of infants under the age of six months (CDC (2009d)). In order to account for potential heterogeneity in compliance with government vaccination

recommendations among different population groups, we separately included all of the above characteristics in our model for pandemic vaccine uptake, rather than combining all criteria into a single binary indicator indicating the respondents' coverage by a government recommendation for pandemic vaccination.

In addition to the above objective measures of health and occupational risk for pandemic influenza, we also include a control for perceived government vaccination recommendation status into the model for pandemic vaccine uptake. Perceived recommendation status for pandemic vaccination was assessed using the question: "Each year, the federal government recommends flu vaccine for high priority groups. This year, the government issues separate recommendations for seasonal flu and H1N1/Swine flu. Were you a member of a high priority group recommended for the vaccine?" For each priority group type, i.e., "Seasonal flu priority group" and "H1N1/Swine flu priority group", respondents could pick one of three permissible answers, i.e., (1) "Yes, I am a priority group member", (2) "No, I am not a priority group member" or "Don't know". We combined the categories (2) and (3) to obtain two binary variables indicating perceived coverage by a government vaccination recommendation for (a) seasonal influenza and (b) 2009 pandemic influenza A(H1N1), respectively. We used perceived coverage by a government vaccination recommendation for pandemic influenza as an additional control variable in the demand equation for pandemic vaccine. While this control variable would not have much relevance within a standard economic framework that assumes fully informed decision makers, evidence on widespread imperfect information concerning individuals' own recommendation status (Maurer et al. (2010b)) coupled with the general importance of health knowledge (Kenkel (1990, 1991)) for the demand of preventive care calls for direct controls for perceived coverage by a pandemic vaccination recommendation in addition to objective indicators of health and occupational

risks associated with the pandemic virus. Moreover, having a direct control for perceived coverage by a government vaccination recommendation for pandemic vaccination allows us to address potential confounding due to individuals' possible confusion concerning the distinct nature and specific recommendations for pandemic vs. seasonal vaccination, which may otherwise violate our conditional exclusion restrictions. Specifically, while we do not need to assume that individuals perceptions regarding the pandemic vaccination recommendation status are perfect, our exclusion restrictions do require that actual and perceived coverage by a government vaccination recommendation for seasonal influenza do not directly affect the uptake of pandemic vaccine, once we condition on individuals' actual and perceived coverage by a government vaccination recommendation for pandemic influenza and other relevant socio-demographic characteristics of the respondents.

*5. Instrumental variables*

Our analysis of consumer learning in vaccination decisions employs individuals' health, activity or occupational risk factors for seasonal influenza and perceived coverage by a government seasonal influenza vaccination recommendation as IVs for previous seasonal vaccination experiences in the statistical model for pandemic vaccine uptake and related attitudes. As in the case of pandemic risk factors, we measured individuals' health and occupational risk factors using a series of questions about respondents' health and demographic characteristics that directly mirrored the 2009 ACIP vaccination recommendations for seasonal vaccination summarized in Table 1. Specifically, we classified respondents as being at elevated health, activity or occupational risk for seasonal influenza if they were recommended for seasonal vaccination by the federal government as implied by the 2009 ACIP recommendations for seasonal influenza vaccine use. Based on this rule, the relevant risk factors for inclusion in the model for seasonal vaccine uptake were being aged

50 years and older; having a high-risk health condition (diabetes, heart disease, chronic lung disease, asthma, neurologic or neuromuscular disease, immune system problems, kidney disease, liver disease and sickle cell disease or hemophilia); being pregnant; being a healthcare worker; or having close contact with children under the age of five, high-risk individuals or persons over the age of 50 years (CDC (2009c)). Beyond these objective risk factors for seasonal influenza, we also used the aforementioned measure for perceived coverage by a government vaccination recommendation for seasonal influenza as an additional IV, aimed at capturing any effects of (potentially imperfect) information and subjective beliefs on the demand for seasonal vaccine.

*IV.C. .Econometric analysis*

Our analysis employed various linear and non-linear models in order to sidestep the ongoing debate about the relative merits and disadvantages of linear vs. non-linear IV models and demonstrate the robustness of our results to different modeling approaches (Angrist (2001), Bhattacharya et al. (2006), Terza et al. (2008)). We also conducted some robustness checks concerning model specification and the choice of measure for seasonal vaccine use. Our estimations employed survey weights provided by KN in order to account for the stratified sample design of our study and the specific forms of non-response mentioned above. Unweighted estimations were quantitatively similar, but more precise. All calculations were carried out using STATA 12.1 SE (StataCorp, College Station, TX).

We first document the association between pandemic and seasonal vaccine uptake using linear probability models and nonlinear probit models that account for the binary nature of our main outcome of interest. These initial descriptive estimations do not account for the potential endogeneity of seasonal vaccination experiences in the structural models for

pandemic vaccine use and pandemic vaccination-related attitudes. Specifically, we estimated descriptive models of the form:

1. Linear Model (OLS):

$$Vax_{H1N1} = \alpha_{H1N1} + \gamma Vax_S + D\theta_{H1N1} + H_{H1N1}\beta_{H1N1} + Z_{H1N1}\rho_{H1N1} + I_{H1N1}\delta_{H1N1} + \varepsilon_{H1N1} \quad (3)$$

2. Probit Model:

$$Vax_{H1N1} = I\{\alpha_{H1N1} + \gamma Vax_S + D\theta_{H1N1} + H_{H1N1}\beta_{H1N1} + Z_{H1N1}\rho_{H1N1} + I_{H1N1}\delta_{H1N1} + \varepsilon_{H1N1} > 0\} \quad (4)$$

with $\varepsilon_{H1N1} \sim N(0,1)$

We then re-estimated the above models using the specific health, activity and occupational risk factors for seasonal influenza (as proxied by government seasonal vaccination recommendations) and respondents' perceived coverage by such government seasonal vaccination recommendations as IVs for previous seasonal vaccination experiences to account for its potential endogeneity in the above models for pandemic-related outcomes. Specifically, we estimated causal models of the form:

3. Linear IV Model (2SLS):

$$Vax_{H1N1} = \alpha_{H1N1} + \gamma Vax_S + D\theta_{H1N1} + H_{H1N1}\beta_{H1N1} + Z_{H1N1}\rho_{H1N1} + I_{H1N1}\delta_{H1N1} + \varepsilon_{H1N1} \quad (5)$$

and

$$Vax_S = \alpha_S + D\theta_S + H_S\beta_{SS} + Z_S\rho_{SS} + I_S\delta_{SS} + H_{H1N1}\beta_{SH1N1} + Z_{H1N1}\rho_{SH1N1} + I_{H1N1}\delta_{SH1N1} + \varepsilon_S \quad (6)$$

4. Bivariate Probit Model:

$$Vax_{H1N1} = I\{\alpha_{H1N1} + \gamma Vax_S + D\theta_{H1N1} + H_{H1N1}\beta_{H1N1} + Z_{H1N1}\rho_{H1N1} + I_{H1N1}\delta_{H1N1} + \varepsilon_{H1N1} > 0\} \quad (7)$$

and

$$Vax_S = I\{\alpha_S + D\theta_S + H_S\beta_{SS} + Z_S\rho_{SS} + I_S\delta_{SS} + H_{H1N1}\beta_{SH1N1} + Z_{H1N1}\rho_{SH1N1} + I_{H1N1}\delta_{SH1N1} + \varepsilon_S > 0\} \quad (8)$$

with $\begin{pmatrix} \varepsilon_{H1N1} \\ \varepsilon_S \end{pmatrix} \sim N \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$

5. Seemingly Unrelated Bivariate Probit Model:

$$Vax_{H1N1} = I\{\alpha_{H1N1} + \gamma Vax_S + D\theta_{H1N1} + H_{H1N1}\beta_{H1N1} + Z_{H1N1}\rho_{H1N1} + I_{H1N1}\delta_{H1N1} + \varepsilon_{H1N1} > 0\} \quad (9)$$

and

$$Vax_S = I\{\alpha_S + D\theta_S + H_S\beta_{SS} + Z_S\rho_{SS} + I_S\delta_{SS} + \varepsilon_S > 0\} \quad (10)$$

with $\begin{pmatrix} \varepsilon_{H1N1} \\ \varepsilon_S \end{pmatrix} \sim N \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$

In the econometric models for pandemic vaccine uptake and pandemic vaccination-related outcomes, we included direct controls for health, activity and occupational risk factors for pandemic influenza respondents' perceived coverage by such a government pandemic vaccination recommendation. Controlling for actual risk factors in the models for pandemic and seasonal vaccination, respectively allows us to capture some of the direct effects of objective health risks on consumers' demand for each specific vaccination as well as potential indirect effects of risk factors on vaccine uptake due to, say, targeted provider recommendations to persons at elevated risks (Maurer (2009)).

The above causal models 3-5 allow for the identification of different parameters of interest, each of which captures learning in vaccination decisions within different populations. As demonstrated by Imbens and Angrist (1994), the IV approach allows us to identify a local average treatment effect (LATE), i.e., a weighted causal effect of previous seasonal vaccination experiences on pandemic outcomes for subsamples of so-called "compliers." "Compliers" are persons who got vaccinated for seasonal influenza because of actual or perceived coverage by a government vaccination recommendation for seasonal influenza, but would not have gotten a seasonal flu vaccination otherwise (see e.g. Harris and Remler (1998) for further illustrations). Making additional assumptions on functional form and error distributions, the bivariate probit and seemingly unrelated bivariate probit models (models 4

and 5), in turn, allow us to recover the average treatment effect (ATE), i.e., the average effect of previous seasonal vaccination experiences on pandemic outcomes in the entire population, as well as the average effect of treatment on the treated (ATT), i.e., the average effect of seasonal vaccination experiences on pandemic outcomes among persons who actually had some previous influenza vaccination experiences. In light of the simulation evidence of Chiburis et al. (2011), we use the bootstrap with 500 replications to compute standard errors for the ATEs and ATTs, respectively.

*6. Instrument validity, instrument relevance and robustness checks for model specification*

The exclusion restrictions above provide valid IVs for estimating causal effects of seasonal vaccine uptake on pandemic vaccination outcomes under the assumption that – conditional on actual and perceived coverage of a government vaccination recommendation for pandemic influenza and all other controls in the model for pandemic uptake - actual and perceived coverage of a government vaccination recommendation for seasonal influenza only indirectly affects pandemic vaccine uptake via its impact on seasonal vaccine use. To illustrate our identification strategy, consider two individuals i and j with identical sociodemographic and unobserved characteristics who are both not at any elevated health, activity or occupational risk for pandemic influenza and who (correctly) believe not to be covered by a government recommendation for pandemic vaccination. Both individuals are also not at any elevated health, activity or occupational risk for seasonal influenza. Yet, individual i (correctly) believes that she is not covered by a government vaccination recommendation for seasonal influenza, whereas individual j (incorrectly) believes to be covered by a government recommendation for seasonal influenza vaccination. Our identification strategy exploits the idea that - given j's belief of being covered by a government seaonsal influenza vaccination recommendation and other things equal - individual j is more likely to get vaccinated for

seasonal influenza than individual i (instrument relevance). Yet, individual j's belief should not *directly* increase her likelihood to get vaccinated for pandemic influenza relative to individual i (instrument validity), since both i and j do not belief to be covered by a government vaccination recommendation for pandemic influenza and have also otherwise identical characteristics. As a result, any difference in i's and j's likelihood of being vaccinated for pandemic influenza ought to be the result of their different propensity to have experiences with seasonal influenza vaccination due to exogenous differences in their beliefs concerning their coverage by a government vaccination recommendation for seasonal influenza. More generally, our IV strategy is based on the idea that health, activity and occupational risk factors and perceived recommendation status for seasonal influenza are likely to induce people to use seasonal influenza vaccine (instrument relevance), but should not have any direct effect on the demand for pandemic vaccine conditional on our direct controls for health, activity and occupational risk factors and perceived recommendation status for pandemic influenza and other relevant socio-demographic characteristics (instrument validity).

One potential challenge to this IV strategy may be the relatively strong age dependence of both health risk and government vaccination recommendations for both seasonal and pandemic vaccine. This issue may be particularly critical if we suspect seasonal and/or pandemic vaccine uptake to be subject to general age trends that are not directly related to individuals' health, activity and occupational risk factors or their perceived vaccination recommendation status. We thus conducted additional robustness checks of our benchmark models that also included flexible controls for age (second order polynomials) in all statistical models, which directly captured potentially confounding age trends in our models for

pandemic vaccine uptake, perceived value and safety of pandemic vaccination (structural outcome equations) and seasonal vaccination experiences (first-stage), respectively.

Moreover, to explore the robustness of the association between pandemic vaccination outcomes and seasonal vaccination experiences to different measures of previous seasonal vaccine use, we re-estimated the above models using the aforementioned measure of "regular seasonal vaccine use" as alternative measure for previous vaccination experiences. The main motivation behind this additional robustness check was to break any potential temporal dependence or "common shocks" implied by, say, common fixed cost of considering both types of vaccinations in the same season or omitted supply-side effects that may affect the uptake of both seasonal and pandemic vaccine (Maurer (2009)).

## V. Results

Table 3 presents our benchmark results for the associations and causal links between pandemic vaccine uptake, perceived value, and perceived safety of pandemic vaccination on the one hand and seasonal vaccination experiences as measured by seasonal vaccine uptake during the 2009 influenza season on the other. Coefficient estimates for the benchmark models are reported in the appendix. The multivariable linear and probit models (columns 1 and 2) show that – conditional on all other controls – persons who were vaccinated for seasonal influenza during the 2009 influenza season were also 32.5 percentage points (OLS) and 27.3 percentage points (probit) more likely to be vaccinated for pandemic influenza. Similarly, persons who were vaccinated for seasonal influenza in 2009 were 32.7 percentage points (OLS) and 29.6 percentage points (probit) more likely to perceive pandemic vaccination as worth the time and expense. Perceived pandemic vaccination safety was also estimated to be 26.6 percentage points (OLS) and 25.0 percentage points (probit) higher

among persons who were vaccinated for seasonal influenza during the pandemic vaccination season.

Columns 3-7 of Table 3 use linear IV models and two specifications of the bivariate probit model to explore whether the above associations reflect at least in part a causal link between seasonal vaccination experiences on the one hand and pandemic vaccination-related outcomes on the other (consumer learning) or whether these associations mainly stem from "reverse causation" or unobserved third factors that affect the demand for both seasonal and pandemic vaccination. As mentioned before, the linear IV models estimate LATEs, whereas the parametric bivariate probit models can be used to estimate ATEs and ATTs, respectively. Consistent with our hypothesis of consumer learning, the linear IV model resulted in an estimated LATE of 16.1 percentage points. Similarly, the bivariate probit model implied an ATE of 21.9 and an ATT of 27.4 percentage points, while the seemingly unrelated bivariate probit model give corresponding estimates of 21.6 (ATE) and 27.3 (ATT), respectively. Testing for the significance of the set of explanatory variables capturing objective and perceived coverage by a seasonal vaccination recommendation in the uptake equation for seasonal influenza vaccine, but which were excluded from the model for pandemic vaccine uptake, clearly indicates a high degree of "instrument relevance" throughout all our models. For example, the first-stage F-statistic of the excluded instruments in the linear IV model is 40.1 and thus easily fulfills the conventional requirement for "instrumental relevance" of a first-stage F-statistic of 10 or larger. Interestingly, the pandemic health, activity and occupational risk factors as well as perceived government recommendation status for pandemic vaccine displayed no statistically significant association with the uptake of seasonal vaccine in the first-stage models for seasonal vaccination experiences, providing

some intuitive support for the validity of our (symmetric) exclusion restrictions in the structural model for pandemic vaccination.

Moving to individual attitudes and perceptions regarding pandemic vaccination, our estimates suggest that there are equally large learning effects from seasonal vaccination experiences on both the perceived value and the perceived safety of pandemic vaccination. Corresponding estimates for LATEs, ATEs and ATTs from the linear IV and bivariate probit models indicate causal effects of roughly 39 percentage points for the perceived value of pandemic vaccination and 31 percentage points for the perceived safety of pandemic vaccination, respectively. Again, tests for "instrument relevance" show that our instruments exert a large effect on seasonal vaccine uptake.

Table 4 explores the robustness of our estimates for the causal effect of seasonal vaccination on pandemic vaccination-related outcomes with regard to two changes in the specification of our empirical models. First, we re-estimate all our models including a second-order polynomial of age as an additional control to capture the potential impact of underlying age trends that are not directly related to individuals' ACIP recommendation status for seasonal or pandemic influenza vaccination and may therefore confound the identification strategy of our baseline analysis. As the first part of Table 4 shows, our estimation results remain largely unchanged if we include second-order polynomials of age as additional controls into our models. The estimated learning effects from seasonal vaccination experiences on pandemic vaccination range from 13.3 percentage points (LATE) to 24.5 percentage points (ATT, bivariate probit). Similarly, the effects of seasonal vaccination experiences on perceived value of pandemic vaccination ranged from 37.1 percentage points (LATE) to 39.2 percentage points (ATE, seemingly unrelated bivariate probit), while the corresponding

effects on perceived safety of pandemic vaccination ranged from 20.6 percentage points (ATE, bivariate probit) to 22.9 percentage points (LATE).

As a second robustness check, we explore the impact of replacing our main explanatory variable of interest – current seasonal vaccination status – with a broader measure of respondents' vaccination history, i.e., whether or not they have been "regular" influenza vaccine users in the past. While the use of current seasonal vaccine use as a proxy for previous vaccination experiences has the advantage of relying on a closer match between this measure and our IVs (current health, activity and occupational risk factors and perceived government recommendation status), it may suffer from a potential correlation between seasonal and pandemic vaccine uptake due to common cost of uptake. It was in principle possible to administer both vaccines during the same visit to a healthcare provider or vaccination clinic, even if the administration of both vaccines did not occur very frequently due to the differential timing of vaccine production and delivery. For example, more than 85% of respondents in our data who report being vaccinated for both seasonal and pandemic influenza also report different vaccination locations or vaccination months for the two vaccinations, ruling out that both vaccines were administered during the same provider visit. Replacing current seasonal vaccination status with regular vaccine use, the second part of Table 4 again shows that our estimation results remain largely unchanged in response to the change in measurement of seasonal vaccination experiences. The estimated causal effects of regular seasonal vaccination on pandemic vaccine uptake range from 14.6 percentage points (LATE) to 22.5 percentage points (ATT, seemingly unrelated bivariate probit). Concerning perceptions of the value and safety of pandemic vaccination, the corresponding learning effects from regular vaccine use range from 34.1 percentage points (LATE) to 38.0

percentage points (ATE, seemingly unrelated bivariate probit) and 21 percentage points (LATE) to 25.3 percentage points (ATT, seemingly unrelated bivariate probit), respectively.

## VI. Discussion

The emergence of the novel influenza A H1N1/09 virus and the corresponding existence of two influenza vaccines with distinct recommendation groups during the 2009-10 influenza pandemic provides us with a unique opportunity to study consumer learning in influenza vaccination decisions by studying the causal effects of past use of seasonal vaccine on the uptake of the new pandemic influenza vaccine. Our estimations showed that a large part of the strong association between seasonal vaccine use and pandemic vaccine uptake during the 2009 influenza A/H1N1 pandemic represent a causal effect of seasonal vaccination experiences on the acceptance of pandemic vaccination, which we interpret as evidence for learning. Using alternative measures for previous seasonal vaccination experiences, we documented this learning effect for both pandemic vaccine uptake as well as for individuals' perceived of pandemic vaccination during the 2009 pandemic. Moreover, our estimations also highlighted a strong effect of seasonal vaccination experiences on perceived safety of pandemic vaccination, which may be an important pathway in consumer learning regarding the potential risks of vaccination and development of more favorable vaccination-related attitudes.

To the best of our knowledge, our study is the first to assess consumer learning in influenza vaccination decisions. The distinct risk characteristics and corresponding vaccination recommendations regarding pandemic and seasonal influenza provide natural exclusion restrictions that allow us to study a possible causal link between seasonal vaccination experiences and acceptance of pandemic vaccination empirically. While our detailed

population-based survey on influenza vaccine use and corresponding risk factors, knowledge, attitudes, beliefs and behaviors provided us with a unique opportunity to capture many important aspects of U.S. adults' influenza vaccination decisions and provided us with credible IVs for a causal analysis, our study is nonetheless limited in several ways. First, it is possible that our results may not fully generalize to all annual influenza epidemics, since our analyses was conducted in the specific context of the 2009 influenza A/H1N1 pandemic in the United States, which was a time of heightened interest in influenza and influenza prevention. A second limitation of our study is the use of self-reported data, which may be subject to specific biases such as recall or social desirability bias. Moreover, while KN makes a large effort to reach out to offline households via its dual address-based and RDD sampling frame, it is nonetheless possible that the use of the Internet as survey mode results in selective participation, which may not be fully corrected by the use of survey weights that calibrate our final sample to the general adult population in the United States.

## VII. Conclusion

Our analyses provide strong evidence for a causal link between seasonal influenza vaccination experiences and acceptance and uptake of pandemic vaccine during the 2009 influenza A/H1N1 pandemic, which is consistent with our hypothesis of consumer learning in vaccination decisions. In our benchmark models, the estimated causal effects of seasonal vaccination experiences on uptake of pandemic vaccine ranged from 16.1 to 27.4 percentage points. These effects are very large in light of an overall uptake rate of pandemic vaccine of just 20 percent and show that public health efforts aimed at increasing the current uptake of influenza vaccine may yield considerable dynamic benefits in terms of improved annual influenza vaccination in the future. These novel insights on the behavioral economic epidemiology of influenza vaccine use thus suggest a "double dividend" of public health

efforts aimed at an increased use of influenza vaccine during any given influenza seasons due to its likely dynamic impact on influenza vaccination decisions during future influenza epidemics or pandemics. Moreover, the large causal impact of seasonal vaccination experiences on the perceived safety of pandemic influenza vaccine further suggests that more favorable perceptions of vaccination safety are likely to be an important pathway underlying the dynamic process of learning from experience with regard to the use of influenza vaccines.

**References**

Almond D. 2006. Is the 1918 Influenza Pandemic Over? Long-term Effects of In Utero Influenza Exposure in the Post-1940 U.S. Population" Journal of Political Economy, 114(4), 672-712.

Almond D. and B. Mazumder. 2005. The 1918 influenza pandemic and subsequent health outcomes: An analysis of SIPP data. American Economic Review 95(3), 258-262.

Angrist J. 2001. Estimation of Limited Dependent Variable Models With Dummy Endogenous Regressors: Simple Strategies for Empirical Practice. Journal of Business and Economics Statistics 19 (1), 2-17.

Belongia, E.A., Irving, S.A.., Waring, S.C., et al. (2010). Clinical Characteristics and 30-Day Outcomes for Influenza A 2009 (H1N1), 2008-2009 (H1N1), and 2007-2008 (H3N2) Infections. Journal of the American Medical Association 304(10):1091-1098.

Bhattacharya J. et al. 2006. Estimating Probit Models with Self-selected Treatments. Statistics in Medicine 25 (3), 389–413.

Centers for Disease Control and Prevention, 2009a. Safety of Influenza A (H1N1) 2009 Monovalent Vaccines –- United States, October 1–November 24, 2009. Morbidity and Mortality Weekly Report 58, 1-6 (early release).

Centers for Disease Control and Prevention. 2009b. Swine Influenza A (H1N1) Infection in Two Children --- Southern California, March--April 2009. Morbidity and Mortality Weekly Report 58(15), 400-402

Centers for Disease Control and Prevention. 2009c. Prevention and Control of Influenza with Vaccines: Recommendations of the Advisory Committee on Immunization Practices (ACIP), 2009. Morbidity and Mortality Weekly Report 58(RR-8):1-52.

Centers for Disease Control and Prevention. 2009d. Use of Influenza A (H1N1) 2009 Monovalent Vaccine: Recommendations of the Advisory Committee on Immunization Practices (ACIP), 2009. Morbidity and Mortality Weekly Report 58, 1–8 (early release).

Centers for Disease Control and Prevention. 2010a. Prevention and Control of Influenza with Vaccines:
Recommendations of the Advisory Committee on Immunization Practices (ACIP), 2010. Morbidity and Mortality Weekly Report 59 (RR-8).

Centers for Disease Control and Prevention. 2010b. The 2009 H1N1 Pandemic: Summary Highlights, April 2009-April 2010. Available at: http://www.cdc.gov/h1n1flu/cdcresponse.htm (Accessed 5 October 2012).

Centers for Disease Control and Prevention. 2010c. Updated CDC estimates of 2009 H1N1 Influenza Cases, Hospitalizations and Deaths in the United States, April 2009 – April 10, 2010. Available at: http://www.cdc.gov/h1n1flu/estimates_2009_h1n1.htm (accessed online: 6 January 2014).

Centers for Disease Control and Prevention. 2011. Final estimates for 2009–10 Seasonal Influenza and Influenza A (H1N1) 2009 Monovalent Vaccination Coverage – United States, August 2009 through May, 2010. Available at: http://www.cdc.gov/flu/professionals/vaccination/coverage_0910estimates.htm (accessed online: 23 January 2013).

Centers for Disease Control and Prevention. Undated. Questions & Answers: Vaccine against 2009 H1N1 Influenza Virus. Available at: http://www.cdc.gov/h1n1flu/vaccination/public/vaccination_qa_pub.htm#s_and_d (accessed online: 12 March 2013).

Chan, T. and B. Hamilton. 2006. Learning, Private Information, and the Economic Evaluation of Randomized Experiments. Journal of Political Economy 114(6): 997-1040.

Chan, T. et al. 2013. Treatment Effectiveness and Side Effects: A Model of Physician Learning. Management Science 59(6):1309-1325.

Chiburis, R. et al. 2011. A Practical Comparison of the Bivariate Probit and Linear IV Estimators.World Bank Policy Research Working Paper 5601.

Ching, A. 2010a. Consumer Learning and Heterogeneity: Dynamics of Demand for Prescription Drugs After Patent Expiration. International Journal of Industrial Organization 28: 619-638.

Ching, A. 2010b. A Dynamic Oligopoly Structural Model for the Prescription Drug Market After Patent Expiration. International Economic Review 51(4): 1175-1207.

Ching A. and M. Ishihara. 2010. The Effects of Detailing on Prescription Decisions under Quality Uncertainty. Quantitative Marketing and Economics 8(2): 123-165.

Ching A. and M. Ishihara. 2012. Measuring the Informative and Persuasive Roles of Detailing on Prescription Decisions. Management Science 58(7):1374-1387.

Ching, A, Erdem, T, and M. Keane. 2013. Invited Paper—Learning Models: An Assessment of Progress, Challenges, and New Developments. Marketing Science 32(6), pp. 913–938.

Chintagunta, P. et al. 2009. Information, Learning and Drug Diffusion: The Case of Cox-2 Inhibitors. Quantitative Marketing and Economics 7(4): 399-443.

Chintagunta, P. et al. 2012. New Drug Diffusion When Forward-Looking Physicians Learn from Patient Feedback and Detailing. Journal of Marketing Research 49(6): 807-821.

Congressional Budget Office. 2006. A Potential Influenza Pandemic: An Update on Possible Macroeconomic Effects and Policy Issues. Washington, DC.

Coscelli A. and M. Shum. 2004. An Empirical Model of Learning and Patient Spillovers in New Drug Entry. Journal of Econometrics 122: 213-246.

Cox N. and K. Subbarao. 1999. Influenza. Lancet 354(9186),1277-82.

Crawford G. and M. Shum. Uncertainty and Learning in Pharmaceutical Demand. Econometrica 73(4): 1137-1173.

Dickstein, M. 2014. Efficient Provision of Experience Goods: Evidence from Antidepressant Choice. Stanford University, mimeo.

Fernandez,J. 2013. An Empirical Model of Learning Under Ambiguity: The Case of Clinical Trials. International Economic Review 54(2): 549-573.

Ferreyra, M. and G. Kosenok. 2011. Learning About New Products: An Empirical Study of Physicians' Behavior. Economic Inquiry 49(3): 876-898.

Harris, K. and D. Remler. 1998. Who Is the Marginal Patient? Understanding Instrumental Variable Estimates of Treatment Effects. Health Services Research 33(5), 1337-1359.

Harris, K. et al. 2010. Influenza Vaccine — Safe, Effective, and Mistrusted. New England Journal of Medicine 363(23), 2183-2185.

Heckman, J. 1981. Heterogeneity and State Dependence. In: S. Rosen (ed.): Studies in Labor Markets. University of Chicago Press, Chicago: 91-140.

Imbens, G.and J. Angrist. 1994. Identification and Estimation of Local Average Treatment Effects. Econometrica. 62(2), 467-476.

Kalra, A. et al. 2011. Understanding Responses to Contradictory Information About Products. Marketing Science 30(6): 1098 – 1114.

Keane, M. 1997. Modeling Heterogeneity and State Dependence in Consumer Choice Behavior. Journal of Business and Economic Statistics 15(3): 310-327.

Kenkel, D. Consumer Health Information and the Demand for Medical Care. The Review of Economics and Statistics 72(4), 587-595.

Kenkel, D. Health Behavior, Health Knowledge, and Schooling. Journal of Political Economy 99(2), 287-305.

Kilbourne, E. 2006. Influenza Pandemics of the 20th Century. Emerging Infectious Diseases 12(1), 9–14.

Knowledge Networks. 2009. Overview of KnowledgePanel Statistical Weighting Protocol. Available from: www.knowledgenetworks.com/ganp/docs/KN-Weighting-Synopsis.pdf (accessed 18 September 2010).

Knowledge Networks. 2010. KnowledgePanel Design Summary. Available from: http://www.knowledgenetworks.com/knpanel/KNPanel-Design-Summary.html (accessed 18 September 2010).

Lee, B. et al. 2010. Vaccination Deep Into a Pandemic Wave Potential Mechanisms for a "Third Wave" and the Impact of Vaccination. American Journal of Preventive Medicine 39(5), e21-e29.

Liao, Q. et al. 2011. Factors Affecting Intention to Receive and Self-reported Receipt of 2009 Pandemic (H1N1) Vaccine in Hong Kong: A Longitudinal Study." PLoS One 6.3, e17713.

Lim H. and A. Ching. 2012. A Structural Analysis of Detailing, Publicity and Correlated Learning: The Case of Statins. University of Toronto, mimeo.

Lindley, M. et al. 2006. The Role of Attitudes in Understanding Disparities in Adult Influenza Vaccination. American Journal of Preventive Medicine 31(4), 281-285.

Mata, de la D. 2011. Estimating a Dynamic Discrete Choice Model of Health Prevention Decisions: An Application to Flu Vaccination, University of Rosario, mimeo.

Maurer J. 2009. Who Has a Clue to Preventing the Flu? Unravelling Supply and Demand Effects on the Uptake of Influenza Vaccinations. Journal of Health Economics 28(3), 704-17.

Maurer J. et al. 2010a. Perceived Seriousness of Seasonal and A(H1N1) Influenzas, Attitudes Toward Vaccination, and Vaccine Uptake Among U.S. Adults: Does the Source of Information Matter? Preventive Medicine, 51(2), 185-187.

Maurer J. et al. 2010b. Awareness of Government Seasonal and 2009 H1N1 Influenza Vaccination Recommendations Among Targeted U.S. Adults: The Role of Provider Interactions. American Journal of Infection Control, 38(6), 489-490.

Mazumder B. et al. 2010. Lingering Prenatal Effects of the 1918 Influenza Pandemic on Cardiovascular Disease. Journal of Developmental Origins of Health and Disease, 1-9.

Meltzer M. et al.1999. The Economic Impact of Pandemic Influenza in the United States: Priorities for Intervention. Emerging Infectious Diseases 5(5),659-671.

Molinari N. et al. 2007. The Annual Impact of Seasonal Influenza in the US: Measuring Disease Burden and Costs. Vaccine 25(27), 5086-5096.

Parente S. et al. 2004. The Role of Consumer Knowledge of Insurance Benefits in the Demand for Preventive Health Care Among the Elderly. Health Economics 14(1), 25-38.

Reiss P. and F. Wolak. 2007. Structural Econometric Modeling: Rationales and Examples from Industrial Organization. In: J. Heckman & E. Leamer (ed.), Handbook of Econometrics, Elsevier, edition 1, volume 6: 4277-4415.

Terza J. et al. 2008. The Use of Linear Instrumental Variables Methods in Health Services Research and Health Economics: A Cautionary Note. Health Services Research 43(3), 1102–1120.

Thompson MG, Shay DK, Zhou H et al. Estimates of Deaths Associated with Seasonal Influenza --- United States, 1976—2007. Morbidity and Mortality Weekly Report, August 27, 2010: 59(33), 1057-1062.

Uscher-Pines, L. et al. 2011. Racial and Ethnic disparities in Uptake and Location of Vaccination for 2009-H1N1 and Seasonal Influenza. American Journal of Public Health 101(7):1252–1255.

U.S. Department of Health and Human Services. 2013. Office of Disease Prevention and Health Promotion. Healthy People 2020. Washington, DC. Available at http://www.healthypeople.gov (accessed February 19, 2013).

U.S. Department of Health and Human Services. 2010. Public Health Emergency Medical Countermeasures Enterprise Review Report. Washington, DC.

Ward, C. 2014. Influenza Immunization Campaigns: Is an Ounce of Prevention Worth a Pound of Cure? American Economic Journal: Applied Economics. 6(1).

World Health Organization. 2009. Pandemic Influenza Preparedness and Response: A WHO Guidance Document. Geneva.

World Health Organization. 2013. Influenza. Global Influenza Pogramme. Available at: http://www.who.int/influenza/en/ (accessed February 19, 2013).

**Tables**

**Table 1: Summary of ACIP vaccination recommendation for seasonal and 2009 H1N1 influenza**

| Population group | Seasonal influenza | 2009 H1N1 pandemic influenza |
|---|---|---|
| Children aged 6 months-18 years | ✓ | ✓ |
| Persons aged 19-24 years | | ✓ |
| Persons aged ≥ 50 years | ✓ | |
| Persons of any age with certain high-risk health conditions[1] | ✓ | |
| Persons aged 25-64 years with certain high-risk health conditions[1] | ✓ | ✓ |
| Health care workers | ✓ | ✓ |
| Pregnant women | ✓ | ✓ |
| Household contacts and caregivers of persons at high risk for complications for seasonal influenza (adults aged ≥ 50 years, persons with certain high-risk health conditions[1], pregnant women, etc.) | ✓ | |
| Household contacts and caregivers of children aged 6 months - 5 years | ✓ | |
| Household contacts and caregivers of children aged < 6 months | ✓ | ✓ |

[1]High-risk health conditions include diabetes, heart disease, chronic lung disease, asthma, neurologic or neuromuscular diseases, immune system conditions, kidney disease, liver disease and sickle cell disease or hemophilia

**Table 2: Sample statistics. Overall and by pandemic vaccine uptake.**

| | Overall sample fractions | | Weighted sample fractions by pandemic vaccine uptake | |
|---|---|---|---|---|
| | Unweighted | Weighted | Vaccinated | Unvaccinated |
| **Outcome variables** | | | | |
| Pandemic vaccine uptake | 0.215 | 0.200 | 1.000 | 0.000 |
| Attitude: Pandemic vaccine valuable | 0.439 | 0.401 | 0.827 | 0.294 |
| Attitude: Pandemic vaccine safe | 0.450 | 0.435 | 0.798 | 0.345 |
| **Explanatory variables** | | | | |
| Main explanatory variables of interest | | | | |
| Seasonal vaccine uptake | 0.461 | 0.391 | 0.832 | 0.281 |
| Regular seasonal vaccine user | 0.394 | 0.313 | 0.622 | 0.236 |
| **Demographic and socioeconomic variables** | | | | |
| Male | 0.466 | 0.483 | 0.434 | 0.495 |
| Female | 0.534 | 0.517 | 0.566 | 0.505 |
| Race: White | 0.452 | 0.694 | 0.708 | 0.690 |
| Race: African American | 0.280 | 0.110 | 0.078 | 0.118 |
| Race: Hispanic | 0.146 | 0.132 | 0.128 | 0.133 |
| Race: Mixed/other race | 0.122 | 0.064 | 0.087 | 0.059 |
| Married or partnered | 0.570 | 0.546 | 0.576 | 0.538 |
| Any children | 0.222 | 0.321 | 0.319 | 0.322 |
| Rural area | 0.126 | 0.163 | 0.149 | 0.166 |
| Urban area | 0.874 | 0.837 | 0.851 | 0.834 |
| Education: High-school or less | 0.345 | 0.435 | 0.390 | 0.446 |
| Education: Some college | 0.334 | 0.286 | 0.276 | 0.289 |
| Education: Bachelor degree or more | 0.321 | 0.279 | 0.334 | 0.265 |
| Household income (USD): 50K or less | 0.480 | 0.491 | 0.434 | 0.505 |
| Household income (USD): 50K-100K | 0.357 | 0.350 | 0.378 | 0.342 |
| Household income (USD): 100K or more | 0.163 | 0.159 | 0.188 | 0.152 |
| Currently employed | 0.463 | 0.554 | 0.529 | 0.561 |
| Covered by health insurance | 0.879 | 0.819 | 0.881 | 0.803 |
| **Risk characteristics** | | | | |
| Age 18-24 | 0.037 | 0.105 | 0.117 | 0.103 |
| Age 18-49 and high-risk health condition | 0.055 | 0.127 | 0.173 | 0.116 |
| Age 50-64 | 0.415 | 0.254 | 0.266 | 0.251 |
| Age 65 and older | 0.333 | 0.166 | 0.210 | 0.155 |
| Healthcare worker or informal care-giver | 0.132 | 0.115 | 0.221 | 0.089 |
| Regular contact with high-risk person (H1N1) | 0.046 | 0.057 | 0.110 | 0.044 |
| Regular contact with high-risk person (Seasonal) | 0.566 | 0.512 | 0.614 | 0.486 |
| **Perceived coverage by vaccination recommendation** | | | | |
| Belief: Covered by H1N1 vaccination recommendation | 0.197 | 0.162 | 0.422 | 0.098 |
| Belief: Covered by seasonal vaccination recommendation | 0.371 | 0.256 | 0.487 | 0.199 |

**Table 3: Association and impact of seasonal influenza vaccination experiences on pandemic vaccine uptake and perceived value and safety of pandemic vaccination**

| | Associations between pandemic and 2009 seasonal vaccine uptake | | Impact of 2009 seasonal vaccine uptake on pandemic vaccination and vaccination-related attitudes | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | | Seemingly Unrelated | |
| | OLS | Probit | Linear IV | Bivariate Probit | | Bivariate Probit | |
| | | APE | LATE | ATE | ATT | ATE | ATT |
| Pandemic Vaccine Uptake | 0.325 | 0.273 | 0.161 | 0.219 | 0.274 | 0.216 | 0.273 |
| | (13.77) | (16.60) | (2.69) | (3.42) | (4.87) | (3.17) | (4.90) |
| "First-stage" F-statistic/$\chi^2$-statistic | --- | --- | 40.1 | 29.7 | | 44.7 | |
| Perceived Value of Pandemic Vaccination | 0.327 | 0.296 | 0.374 | 0.389 | 0.385 | 0.382 | 0.379 |
| | (11.46) | (13.09) | (4.68) | (4.75) | (5.23) | (4.28) | (4.58) |
| "First-stage" F-statistic/$\chi^2$-statistic | --- | --- | 40.1 | 28.4 | | 43.7 | |
| Perceived Safety of Pandemic Vaccination | 0.266 | 0.250 | 0.244 | 0.232 | 0.233 | 0.231 | 0.233 |
| | (9.18) | (9.98) | (3.20) | (2.66) | (3.08) | (2.79) | (2.71) |
| "First-stage" F-statistic/$\chi^2$-statistic | --- | --- | 40.1 | 30.2 | | 44.7 | |

**Table 4: Robustness Analysis: The impact of seasonal influenza vaccination experiences on pandemic vaccine uptake and perceived value and safety of pandemic vaccination**

**Inclusion of additional quadratic age trends in the equations for pandemic and seasonal vaccine uptake**

| | Impact of 2009 seasonal vaccine uptake on pandemic vaccination and vaccination-related attitudes | | | | |
|---|---|---|---|---|---|
| | Linear IV | Bivariate Probit | | Seemingly Unrelated Bivariate Probit | |
| | LATE | ATE | ATT | ATE | ATT |
| Pandemic Vaccine Uptake | 0.133 | 0.184 | 0.245 | 0.180 | 0.241 |
| | (1.80) | (2.25) | (2.92) | (2.24) | (3.01) |
| "First-stage" F-statistic/$\chi^2$-statistic | 24.68 | 19.7 | | 36.3 | |
| Perceived Value of Pandemic Vaccination | 0.371 | 0.383 | 0.380 | 0.392 | 0.388 |
| | (3.66) | (3.57) | (4.16) | (4.25) | (4.02) |
| "First-stage" F-statistic/$\chi^2$-statistic | 24.68 | 19.4 | | 36.5 | |
| Perceived Safety of Pandemic Vaccination | 0.229 | 0.206 | 0.208 | 0.221 | 0.223 |
| | (2.52) | (2.00) | (2.07) | (2.26) | (2.28) |
| "First-stage" F-statistic/$\chi^2$-statistic | 24.68 | 20.0 | | 35.5 | |

**Using regular instead of 2009 seasonal vaccine uptake as main explanatory variable of interest**

| | Impact of regular seasonal vaccine uptake on pandemic vaccination and vaccination-related attitudes | | | | |
|---|---|---|---|---|---|
| | Linear IV | Bivariate Probit | | Seemingly Unrelated Bivariate Probit | |
| | LATE | ATE | ATT | ATE | ATT |
| Pandemic Vaccine Uptake | 0.146 | 0.193 | 0.220 | 0.200 | 0.225 |
| | (2.51) | (2.89) | (3.74) | (2.43) | (4.00) |
| "First-stage" F-statistic/$\chi^2$-statistic | 63.66 | 42.7 | | 40.5 | |
| Perceived Value of Pandemic Vaccination | 0.341 | 0.376 | 0.375 | 0.380 | 0.378 |
| | (4.48) | (5.11) | (5.23) | (4.88) | (5.01) |
| "First-stage" F-statistic/$\chi^2$-statistic | 63.66 | 42.0 | | 40.2 | |
| Perceived Safety of Pandemic Vaccination | 0.210 | 0.238 | 0.238 | 0.252 | 0.253 |
| | (2.69) | (3.09) | (3.18) | (3.06) | (3.05) |
| "First-stage" F-statistic/$\chi^2$-statistic | 63.66 | 42.2 | | 40.2 | |

# Appendix

**Table A1: Coefficient estimates of models treating seasonal vaccination status as exogenous.**

| | Pandemic vaccine uptake | | Perceived value of pandemic vaccine | | Perceived safety of pandemic vaccine | |
|---|---|---|---|---|---|---|
| | OLS Coefficient [t-statistic] | Probit Coefficient [t-statistic] | OLS Coefficient [t-statistic] | Probit Coefficient [t-statistic] | OLS Coefficient [t-statistic] | Probit Coefficient [t-statistic] |
| Seasonal vaccine uptake | 0.325 | 1.381 | 0.327 | 0.877 | 0.266 | 0.701 |
| | [13.77]*** | [13.91]*** | [11.46]*** | [11.14]*** | [9.18]*** | [9.00]*** |
| Sex: Female | 0.007 | 0.066 | -0.001 | -0.010 | -0.027 | -0.078 |
| | [0.37] | [0.70] | [-0.03] | [-0.14] | [-1.02] | [-1.05] |
| Race: African American | -0.019 | -0.115 | 0.030 | 0.093 | -0.009 | -0.020 |
| | [-0.84] | [-0.90] | [0.81] | [0.85] | [-0.23] | [-0.19] |
| Race: Hispanic | 0.036 | 0.223 | 0.009 | 0.037 | 0.006 | 0.023 |
| | [1.12] | [1.37] | [0.22] | [0.30] | [0.14] | [0.19] |
| Race: Mixed/other race | 0.088 | 0.442 | -0.005 | -0.023 | -0.004 | -0.014 |
| | [2.09]* | [2.61]** | [-0.09] | [-0.15] | [-0.07] | [-0.09] |
| Education: Some college | 0.004 | -0.009 | 0.013 | 0.036 | 0.006 | 0.019 |
| | [0.18] | [-0.08] | [0.41] | [0.39] | [0.19] | [0.20] |
| Education: Bachelor degree or higher | 0.033 | 0.135 | 0.048 | 0.141 | 0.089 | 0.249 |
| | [1.36] | [1.17] | [1.50] | [1.49] | [2.64]** | [2.65]** |
| Health insurance status: Insured | 0.007 | 0.104 | 0.071 | 0.219 | 0.063 | 0.182 |
| | [0.27] | [0.58] | [1.89]+ | [1.84]+ | [1.64] | [1.61] |
| Urbanity: Rural | -0.004 | -0.004 | -0.026 | -0.082 | -0.035 | -0.098 |
| | [-0.19] | [-0.04] | [-0.78] | [-0.80] | [-0.93] | [-0.92] |
| Marital status: Married or partnered | 0.012 | 0.056 | -0.022 | -0.064 | -0.043 | -0.119 |
| | [0.53] | [0.51] | [-0.73] | [-0.74] | [-1.40] | [-1.40] |
| Family members: Any children | 0.023 | 0.117 | -0.021 | -0.063 | -0.035 | -0.100 |
| | [1.01] | [1.06] | [-0.69] | [-0.70] | [-1.14] | [-1.14] |
| Employment status: Employed | 0.020 | 0.091 | -0.035 | -0.102 | -0.039 | -0.109 |
| | [1.02] | [0.96] | [-1.27] | [-1.24] | [-1.34] | [-1.34] |
| Household income (USD): 50K-100K | 0.000 | -0.002 | -0.029 | -0.092 | -0.040 | -0.118 |
| | [0.00] | [-0.01] | [-0.96] | [-1.03] | [-1.29] | [-1.32] |
| Household income (USD): 100K or more | -0.019 | -0.088 | -0.035 | -0.109 | 0.064 | 0.17 |
| | [-0.59] | [-0.55] | [-0.85] | [-0.88] | [1.43] | [1.39] |
| Risk: Healthcare worker | 0.085 | 0.343 | -0.019 | -0.052 | 0.045 | 0.125 |
| | [2.22]* | [2.40]* | [-0.46] | [-0.44] | [1.02] | [1.05] |
| Risk: Regular contact with high-risk person (H1N1) | 0.054 | 0.165 | -0.002 | 0.003 | -0.028 | -0.079 |
| | [0.99] | [0.79] | [-0.03] | [0.01] | [-0.41] | [-0.41] |
| Risk: Age 18-64 and chronic disease | -0.035 | -0.156 | 0.022 | 0.065 | 0.002 | 0.007 |
| | [-1.43] | [-1.41] | [0.65] | [0.66] | [0.05] | [0.07] |
| Risk: Age 18-24 | 0.069 | 0.383 | 0.008 | 0.034 | 0.007 | 0.029 |
| | [1.70]+ | [1.91]+ | [0.13] | [0.21] | [0.12] | [0.17] |
| Belief: Covered by H1N1 recommendation | 0.268 | 0.894 | 0.146 | 0.411 | 0.085 | 0.233 |
| | [8.13]*** | [8.30]*** | [4.10]*** | [4.07]*** | [2.33]* | [2.33]* |
| Intercept | -0.032 | -2.168 | 0.224 | -0.762 | 0.315 | -0.497 |
| | [-1.13] | [-10.46]*** | [4.46]*** | [-4.87]*** | [6.35]*** | [-3.48]*** |

**Table A2: Coefficient estimates of models for pandemic vaccine uptake treating seasonal vaccination status as endogenous.**

| | Linear IV | | Bivariate probit | | Seemingly unrelated bivariate probit | |
|---|---|---|---|---|---|---|
| | Outcome equation | First stage | | | | |
| | Pandemic vaccine uptake | Seasonal vaccine uptake | Pandemic vaccine uptake | Seasonal vaccine uptake | Pandemic vaccine uptake | Seasonal vaccine uptake |
| Seasonal vaccine uptake | 0.161 | | 0.947 | | 0.937 | |
| | [2.69]** | | [3.46]*** | | [3.36]*** | |
| Sex: Female | 0.007 | -0.002 | 0.066 | -0.005 | 0.067 | -0.003 |
| | [0.35] | [-0.06] | [0.71] | [-0.07] | [0.71] | [-0.04] |
| Race: African American | -0.034 | -0.055 | -0.157 | -0.188 | -0.156 | -0.174 |
| | [-1.44] | [-1.67]+ | [-1.21] | [-1.74]+ | [-1.21] | [-1.60] |
| Race: Hispanic | 0.021 | -0.082 | 0.185 | -0.266 | 0.183 | -0.266 |
| | [0.63] | [-2.45]* | [1.13] | [-2.29]* | [1.12] | [-2.27]* |
| Race: Mixed/other race | 0.08 | -0.032 | 0.405 | -0.087 | 0.405 | -0.076 |
| | [1.68]+ | [-0.55] | [2.26]* | [-0.47] | [2.26]* | [-0.42] |
| Education: Some college | 0.003 | 0.003 | -0.012 | 0.011 | -0.014 | -0.002 |
| | [0.14] | [0.08] | [-0.10] | [0.11] | [-0.12] | [-0.02] |
| Education: Bachelor degree or higher | 0.03 | -0.019 | 0.127 | -0.067 | 0.128 | -0.05 |
| | [1.22] | [-0.61] | [1.11] | [-0.67] | [1.13] | [-0.50] |
| Health insurance status: Insured | 0.028 | 0.059 | 0.163 | 0.198 | 0.166 | 0.21 |
| | [1.00] | [1.69]+ | [0.91] | [1.59] | [0.93] | [1.69]+ |
| Urbanity: Rural | -0.009 | -0.033 | -0.013 | -0.097 | -0.012 | -0.088 |
| | [-0.39] | [-1.00] | [-0.11] | [-0.92] | [-0.10] | [-0.83] |
| Marital status: Married or partnered | 0.016 | 0.018 | 0.066 | 0.051 | 0.071 | 0.082 |
| | [0.73] | [0.65] | [0.61] | [0.56] | [0.66] | [0.92] |
| Family members: Any children | 0.011 | -0.008 | 0.079 | -0.026 | 0.076 | -0.028 |
| | [0.47] | [-0.24] | [0.70] | [-0.25] | [0.68] | [-0.27] |
| Employment status: Employed | -0.002 | -0.038 | 0.024 | -0.111 | 0.024 | -0.107 |
| | [-0.08] | [-1.40] | [0.24] | [-1.28] | [0.23] | [-1.23] |
| Household income (USD): 50K-100K | 0.013 | 0.082 | 0.034 | 0.266 | 0.033 | 0.248 |
| | [0.49] | [2.88]** | [0.26] | [2.92]** | [0.25] | [2.75]** |
| Household income (USD): 100K or more | -0.006 | 0.089 | -0.051 | 0.293 | -0.056 | 0.248 |
| | [-0.19] | [2.14]* | [-0.32] | [2.28]* | [-0.36] | [1.94]+ |
| Risk: Healthcare worker | 0.112 | 0.125 | 0.407 | 0.383 | 0.407 | 0.374 |
| | [2.81]** | [3.15]** | [2.81]** | [3.18]** | [2.83]** | [3.14]** |
| Risk: Contact with high-risk person (H1N1) | 0.06 | 0.035 | 0.184 | 0.12 | 0.165 | |
| | [1.03] | [0.54] | [0.86] | [0.60] | [0.81] | |
| Risk: Age 18-64 and chronic disease | -0.025 | 0.028 | -0.125 | 0.094 | -0.13 | |
| | [-0.98] | [0.72] | [-1.11] | [0.82] | [-1.18] | |
| Risk: Age 18-24 | 0.047 | -0.058 | 0.3 | -0.188 | 0.328 | |
| | [1.11] | [-1.12] | [1.46] | [-1.05] | [1.65]+ | |
| Belief: Covered by recommendation (H1N1) | 0.308 | -0.035 | 0.968 | -0.12 | 0.983 | |
| | [8.25]*** | [-0.78] | [8.41]*** | [-0.85] | [8.18]*** | |
| Risk: Contact with high-risk person (seasonal) | | 0.031 | | 0.101 | | 0.112 |
| | | [1.18] | | [1.22] | | [1.37] |
| Risk: Age 18-49 and chronic disease | | 0.05 | | 0.13 | | 0.215 |
| | | [0.86] | | [0.73] | | [1.48] |
| Risk: Age 50-64 | | 0.059 | | 0.166 | | 0.224 |
| | | [1.76]+ | | [1.53] | | [2.29]* |
| Risk: Age 65 or older | | 0.148 | | 0.435 | | 0.461 |
| | | [3.60]*** | | [3.45]*** | | [3.86]*** |
| Belief: Covered by recommendation (seasonal) | | 0.399 | | 1.114 | | 1.066 |
| | | [10.56]*** | | [9.61]*** | | [12.57]*** |
| Intercept | 0.018 | 0.169 | -2.001 | -0.967 | -2.003 | -1.022 |
| | [0.51] | [3.65]*** | [-8.38]*** | [-5.88]*** | [-8.42]*** | [-6.40]*** |
| Rho | | | | 0.266 | | 0.271 |
| | | | | [1.71]+ | | [1.71]+ |

**Table A3: Coefficient estimates of models for perceived value of pandemic vaccine treating seasonal vaccination status as endogenous.**

| | Linear IV | | Bivariate probit | | Seemingly unrelated bivariate probit | |
|---|---|---|---|---|---|---|
| | Outcome equation | First stage | | | | |
| | Belief: Pandemic vaccine valuable | Seasonal vaccine uptake | Belief: Pandemic vaccine valuable | Seasonal vaccine uptake | Belief: Pandemic vaccine valuable | Seasonal vaccine uptake |
| Seasonal vaccine uptake | 0.374 | | 1.05 | | 1.032 | |
| | [4.68]*** | | [4.41]*** | | [4.31]*** | |
| Sex: Female | -0.001 | -0.002 | -0.01 | -0.003 | -0.011 | 0 |
| | [-0.03] | [-0.06] | [-0.14] | [-0.03] | [-0.14] | [0.00] |
| Race: African American | 0.035 | -0.055 | 0.109 | -0.187 | 0.107 | -0.173 |
| | [0.90] | [-1.67]+ | [0.98] | [-1.73]+ | [0.96] | [-1.58] |
| Race: Hispanic | 0.013 | -0.082 | 0.053 | -0.274 | 0.051 | -0.274 |
| | [0.31] | [-2.45]* | [0.41] | [-2.33]* | [0.40] | [-2.29]* |
| Race: Mixed/other race | -0.002 | -0.032 | -0.014 | -0.074 | -0.015 | -0.064 |
| | [-0.05] | [-0.55] | [-0.09] | [-0.40] | [-0.10] | [-0.35] |
| Education: Some college | 0.013 | 0.003 | 0.037 | 0.013 | 0.038 | 0 |
| | [0.42] | [0.08] | [0.40] | [0.13] | [0.40] | [0.00] |
| Education: Bachelor degree or higher | 0.049 | -0.019 | 0.143 | -0.062 | 0.142 | -0.043 |
| | [1.52] | [-0.61] | [1.51] | [-0.62] | [1.50] | [-0.43] |
| Health insurance status: Insured | 0.065 | 0.059 | 0.196 | 0.203 | 0.198 | 0.213 |
| | [1.67]+ | [1.69]+ | [1.57] | [1.62] | [1.58] | [1.71]+ |
| Urbanity: Rural | -0.024 | -0.033 | -0.076 | -0.1 | -0.077 | -0.092 |
| | [-0.73] | [-1.00] | [-0.74] | [-0.96] | [-0.75] | [-0.87] |
| Marital status: Married or partnered | -0.023 | 0.018 | -0.069 | 0.049 | -0.07 | 0.081 |
| | [-0.77] | [0.65] | [-0.78] | [0.53] | [-0.80] | [0.90] |
| Family members: Any children | -0.017 | -0.008 | -0.049 | -0.02 | -0.05 | -0.022 |
| | [-0.57] | [-0.24] | [-0.54] | [-0.20] | [-0.54] | [-0.21] |
| Employment status: Employed | -0.029 | -0.038 | -0.078 | -0.116 | -0.081 | -0.109 |
| | [-0.97] | [-1.40] | [-0.87] | [-1.32] | [-0.90] | [-1.25] |
| Household income (USD): 50K-100K | -0.032 | 0.082 | -0.105 | 0.262 | -0.103 | 0.245 |
| | [-1.05] | [2.88]** | [-1.15] | [2.87]** | [-1.13] | [2.70]** |
| Household income (USD): 100K or more | -0.039 | 0.089 | -0.121 | 0.286 | -0.118 | 0.241 |
| | [-0.91] | [2.14]* | [-0.97] | [2.22]* | [-0.94] | [1.88]+ |
| Risk: Healthcare worker | -0.026 | 0.125 | -0.081 | 0.388 | -0.077 | 0.38 |
| | [-0.63] | [3.15]** | [-0.66] | [3.20]** | [-0.64] | [3.16]** |
| Risk: Regular contact with high-risk person (H1N1) | -0.004 | 0.035 | -0.004 | 0.133 | 0.004 | |
| | [-0.05] | [0.54] | [-0.02] | [0.65] | [0.02] | |
| Risk: Age 18-64 and chronic disease | 0.019 | 0.028 | 0.054 | 0.06 | 0.057 | |
| | [0.56] | [0.72] | [0.55] | [0.52] | [0.58] | |
| Risk: Age 18-24 | 0.014 | -0.058 | 0.06 | -0.199 | 0.047 | |
| | [0.24] | [-1.12] | [0.35] | [-1.10] | [0.28] | |
| Belief: Covered by H1N1 vaccination recommendation | 0.135 | -0.035 | 0.367 | -0.126 | 0.366 | |
| | [3.25]** | [-0.78] | [3.01]** | [-0.91] | [2.94]** | |
| Risk: Regular contact with high-risk person (seasonal) | | 0.031 | | 0.091 | | 0.103 |
| | | [1.18] | | [1.07] | | [1.21] |
| Risk: Age 18-49 and chronic disease | | 0.05 | | 0.192 | | 0.243 |
| | | [0.86] | | [1.08] | | [1.68]+ |
| Risk Age 50-64 | | 0.059 | | 0.203 | | 0.251 |
| | | [1.76]+ | | [1.83]+ | | [2.52]* |
| Risk: Age 65 or older | | 0.148 | | 0.438 | | 0.472 |
| | | [3.60]*** | | [3.49]*** | | [3.98]*** |
| Belief: Covered by seasonal vaccination recommendation | | 0.399 | | 1.112 | | 1.055 |
| | | [10.56]*** | | [9.75]*** | | [12.37]*** |
| Intercept | 0.21 | 0.169 | -0.813 | -0.975 | -0.806 | -1.034 |
| | [3.71]*** | [3.65]*** | [-4.76]*** | [-5.89]*** | [-4.75]*** | [-6.44]*** |
| Rho | | | -0.117 | | -0.104 | |
| | | | [-0.75] | | [-0.67] | |

**Table A4: Coefficient estimates of models for perceived safety of pandemic vaccine treating seasonal vaccination status as endogenous.**

| | Linear IV | | Bivariate probit | | Seemingly unrelated bivariate probit | |
|---|---|---|---|---|---|---|
| | Outcome equation | First stage | | | | |
| | Belief: Pandemic vaccine safe | Seasonal vaccine uptake | Belief: Pandemic vaccine safe | Seasonal vaccine uptake | Belief: Pandemic vaccine safe | Seasonal vaccine uptake |
| Seasonal vaccine uptake | 0.244 | | 0.61 | | 0.608 | |
| | [3.20]** | | [2.74]** | | [2.76]** | |
| Sex: Female | -0.027 | -0.002 | -0.078 | -0.009 | -0.078 | -0.006 |
| | [-1.02] | [-0.06] | [-1.04] | [-0.11] | [-1.04] | [-0.07] |
| Race: African American | -0.011 | -0.055 | -0.029 | -0.185 | -0.029 | -0.172 |
| | [-0.28] | [-1.67]+ | [-0.27] | [-1.73]+ | [-0.27] | [-1.58] |
| Race: Hispanic | 0.004 | -0.082 | 0.014 | -0.268 | 0.014 | -0.268 |
| | [0.09] | [-2.45]* | [0.12] | [-2.28]* | [0.12] | [-2.25]* |
| Race: Mixed/other race | -0.005 | -0.032 | -0.018 | -0.083 | -0.018 | -0.072 |
| | [-0.08] | [-0.55] | [-0.12] | [-0.45] | [-0.12] | [-0.39] |
| Education: Some college | 0.006 | 0.003 | 0.018 | 0.012 | 0.018 | 0 |
| | [0.19] | [0.08] | [0.20] | [0.12] | [0.19] | [-0.00] |
| Education: Bachelor degree or higher | 0.089 | -0.019 | 0.247 | -0.063 | 0.248 | -0.045 |
| | [2.63]** | [-0.61] | [2.62]** | [-0.63] | [2.63]** | [-0.45] |
| Health insurance status: Insured | 0.066 | 0.059 | 0.193 | 0.2 | 0.194 | 0.211 |
| | [1.67]+ | [1.69]+ | [1.65]+ | [1.60] | [1.66]+ | [1.69]+ |
| Urbanity: Rural | -0.036 | -0.033 | -0.101 | -0.099 | -0.101 | -0.09 |
| | [-0.95] | [-1.00] | [-0.94] | [-0.95] | [-0.94] | [-0.85] |
| Marital status: Married or partnered | -0.042 | 0.018 | -0.116 | 0.048 | -0.115 | 0.079 |
| | [-1.38] | [0.65] | [-1.36] | [0.53] | [-1.35] | [0.88] |
| Family members: Any children | -0.037 | -0.008 | -0.107 | -0.023 | -0.107 | -0.025 |
| | [-1.17] | [-0.24] | [-1.19] | [-0.22] | [-1.19] | [-0.24] |
| Employment status: Employed | -0.042 | -0.038 | -0.121 | -0.113 | -0.121 | -0.108 |
| | [-1.36] | [-1.40] | [-1.40] | [-1.29] | [-1.40] | [-1.24] |
| Household income (USD): 50K-100K | -0.039 | 0.082 | -0.11 | 0.264 | -0.111 | 0.246 |
| | [-1.22] | [2.88]** | [-1.23] | [2.88]** | [-1.24] | [2.71]** |
| Household income (USD): 100K or more | 0.065 | 0.089 | 0.177 | 0.29 | 0.176 | 0.246 |
| | [1.46] | [2.14]* | [1.44] | [2.24]* | [1.43] | [1.91]+ |
| Risk: Healthcare worker | 0.049 | 0.125 | 0.14 | 0.39 | 0.14 | 0.381 |
| | [1.08] | [3.15]** | [1.14] | [3.21]** | [1.14] | [3.17]** |
| Risk: Regular contact with high-risk person (H1N1) | -0.027 | 0.035 | -0.075 | 0.135 | -0.08 | |
| | [-0.39] | [0.54] | [-0.40] | [0.67] | [-0.42] | |
| Risk: Age 18-64 and chronic disease | 0.003 | 0.028 | 0.012 | 0.085 | 0.011 | |
| | [0.09] | [0.72] | [0.12] | [0.71] | [0.11] | |
| Risk: Age 18-24 | 0.004 | -0.058 | 0.016 | -0.186 | 0.022 | |
| | [0.07] | [-1.12] | [0.10] | [-1.04] | [0.13] | |
| Belief: Covered by H1N1 vaccination recommendation | 0.09 | -0.035 | 0.255 | -0.123 | 0.258 | |
| | [2.26]* | [-0.78] | [2.27]* | [-0.88] | [2.23]* | |
| Risk: Regular contact with high-risk person (seasonal) | | 0.031 | | 0.103 | | 0.115 |
| | | [1.18] | | [1.22] | | [1.37] |
| Risk: Age 18-49 and chronic disease | | 0.05 | | 0.162 | | 0.238 |
| | | [0.86] | | [0.88] | | [1.63] |
| Risk Age 50-64 | | 0.059 | | 0.181 | | 0.235 |
| | | [1.76]+ | | [1.65]+ | | [2.39]* |
| Risk: Age 65 or older | | 0.148 | | 0.45 | | 0.478 |
| | | [3.60]*** | | [3.57]*** | | [4.01]*** |
| Belief: Covered by seasonal vaccination recommendation | | 0.399 | | 1.107 | | 1.055 |
| | | [10.56]*** | | [9.49]*** | | [12.32]*** |
| Intercept | 0.322 | 0.169 | -0.47 | -0.975 | -0.47 | -1.03 |
| | [5.69]*** | [3.65]*** | [-2.91]** | [-5.93]*** | [-2.93]** | [-6.46]*** |
| Rho | | | 0.060 | | 0.061 | |
| | | | [0.44] | | [0.45] | |