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THE EFFECT OF THE 2009 INFLUENZA PANDEMIC ON ABSENCE FROM WORK

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ABSTRACT

In July 2009, the World Health Organization declared the first flu pandemic in nearly 40 years. Although the health effects of the pandemic have been studied, there is little research examining the labor productivity consequences. Using unique sick leave data from the Chilean private health insurance system, we estimate the effect of the pandemic on missed days of work. We estimate that the pandemic increased mean flu days missed by 0.042 days per person-month during the 2009 peak winter months (June and July), representing an 800% increase in missed days relative to the sample mean. Calculations using the estimated effect imply a minimum 0.2% reduction in Chile's labor supply.

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1. INTRODUCTION

In July 2009, the World Health Organization declared the first flu pandemic in nearly 40 years. The 2009 flu pandemic caused almost 18,500 confirmed deaths and cases were reported from 214 countries worldwide (WHO, 2010). Several studies have evaluated the effects of the 2009 pandemic on mortality (Azziz-Baumgartner *et al.,* 2012; Lemaitre *et al.,* 2012; Nguyen and Noymer, 2013; Sypsa *et al.,* 2011; Yang *et al.,* 2012a), finding that the 2009 pandemic significantly increased mortality rates from influenza-like illnesses relative to previous non-pandemic flu seasons. Excess mortality because of the 2009 pandemic ranged from a low of approximately 0.79 deaths per 100,000 in the USA to a high of 2.7 deaths per 100,000 individuals in Argentina. Prior research has also examined the effects of the 2009 pandemic on healthcare utilization, including physician visits, visits to emergency departments, and hospitalizations (Jacks *et al.,* 2012; Rodríguez-Rieiro *et al.,* 2012; Rubinson *et al.,* 2013; Schanzer and Schwartz, 2013; Uscher-Pines and Elixhauser, 2006; Weinberger *et al.,* 2012; Yang *et al.,* 2012b); nearly all of these studies find significant increases in healthcare utilization in the 2009 flu season relative to earlier non-pandemic flu seasons.

Although our understanding of the mortality and health utilization effects due to the 2009 flu pandemic has grown rapidly, significant gaps remain with respect to understanding the effects of the pandemic on non-health outcomes including short-term work productivity and missed days of work (Dawood *et al.,* 2012). Galante *et al.* (2012) surveyed 396 patients in Spain who had either an inpatient or outpatient visit regarding their days missed from work. The survey period in this study only captured estimates of missed days of work in the week before the patient was treated until recovery, thus excluding estimates of missed days of work for individuals who never interacted with the medical care system, and missing estimates of missed days of work because of

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any flu-related relapses post-recovery. de Blasio *et al.* (2012) evaluate sick leave in Norway due to the pandemic, but as noted by the authors, because self-certified sick leave is not captured by the data, the true effects of the pandemic on sick leave are likely to be understated. Aside from Galante *et al.* (2012) and de Blasio *et al.* (2012), existing research on pandemics and missed days of work is either focused on pandemics from several decades ago, or is based on simulations with limited applications (Brainerd and Siegler, 2003; Jonung and Roeger, 2006; Meltzer *et al.,* 1999).

Influenza is an infectious disease with the potential to have large and damaging effects on the national and world economy. When considering the relationship between health and labor productivity, the flu is potentially an important factor that affects the general working population.[1] The labor productivity costs, as measured by missed days of work, are a potentially critical component of the full cost of a pandemic, and yet we have little evidence regarding its magnitude. While any influenza season is associated with a rise in sickness absences (Akazawa *et al.,* 2003), we are likely disproportionately interested in the effects of especially virulent flu seasons, because the health and non-health effects of pandemics are likely to be substantially larger. Pandemics, which typically occur because of unanticipated changes in the virulence of the flu strain, also potentially necessitate immediate investment by country governments in new vaccine procurement and investment in public health strategies aimed at fighting the spread of the disease. A full understanding of the costs of pandemics will thus aid in government decision-making both with respect to the level of immediate investment in containing the pandemic and R&D investments in technologies aimed at speeding up the vaccine creation process in the future. In this paper, using unique sick leave data from the Chilean private health insurance system, we estimate the labor productivity cost of the 2009 pandemic with respect to missed days of work in Chile. Unlike many healthcare systems in the developed world, sick leave in Chile is based on physician diagnosis of illness and is reimbursed by the health insurance system, which provides a unique opportunity to accurately study work absences directly related to the pandemic. Our empirical strategy takes advantage of the fact that the pandemic occurred during the well-defined peak winter months in Chile of June and July of 2009. The timing of the pandemic allows us to compare work absences during the pandemic with work absences in a typical flu season while accounting for secular changes in work absences over the 2007–2010 time period.

Broadly, our paper fits into the economic literature on the relationship between health and labor market outcomes. Understanding the importance of health in explaining labor outcomes has long interested economists although estimating this relationship is difficult in many contexts because of the empirical challenges of determining the causal direction between health and labor outcomes. Currie and Madrian (1999) summarize much of the early literature in this field, '[A]lthough many studies attempt to go beyond ordinary least squares in order to deal with measurement error and the endogeneity of health, it is difficult to find compelling sources of identification. The majority of these studies rely on arbitrary exclusion restrictions, and estimates of some quantities appear to be quite sensitive to the identification assumptions' (p. 3320). More recent work, using matching and difference-in-difference research designs, has focused on the employment effects of non-infectious diseases such as cancer (Bradley *et al.,* 2005, 2002; Moran *et al.,* 2011). While employment no doubt affects health independently, it has little impact on the strength of the influenza virus in any year or the timing with which the influenza virus typically operates. We isolate the effect of a short-term health shock on labor productivity by taking advantage of these characteristics of the disease. We leverage the rich sick leave data to directly link the effects of the pandemic on lost workdays, providing estimates of the labor productivity costs associated with a health shock.

In the next section, we describe the Chilean sick leave system and introduce the data. In Section 3, we outline our empirical strategy and present the results in Section 4. We conclude with a discussion of the implications of our results in Section 5.

[1]Studies have also identified significant effects of influenza on birth outcomes, as well as longer term effects on socioeconomic status and labor force participation for individuals who were exposed to influenza in utero (Currie and Schwandt, 2013; Schwandt, 2014).

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2. BACKGROUND

2.1. Sick leave

According to a recent survey from the World Health Organization (Scheil-Adlung and Sandner, 2010), as many as 145 countries worldwide have systems that provide sick leave compensation. Sick leave is an important social insurance program that protects workers and firms against lost wages resulting from illness.[2]

In Chile, both the private (ISAPRE) and public (FONASA) health insurance systems reimburse individuals their daily income for non-work-related health absences. There are four steps involved in filing a sickness insurance claim and receiving compensation in the Chilean sick leave system. First, an employee requesting compensation for a work absence must consult with a physician to obtain a diagnosis regarding the cause of illness. Second, after diagnosing the illness, the physician writes and signs a sick claim form, called a *licencia*, and specifies the number of days on the licencia that the employee needs to rest before returning to work. Third, the licencia is then sent to the employee's employer so that they can verify that the worker is employed at the time of issue. Finally, the form is sent to the employee's primary insurer (ISAPRE or FONASA), where a panel of physicians evaluates the licencia's validity and notifies the worker whether they will receive compensation.

The ISAPRE evaluation may result in three different outcomes: the licencia may be approved as is, reduced (approved in part), or rejected (not approved at all). Typically, individuals request more days than they are approved. If an individual is approved less than 11 days of sick leave for an illness episode, then they are only reimbursed their daily income starting on the fourth day of the illness. If an individual is approved 11 or more days of sick leave for an illness episode, then they are reimbursed all of the missed days of work. Individuals who relapse because of illness or require more days than initially granted to recuperate are allowed to submit another licencia. If individuals do not return to work after the ISAPRE-approved number of days, then they forgo their income for those days[3]; thus, the number of days approved by ISAPRE provides a strong lower bound estimate for employee absences. The maximum monthly reimbursement is capped at approximately 2500 US dollars, which is approximately twice the average monthly salary of an individual in the private health insurance system in Chile.

This system requires and generates a set of data detailing sick leave requests and approvals, which we leverage to study changes in work absences due to exogenous changes in illness propensity resulting from a virulent flu strain in 2009.

2.2. Data

We utilize a unique panel dataset that contains private health insurance claims data from all employed, privately insured Chileans between January 2007 and December 2010. Nearly 1.4 million individuals are observed monthly in these data. Individuals enrolled in the private health insurance system tend to be younger, have higher income, be more educated, and have smaller families compared with the remaining population that is enrolled in the Chilean public health insurance system (Duarte, 2012). Because the private health insurance system in Chile not only reimburses for health care treatments but also reimburses income for missed days of work, information is collected on all sick leave applications filed by all employed individuals.

The Chilean sick leave data contain information on the total number of days requested by an individual to cover health-related absences, the total number of days approved by the insurer, International Classification of Diseases (ICD-10) disease diagnosis information on the underlying reason for the request, and data on the month and year of the request. We combine this information with standard health insurance claims data information including age, gender, region, enrollment information, and primary insurer for a longitudinal panel of

[2]Sick leave provisions typically consist of income reimbursement that either partially or fully covers lost income because of illness and some limit on the total number of days employees are allowed to be covered by sick leave. The majority of countries with sick leave systems cover sick leave up to a month or more and replace at least 50% of employee's income (Scheil-Adlung and Sandner, 2010).

[3]Pandemics may also have effects on presenteeism (working while sick), but the sick leave data does not allow us to estimate these effects.

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approximately 1.4 million individuals each month. The sick leave and health insurance data allow us to precisely estimate the effect of the 2009 flu pandemic on the number of days missed from work and the associated economic costs in the Chilean private health insurance system.

We provide estimates of the effect of the pandemic on days requested and days approved because both measures provide complementary information about work absences. We find large effects on both outcomes, suggesting that they are informative of changes in labor productivity. The estimates using the two measures also provide very similar results proportional to their respective means.

In Table I, we present relevant descriptive statistics, by year, for the variables we use to estimate the regression model. The mean age in our data is relatively constant around 42 years old, and the majority of privately insured people are men. The effect of the 2009 pandemic can be observed in the raw summary statistics. We observe a pattern of high days requested and approved during the 2009 pandemic year. Moreover, even conditional on a flu claim, we find the mean number of days requested was approximately 1 day higher in 2009 than in the other years. These results imply that in 2009, there were more claims, and the claims covered longer periods of work absences than in other flu seasons. These raw patterns will be confirmed in the empirical analysis.

3. EMPIRICAL STRATEGY

Our empirical strategy estimates the effect of the 2009 pandemic on work absences in Chile and exploits the fact that (i) the flu is seasonal in nature and generally occurs during the May to August months, with peak transmission in June and July, and (ii) the pandemic occurred in a single year, 2009. As typical in this literature, we condition on month fixed effects to account for seasonal variation in outcomes such as the effects of a typical (non-pandemic) flu season and labor market patterns. We also include year fixed effects to account for any changes over time that may independently affect labor outcomes, such as economic policies that vary over the 2007–2010 time period. This difference-in-differences approach, standard in the literature, compares the outcomes of interest in populations in an affected year (2009) and time period (June–July) with control groups taken from years before and after the 2009 flu pandemic year (Nguyen and Noymer, 2013;

Table I. Summary statistics by year

	Year			
	2007	2008	2009	2010
Age, mean (SD)	41.27 (13.13)	41.39 (13.2)	41.68 (13.26)	41.91 (13.33)
Male, *N* (%)	10,357,577 (66)	10,699,939 (65)	10,746,936 (65)	10,976,434 (65)
Flu claim, *N* (%)	33,788 (0.21)	27,138 (0.17)	65,601 (0.4)	40,340 (0.24)
Flu number of days requested, mean (SD)	0.01 (0.36)	0.01 (0.31)	0.03 (0.52)	0.01 (0.36)
Flu number of days approved, mean (SD)	0.004 (0.163)	0.003 (0.141)	0.01 (0.227)	0.004 (0.161)
Flu number of days requested during flu season, mean (SD)	0.04 (0.62)	0.01 (0.37)	0.13 (1.11)	0.01 (0.36)
Flu number of days approved during flu season, mean (SD)	0.012 (0.261)	0.005 (0.174)	0.049 (0.459)	0.004 (0.17)
Flu number of days requested per episode, mean (SD)	5.99 (4.91)	5.79 (4.83)	6.87 (4.51)	5.74 (4.65)
Flu number of days approved per episode, mean (SD)	1.9 (2.97)	1.81 (2.94)	2.53 (2.55)	1.65 (2.85)
Flu number of days requested per episode during flu season, mean (SD)	6.06 (4.75)	5.8 (4.78)	7.16 (4.24)	5.85 (5.05)
Flu number of days approved per episode during flu season, mean (SD)	1.89 (2.64)	1.84 (2.97)	2.7 (2.13)	1.74 (3.18)
N	15,800,138	16,356,740	16,483,874	16,901,659

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Weinberger *et al.,* 2012). We define the pandemic flu season for Chile using a strict peak winter 2-month window, from June 1 to July 31 of each year, and define individuals as having influenza if they have one of the following diagnosis codes: J10 (influenza—influenza virus identified), J11 (influenza—influenza virus not identified), J12 (adenovirus pneumonia), J13 (*Streptococcus pneumoniae* pneumonia), and J18 (pneumonia —unspecified organism). We also show that our results are robust to expanding the definition of the flu season to the May–August months.

We first use information on primary policy holders from the private health insurance eligibility files and identify whether an individual was enrolled in a private health insurance plan in a given year-month. Using all enrolled individuals in a given year-month as the unit of analyses, we then examine three primary outcomes: (i) the total number of days requested by an individual to be reimbursed for influenza-like illnesses, (ii) the total number of days approved by the private insurance company for influenza-like illnesses, and (iii) the probability of filing an influenza-related sick leave claim. We focus the analysis on the first two outcomes, because they are ultimately the key parameters of interest, but we also decompose the results to understand whether the intensive or extensive margins dominate the effects.We estimate the following equation:

$$Y_{imt} = \alpha_t + \gamma_m + \beta X'_{imt} + \delta D_{mt} + \varepsilon_{imt} \tag{1}$$

where Y_{imt} represents one of our outcome measures (discussed earlier) for individual i in calendar month m and year t. The pandemic is represented by D_{mt}, the interaction of an indicator for the year 2009 and an indicator for the Chilean peak winter months of June and July. For the reasons noted earlier, the model includes calendar month and year fixed effects. The specification also controls for demographic characteristics X_{imt} including age, sex, primary insurer, and region dummies. Age is included as a continuous variable, sex is included as binary variable indicating if the respondent is male, and we include binary indicator variables for all primary insurers in the data.

Given that we account for the independent effects of the flu season (through calendar month fixed effects) and annual changes in labor market conditions, δ captures the difference-in-differences estimate of the effect of the 2009 flu pandemic. We adjust all standard errors to account for within-individual clustering.

To test the robustness of our results, we conduct five additional analyses. We leverage the rich controls in our data and its longitudinal nature to test whether our estimates are significantly affected by the inclusion of additional covariates and individual fixed effects. In the first analysis, we include additional controls for enrollee monthly salary, insurance plan type,[4] number of dependents, and job type.[5] In the second analysis, we include the new controls listed earlier and estimate regression models with individual fixed effects, thus taking advantage of the longitudinal nature of the data. The individual fixed effects model allows us to control for unobserved time-invariant heterogeneity across individuals. In the third analysis, we include the additional controls and individual fixed effects while limiting the sample to only those individuals who were continuously enrolled in all 48 months. By using a balanced sample, we further reduce concerns that employee attrition or enrollment is driving our results. Finally, we also perform two placebo tests, one in which we define the pandemic months as occurring in the summer (January and February) of 2009 and a second placebo test where we define the pandemic as occurring in the winter months (June and July) of 2010.

4. RESULTS

4.1. Graphical analysis

The labor productivity effect of the pandemic is striking and can be observed graphically. Figure 1 displays the total number of sick leave claims filed for influenza-like illnesses by privately enrolled individuals over the

[4]Whether the health insurance policy is an individual, couple, or group health insurance plan.
[5]Self-employed or not.

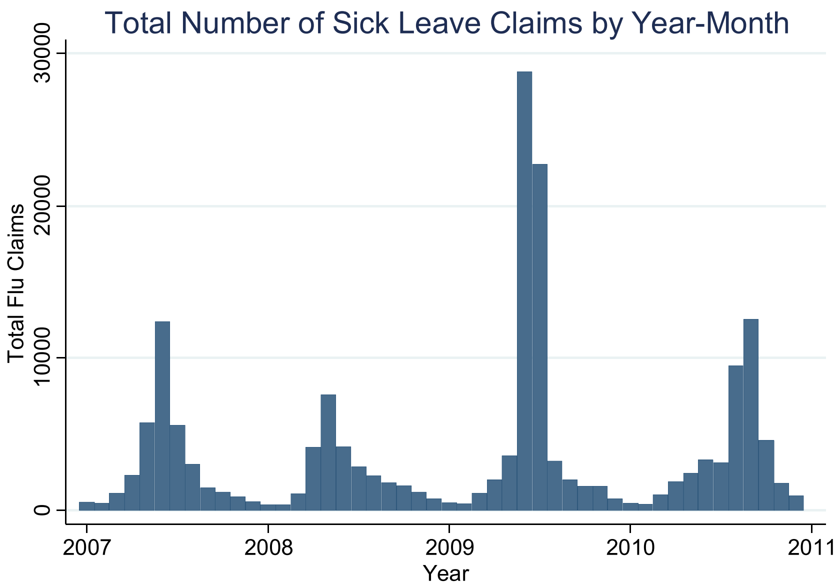

Figure 1. Total number of sick leave claims by year–month. [Colour figure can be viewed at wileyonlinelibrary.com]

2007 to 2010 data years. Figure 1 presents a very salient change in the number of claims filed for influenza-like illnesses during the pandemic year. In each of the 2007, 2008, and 2010 years, there is a noticeable increase in the total number of claims filed for influenza-like illnesses during the winter months when compared with the non-winter months, but this differential increase is significantly higher in the 2009 pandemic year. The total number of days requested and the total number of days approved for influenza-like illnesses for all enrollees also show the same pattern as Figure 1 (Figure S1 and S2).

The effect of the pandemic on worker absences is clear in our figures. The number of claims in the seasonal flu months is dramatically higher in 2009 than any other year. We observe flu seasons in years both before and after the pandemic, and the patterns do not suggest that the spike in 2009 represents the effects of a new policy change beginning in 2009. The number of claims during the 2010 flu season is similar in magnitude to the pre-pandemic flu seasons, such that we can reasonably attribute the 2009 increase to the pandemic.

4.2. Regression estimates

Next, we translate the results in the figures into regression estimates by estimating Equation 1 using data on all individual enrollee months. In Table II, column (1), we show the effect of the pandemic on the mean number of days requested for influenza-like illnesses. The regression results confirm the basic findings from Figure 1: during the pandemic, the mean number of days requested for influenza increased by approximately 0.11 days per person-month. The estimated coefficient represents a 691% increase in days requested compared with the sample mean of 0.0159.

This estimate is robust to a variety of sensitivity checks.[6] In Table II, column (2), we add the additional previously described controls and find that the effect of the pandemic on days requested is basically unchanged. In column (3), we add individual fixed effects and again find essentially no change to the column (1) estimate.

[6]We also tested the sensitivity of the ordinary least squares estimates to negative binomial regression models, but the negative binomial regressions did not converge even for the simplest regression specifications for the full data. Regressions converged for a random 5% sample of the data for the simplest regression specifications (columns 1 and 2, Tables II and IV), and these estimated coefficients were close in magnitude and statistical significance to the ordinary least squares estimates. We include the negative binomial results in Tables S1 and S2.

Table II. Estimates of additional flu days requested because of the 2009 pandemic

	(1)	(2)	(3)	(4)
	Flu days requested	Flu days requested	Flu days requested	Flu days requested
Pandemic	0.1098*** (0.00069)	0.1099*** (0.00069)	0.1099*** (0.0003)	0.0946*** (0.00034)
Mean of dependent variable	0.0159	0.0159	0.0159	0.0131
Additional controls[a]	No	Yes	Yes	Yes
Individual fixed effects	No	No	Yes	Yes
Only observed all 4 years	No	No	No	Yes
R^2	0.005	0.005	0.039	0.030
Number of observations	65,542,411	65,542,411	65,542,411	39,324,624

Observations are person-month. Standard errors are in parentheses. All regression specifications included region, primary insurer, age, month, and year controls. Standard errors adjusted to allow for arbitrary variance–covariance matrix at the individual level over time.
[a]Additional controls include number of dependents, taxable income, type of worker, and plan type.
***Significant at the $p < 0.001$ level.

There is little reason to think that our sample composition would react to the strength of the flu. Individuals can move into or out of private insurance, but our estimates are only affected if this is correlated with the pandemic. The consistency of the estimates when individual fixed effects are included in the main specification highlights that changes in sample composition are not driving the results. We can also test for this possibility by restricting the analyses to individuals that remain continuously in the sample. We subset the data sample to individuals who are enrolled continuously in every month over the 2007 to 2010 time period and present the estimates in column (4). Again, the findings are very similar, as the mean number of flu days requested increased by 0.095 per person-month, compared with 0.11 in analyses using the entire sample. Overall, given the nature of the primary research design, and the fact that individual movement into and out of the private health insurance system is not likely to be dependent on the flu season, it is not surprising that our results are robust to changes in the set of covariates or the analysis sample.

The results described in Table II present the overall effect of the pandemic on the number of days requested. This total effect is a combination of additional claims (number of unique people missing any work monthly) and changes in the number of absent days per claim. In order to better understand what drives work loss, we estimate two-part models (Boles *et al.,* 2004) aimed at differentiating between the pandemic causing more work absences (the extensive margin) or longer work absences, measured as an increase in number of days requested and approved per flu episode (the intensive margin).

First, in column (1) of Table III, we reestimate Equation 1 but replace the outcome variable with an indicator equal to 1 if the person had a flu claim in that year-month. We estimate that the pandemic increases the probability of making a claim by 1.5 percentage points, statistically significant at the 1% level. On the intensive margin, we study the relationship between the pandemic and number of days missed conditional on filing a claim and present the results in column (2). Conditional on filing a claim, we estimate that the pandemic increased the number of days requested by 0.97 days. The mean number of days requested per influenza was approximately 5.8 in non-pandemic years. Given that pandemic flu increased days requested conditional on filing a claim by approximately 1, we determine that 85% of total pandemic work loss was due to new cases—the extensive margin—and 15% was due to more severe flu keeping people home longer—the intensive margin.

One concern with the estimates presented in column (2) is that, given such a large extensive margin effect, the pandemic may have also impacted the marginal person that misses work because of the pandemic. Consequently, the pandemic may have impacted not only the length of work absences but also the composition of people missing work. If there are differences in the underlying propensity to take short (or long) absences among this population, then our estimates aggregate the causal impact of the pandemic and compositional changes of the sick population.

To tease out these two mechanisms, we estimate the causal impact of the pandemic on the number of missed work days, holding the intensive margin constant by using the following approach (found in Alpert *et al.* (2015)).

Table III. Decomposition of the 2009 pandemic effect for days requested

	(1)	(2)	(3)
Dependent variable	Any flu claim	Flu days requested	Flu days requested
Pandemic	0.0149*** (0.00008)	0.9676*** (0.05852)	0.0892*** (0.00051)
Mean of dependent variable	0.0025	6.2400	0.0159
R^2	0.006	0.036	0.006
Number of observations	65,542,411	166,867	65,542,411

Observations are person-month. Standard errors are in parentheses. All regression specifications included region, primary insurer, age, month, and year controls. Standard errors adjusted to allow for arbitrary variance–covariance matrix at the individual level over time. Column 3 estimates pandemic effects holding the intensive margin constant, refer to the text for more details.
***Significant at the $p < 0.001$ level.

For the sample with positive missed days in the pre-pandemic years, we estimate a regression equation of missed days on observable characteristics. We then use these estimates to predict missed days conditional on covariates *for all years* $\left(\hat{Y}_{imt}\right)$ and replace Y_{imt} with this predicted value for anyone with any missed days of work (those with no missed days are unchanged). The new outcome variable is the number of missed days, holding the intensive margin fixed across the entire sample. Conditional on covariates, this measure *only* varies because of the extensive margin. The results of this approach are also not affected by changes in the marginal person missing work. We reestimate Equation 1 with this modified outcome. Using this modified method, we find similar effects as column (2), with the modified methods implying that extensive margin effects explain over 81% (0.0892/0.1098) of the total effect.

In Tables IV and V, we reestimate Equation 1 but with days approved as the dependent variable of interest. Our preferred specification, Table IV, column (1), implies that the mean number of flu days approved increased by 0.042 per person-month during the pandemic, which is approximately 40% of the increase in the total number of days requested. As in the case of days requested, the estimates do not vary much with the inclusion of additional covariates, inclusion of individual fixed effects, and limiting the analytical sample to the continuously enrolled. Compared with the sample mean of 0.0053, the estimated coefficient implies that the pandemic increased the number of flu days approved by 800%. Proportional to their respective sample means, we estimate a larger relative effect using 'days approved', the outcome that is monitored and regulated by IASPRE physicians, but both measures suggest large productivity effects.

As before, we can look at the decomposition of days approved using the two models described earlier. The results from Table V again highlight the importance of the extensive margin in understanding the effects of the pandemic. The simple decomposition results imply that 74% of the increase in the days approved variable is due to the extensive margin, that is, more cases of flu, and that 26% of the increase in total days approved

Table IV. Estimates of additional flu days approved because of the 2009 pandemic

	(1)	(2)	(3)	(4)
	Flu days approved	Flu days approved	Flu days approved	Flu days approved
Pandemic	0.0424*** (0.00029)	0.0424*** (0.00029)	0.0425*** (0.00013)	0.0379*** (0.00015)
Mean of dependent variable	0.0053	0.0053	0.0053	0.0043
Additional controls[a]	No	Yes	Yes	Yes
Individual fixed effects	No	No	Yes	Yes
Only observed all 4 years	No	No	No	Yes
R^2	0.003	0.003	0.040	0.028
Number of observations	65,542,411	65,542,411	65,542,411	39,324,624

Observations are person-month. Standard errors are in parentheses. All regression specifications included region, primary insurer, age, month, and year controls. Standard errors adjusted to allow for arbitrary variance–covariance matrix at the individual level over time.
[a]Additional controls include number of dependents, taxable income, type of worker, and plan type.
***Significant at the $p < 0.001$ level.

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Table V. Decomposition of the 2009 pandemic effect for days approved

	(1)	(2)	(3)
Dependent variable	Any flu claim	Flu days approved	Flu days approved
Pandemic	0.0149*** (0.00008)	0.6458*** (0.03805)	0.039*** (0.00023)
Mean of dependent variable	0.0025	2.0700	0.0053
R^2	0.006	0.049	0.040
Number of observations	65,542,411	166,867	65,542,411

Observations are person-month. Standard errors are in parentheses. All regression specifications included region, primary insurer, age, month, and year controls. Standard errors adjusted to allow for arbitrary variance–covariance matrix at the individual level over time. Column 3 estimates pandemic effects holding the intensive margin constant, refer to the text for more details.
***Significant at the $p < 0.001$ level.

was due to the intensive margin. Analyses that hold the intensive margin effect constant imply larger extensive margin effects, as the extensive margin now explains 93% (0.039/0.042) of the total pandemic effect.

4.3. Heterogeneity

The effects of the pandemic may not have been homogenous. Understanding the consequences of a pandemic of different populations is especially important given that policies encouraging preventive measures can target interventions at specific groups of individuals. In Table VI, we present results of heterogeneous pandemic flu effects on several demographic groups. Each row represents the regression coefficient for the pandemic dummy variable from a regression that only uses observations from a specific subpopulation (male or female, age group, and region). We present breakdowns by additional variables including the number of dependents and income in Table S3. The first row of Table VI implies that men requested on average 0.088 more days per month because of the pandemic and were approved 0.034 days per month because of the pandemic, while the second row implies that women requested almost twice as many, 0.151 more days per month, and were approved 0.058 days per month because of the pandemic. This finding is possibly related to the fact that women, relative to men, are more likely to be employed in the service sector and potentially more involved in child care-related activities, thus likely to be in environments that are at higher risk for transmission of disease,[7] although other explanations are also possible.

For the age group stratifications, the results for all three outcome variables imply larger effects of the pandemic on younger individuals. These findings are consistent with the idea that unlike seasonal flu, pandemic flu is virulent enough to affect individuals that otherwise would not have been sick in a typical flu year. Finally, we also examine if pandemic flu had differential effects for individuals in different regions of Chile. One might expect differential effects by location because climate in the southern part of Chile (dry) is more conducive to virus transmission than the climate in the northern part of Chile (rainy temperate). Consistent with these expectations, we find approximately 50% larger effects on the days requested, days approved, and the probability of a flu claim in the southern and center regions of Chile when compared with the northern region in Chile.

4.4. Placebo tests

Finally, in addition to testing the sensitivity of results to additional controls, fixed effects, and sample restriction, we also performed several placebo tests (Table VII). We run one set of placebo test regressions where we exclude the 2009 data year from the analyses and define the pandemic as occurring in 2010, a non-pandemic year (Table VII, column 1). We also consider a set of placebo test regressions where we keep the pandemic year the same (2009) but now define the peak flu months as the summer months (January and February) (Table VII, column 2). We perform each of these analyses for the days requested, days approved, and the probability of

[7]In the privately insured population, we find that 25% of women are employed in the retail sector, compared with 18.4% for men.

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Table VI. The 2009 pandemic effects in specific subpopulations (gender, age, and geography)

	(1)	(2)	(3)	N
Dependent variable	Flu days requested	Flu days approved	P (flu claim)	
Male	0.0877*** (0.0003)	0.0342*** (0.0001)	0.0122*** (0.00004)	42,780,886
Female	0.1516*** (0.0006)	0.0579*** (0.0003)	0.0199*** (0.0001)	22,761,525
Age ≤35	0.1478*** (0.0005)	0.0568*** (0.0002)	0.0203*** (0.0001)	26,070,709
35<Age ≤55	0.1049*** (0.0004)	0.0408*** (0.0002)	0.0141*** (0.0001)	30,161,478
Age > 55	0.0327*** (0.0006)	0.0126*** (0.0003)	0.0041*** (0.0001)	10,713,829
Region = south	0.1113*** (0.0007)	0.0423*** (0.0003)	0.0144*** (0.0001)	14,918,584
Region = north	0.076*** (0.0006)	0.0273*** (0.0003)	0.0102*** (0.0001)	11,824,044
Region = center	0.1199*** (0.0004)	0.0472*** (0.0002)	0.0165*** (0)	38,799,488
Mean of dependent variable entire sample	0.0159	0.0053	0.0025	

Observations are person-month. Standard errors are in parentheses. All regression specifications included individual fixed effects, controls for primary insurer, and type of worker. Other covariates vary across regressions here and in Table S3 on the basis of the demographic group that is being analyzed.
***Significant at the $p < 0.001$ level.

Table VII. Placebo regressions

	Summer 2009[a]	2010[b]
Flu days requested	−0.0186*** (0.0003)	−0.0198*** (0.00028)
Flu days approved	−0.0078*** (0.00013)	−0.006*** (0.00012)
P (flu claim)	−0.0023*** (0.00004)	−0.0033*** (0.00004)
N	65,542,411	49,058,537

[a]Results are from regressions with all observations, but pandemic is assigned to summer months of January/February 2009 instead of the winter months.
[b]Results are from regressions where we dropped the 2009 data and reassigned the pandemic indicator to be in the winter months of 2010. Observations are person-month. Standard errors are in parentheses. All regression specifications included region, primary insurer, age, number of dependents, taxable income, type of worker, plan type, month, year controls, and individual fixed effects. Standard errors adjusted to allow for arbitrary variance–covariance matrix at the individual level over time.
***Significant at the $p < 0.001$ level.

filing a claim outcome variables. We find much smaller magnitudes on the pandemic variable for all of the outcome variables, and all the coefficients are negative.

5. DISCUSSION AND CONCLUSION

In this study, we use unique data on sick leave days from the private health insurance market in Chile to estimate the effect of the 2009 influenza pandemic on missed days of work. We find substantial negative effects of pandemic flu on short-term labor market participation. Unlike some of the previously studied diseases (such as cancer), pandemic flu is contagious in nature and has the potential to affect a larger group of individuals. Thus, as expected, our estimated pandemic flu effects on employment are significantly larger than many of the existing estimates of employment effects found in the literature.

Prior worker absenteeism studies also potentially overstate absenteeism costs because of anticipatory offsets. Firms anticipate some worker absences and train other workers to fill in during these periods and thus may not experience the true cost of the absenteeism. However, the flu pandemic of 2009 was so widespread and concentrated in such a short period of time that firms would likely have been unable to compensate in the typical way. Therefore, our study improves on existing worker absence studies as it identifies a better estimate of the true cost of worker absence.

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Estimates from our analyses suggest that the pandemic resulted in individuals requesting reimbursement for 0.110 more days per month and insurers approving an additional 0.042 days per month for influenza-like illnesses. Since individuals forgo income for not returning to work after the total number of days approved, we use the days approved estimate as our preferred measure of the number of missed days of work because of the pandemic. Using the days approved coefficient (0.042) as a conservative estimate of missed days of work in the private insurance population, taking the entire population at risk as 1,400,000 individuals per month and the pandemic window as 2 months, we calculate that the pandemic resulted in over 117,600 total days of missed work. Assuming 21 days a month as the total number of days available to work in a month, these calculations imply a 0.2% reduction in labor supply among privately insured employees.

Estimates from Tables II and III of the pandemic's effects on work loss days are based on a definition of the flu season in Chile as June and July. To test the sensitivity of the total estimates of missed days of work to our definition of the flu season, we reestimated Equation 1, now defining the flu season as being composed of the May–August months. Defining the flu season in this manner decreases the days approved estimate from 0.042 to 0.021 (standard error 0.0002), but increases the total number of individuals at risk for contracting the disease. The net effect of these two changes leads to an identical estimate for the total number of missed days of work.[8]

Our findings have several implications. First—using our estimates for work loss with the standard 2-month window and data on average monthly wages in the private health insurance sector in Chile (1198 US dollars in 2009 (Duarte, 2012))—we estimate a minimum net loss of approximately 6.7 million US dollars in private sector productivity because of the 2009 pandemic. We note that this estimate is likely to be a significant lower bound for the pandemic's total effects on absenteeism in Chile because only employees enrolled in private health insurance are captured in these calculations. Individuals in the public health insurance system are typically less healthy and have more children[9] than individuals in the private health insurance system, which suggests that estimates from the private health system will represent a lower bound (total) estimate for the effects of the pandemic on the Chilean workforce. Because approximately 76% of the overall population is in the public health insurance sector (Duarte, 2012), assuming similar effects of the pandemic in the public health insurance sector increases the total work loss estimates by a substantial amount. A back of the envelope calculation using estimates of missed days of work from the private health insurance system, the share of public health insurance sector that is employed (55%), and mean wages for this group (~$55 per day) implies a lower bound national (public and private enrollees) estimate of 16 million US dollars.[10] Extrapolating to the USA requires assumptions that influenza transmission works similarly in the USA and Chile, but it provides a useful benchmark to help understand the potential economic consequences in a larger and more developed country. Applying our estimates to the USA, we calculate that the pandemic would have led to a labor productivity loss of approximately $2 billion.[11] A comparison of this value directly with existing estimates of worker absenteeism due to seasonal influenza in the USA (Akazawa *et al.,* 2003) implies pandemic influenza effects that are approximately 400% larger.[12]

[8]In the case of using just June and July as flu season months, we estimate the total number of days of missed work of 117,600 (0.042 * 1,400,000 * 2). Using the broader definition of a flu season, we estimate a total number of days of missed work of 117,600 (0.021 * 1,400,000 * 4).

[9]Number of children is a strong predictor of days lost from work because of illness (Vistnes, 1997).

[10]This estimate is dependent on several factors including the size the population, the employment to population ratio, and the wage rate for the employed.

[11]There are approximately 160,000,000 people aged 18–65 years in the USA, and 62% are currently employed. Assuming pandemic effects that are equivalent to the one estimated from the Chilean private health insurance system and a daily wage of $170 per person for a US worker would imply an approximate two billion dollar loss in the USA.

[12]We note that a 400% estimated difference difference between typical influenza and pandemic influenza is likely to be a lower bound because Akazawa M, Sindelar JL, and Paltier AD (2003) analyze data from the 1995/1996 influenza season. Seasonal influenza vaccination rates in 1995/1996 were substantially lower than seasonal influenza rates during the time of the pandemic (Clarke *et al.,* 2015); thus, one would expect that work loss estimates taken from that time period are potentially higher than work loss estimates taken from the late 2000s. Furthermore, as noted by the authors, it is possible that their estimated magnitudes are biased upwards because they are derived from cross-sectional multivariate regressions where the dependent variable is total missed days of work.

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Estimating the productivity cost of pandemics also allows for a correct valuation of the benefits of prevention efforts aimed at containing the spread of the disease, the benefits derived from rapid new vaccine development in anticipation of virulent strains, and universal influenza vaccine development. For example, during the 2009 pandemic, several governments (Hine, 2010) contracted with pharmaceutical firms to produce a new influenza vaccine in anticipation of the pandemic. Typically, vaccine production using egg cell-based technologies requires a lag time of approximately 6 to 9 months for the production of a new influenza vaccine (tailored to anticipated strains). However, new vaccine production is now possible in as little as 3 months with the aid of innovative and more costly cell culture-based technologies. An understanding of the full potential costs of pandemics would aid long-term government and firm decision-making regarding investment in technologies that reduce the time to vaccine delivery. It would also aid in short-term government decision-making with respect to new vaccine purchases, which are typically aimed at combating the effects of unexpected strains. To our knowledge, Chile did not have access to vaccines that were effective against the 2009 pandemic H1N1 strain during the winter months of 2009. Chile's lack of access to pandemic vaccination allows for cost–benefit calculations with respect to obtaining and providing such a vaccination. We make three assumptions in our calculations: (i) Chile was able to obtain a vaccine that was 80% effective against the pandemic H1N1 strain; (ii) Chile was able to provide the vaccine at the typical Chile influenza vaccine price of $12 to the privately insured population; and (iii) the private insurance population would be vaccinated to herd immunity level (36%, Plans-Rubió, 2012). Given these assumptions, the expected reduction in work loss productivity is approximately 11% higher than H1N1 vaccination spending—implying that investment in vaccination would have been cost saving, even when only taking into account benefits from work loss (vaccination spending = $6,048,000 versus expected improvement in work loss = $6,700,000).[13]

Our estimates imply that the pandemic reduced flu-related work productivity by 700–800% relative to the sample mean. However, the impact of the pandemic was not limited to Chile, as evidenced by cases being detected in 214 countries worldwide. Because of the nature of the disease and increased interconnectedness between countries all across the world, influenza has consequences not only for local but also for regional and global populations. The identified pandemic effect in Chile implies large potential global productivity losses before even considering the cost due to morbidity and mortality. More research is needed to understand the global impact of pandemic flu both for health and non-health outcomes. Additionally, comprehensive analyses that take into account health loss and economic loss are needed to understand the returns to investment in new vaccine and vaccine technology development.

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[13]We use relatively conservative values for these calculations. For example, Plans-Rubió (2012) also calculates with alternative assumptions that with 80% vaccine effectiveness, herd immunity during the 2009 pandemic may potentially be achieved by vaccinating just 10% of the population. Assuming vaccination for just 10% of the population would imply spending $1,680,000, again compared to a gain in work productivity of $6,700,000.

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