An Empirical Analysis of Insurance Status and Vaccine Uptake

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Abstract

COVID-19 vaccines are provided freely by the government of the USA, but vaccine uptake has become a bottleneck towards stopping the spread of COVID-19. This project investigates how insurance status might affect someone's likelihood of receiving the COVID-19 vaccine due to the structural barriers that uninsured people face, such as misinformation about vaccine costs, a lack of opportunities to build trust with the healthcare system, and a lack of insurance coverage for potential vaccine side-effects. Furthermore, we account for how trust may play a different role in vaccine hesitancy among different populations and how different kinds of insurance may have varied impacts on trust by separately accounting for the effects of public vs. private insurance and also measuring the differential impacts of insurance on different demographics. While we conclude that there is no statistically significant effect of insurance coverage on vaccine uptake, our closest approximation of an unbiased estimate indicates that this does have a real-world significance. In the context of the United States population, the 4.06 percentage point increase in the likelihood of receiving a vaccine associated with insurance coverage when controlling for state fixed effects, time fixed effects, demographic variables, and state specific medicaid expansion can increase the amount of vaccination by millions and consequently save many lives.

Introduction and Background

In early 2020, the entire world responded to the rapid spread of the airborne and extremely contagious COVID-19 virus. Unlike other widespread viruses, the COVID-19 virus also had a significantly higher rate of severe illness and death (Ryan, 2020). After more than half a year of intermittent lockdowns in the United States, the COVID-19 vaccine was authorized under FDA Emergency Use and distributed around the country (FDA, 2020). These vaccines offer very high protection against severe illness and death and also significantly decrease the likelihood of catching COVID-19 (Pilishvili, et al. 2021). For that reason, public health officials have made concentrated efforts to increase the COVID-19 vaccination rate. When people who had earlier decided to get the vaccine were able to get a vaccine during the first few months, the demand exceeded the supply. However, supply exceeded the demand by the early months of the summer, and public health efforts have seen a limited efficacy since then (Ratner, 2021).

As a vaccine fairly reliably protects individuals against severe illness or death and also lowers the probability of increased spread, and hence mutation of COVID-19, we think that it is important to find more ways to increase COVID-19 vaccine uptake. Since public health efforts to increase vaccination uptake have stagnated, more coercive methods have established themselves in the COVID-19 discourse. As outlined by the 2008 ACLU pandemic preparedness manual, because vaccine mandates of a certain degree are coercive measures which may cause increased public backlash and set risky precedents, it is important to see how we can increase the vaccination rate without such measures for this pandemic and any future pandemics (Annas, et al., 2008). An often overlooked salient variable is insurance status, and we are interested in whether there is a causal relationship between insurance status and vaccine uptake.

While it is true that COVID-19 vaccines are free, we think that the uninsured face barriers that affect their likelihood of vaccination in comparison to the insured. According to a June 2021 New York Times article by Kliff, many people are not aware that vaccines are free, and a third of unvaccinated adults in the conducted analysis expressed concern about whether their insurance would cover vaccine costs. It can be postulated that an uninsured person might be less likely to receive the vaccination out of fear that they could get a huge bill. Furthermore, uninsured people are far less likely to see a doctor, a practice which builds trust in the medical system, or consult their doctor, which is commonly dispensed advice for people who are contemplating whether or not they should get the vaccine. A New York Times op-ed by Tufekci published in mid-October of 2021 alluded to how a lack of trust may be increased by "the sorry state of health insurance in this country and the deep inequities in health care," as these facts may increase a person's likelihood of subscribing to unsubstantiated claims spread by cynical actors who attack our public health and government institutions. Furthermore, the author cited a Kaiser Family Foundation Poll showing that insurance is "the most powerful predictor"of who remains unvaccinated. Can we draw any causal relationship here? The goal of our project is to make a causal inference about whether a lack of coverage may be playing a role in this limited efficacy.

As we investigate what role insurance status plays in a person's decision to get vaccinated, we would also like to look at the differential impacts of public vs. private insurance and how insurance status may affect demographics differently. For example, we are interested in the differential effect of insurance status on people who have Medicaid vs. private health insurance. According to a study reported by Barnett and Sommers in 2017, people who receive Medicaid are quite happy with their coverage, and a national survey found that Medicaid is "as good as or, in some cases, better than private coverage" on most metrics for quality of healthcare coverage. People who have good experience with public health insurance have more opportunity to build trust in government-funded health infrastructure, good relationships with doctors, and also develop familiarity with the government doing something for them. People who have good experience with privately funded health insurance also build more trust with medical infrastructure, but it isn't associated with the government. For that reason, we think there may be a differential impact given the type of insurance. Another area to investigate might be how insurance status has a differential effect on the vaccination uptake of people from different demographics. For instance, there has been a racialized abuse of power in our public health system (for example, the Tuskegee vaccinations), and so building trust might be a larger part of increasing vaccine uptake among certain groups (Bajaj, 2021). If we can conclude that there is a causal relationship between insurance status and vaccination uptake and are able to investigate some of the particularities about which combinations of insurance type and subset of the population can create larger effects, we can create further knowledge about what role insurance status plays in COVID-19 vaccine uptake.

Literature Review

The Coronavirus vaccine is distinct from other vaccines in that it is free unilaterally, so unfortunately, very little literature exists on insurance status and COVID vaccine uptake. Nonetheless we found that Smith, Stevenson, and Chu (2006) performed a distinctive analysis on a sample of 8324 children from the National Immunization Survey performed in 2001 and 2002. They found that children who were uninsured at some point were more likely to not have completed their vaccine on time. As such, the intricacies around provision of insurance in United State's healthcare can prove to be a barrier to vaccination uptake of other vaccines. We think that people's experiences with insurance and vaccines can influence their experience with COVID vaccine uptake.

There has been prior research on the topic of political spectrum and beliefs about vaccination rates. Rabinowitz et al conducted an analysis between perceptions about science behind vaccination and political leanings for 367 adults. They found that liberals were more likely to call the science behind vaccination as facts rather than beliefs whereas conservatives were more likely to call vaccination as beliefs rather than facts. Moreover, Liberals were likely to underestimate the amount of people that agree with them while conservatives were more likely to overestimate the amount of people that agree with them. Similarly, conservatives and moderates were less likely to have declared their child as completely vaccinated. Thus, we think that there is evidence that certain demographic factors determine the decision to take up the Covid vaccine.

A dissertation by (Couzens n.d.) tried to analyze the impact of Medicaid expansion on childhood vaccination rates in 29 states for the period 2010-2018 and employed a difference in difference approach. The study concludes that broad coverage might reduce but not close the vaccination gap between high income and low income students. Couzens identifies some possible OVBs, such as political leanings among close family member's and educational attainments, which may determine beliefs about vaccines.

Stoecker, Stewart, and Lindley, performed a difference-in-difference to analyze the impacts of different medicaid provisions (coverage for vaccines, prohibiting cost-sharing, and copayment amounts) on influenza vaccination rates. The research showed that state medicaid policies can impose a barrier to vaccination rates. For copayment amounts, the research found that a dollar increase in copayment for vaccination is associated with a 6-7 percentage decrease in vaccine coverage. For the other two policy provisions(prohibiting cost-sharing and copayment amounts), the results were mixed. Generally, increased policy provisions for vaccinations resulted in increased influenza vaccination uptake. As such, we think that there is a reasonable chance that residents of certain states might have experienced restrictions to vaccination due to health insurance packages. This experience might influence or create false beliefs about coronavirus's uptake. This research piece made us believe that we should include state fixed effects in our regressions.

While very little research has been conducted on COVID-19 vaccination uptake and insurance status, we believe that our analysis could be a meaningful attempt in filling this important gap in the literature.

Data and Methodology

Our core question is, “What is the effect of insurance coverage on vaccination uptake?” and we seek to measure it by conducting a series of multivariate regressions using survey data obtained from the Roper Institute. For our data analysis, we use multiple cross-sectional datasets from the Henry J. Kaiser Family Foundation’s COVID-19 Vaccine Monitor survey. This survey is conducted approximately monthly, designed to capture public opinion on matters relating to the COVID-19 pandemic and response. In September, for example, it features a range of (83) opinion-based questions and a wide array of demographic information, yet questions vary by month. In September, there are 1519 respondents, with oversamples of Black and Hispanic respondents, so we will include controls for race. While the questions and number of respondents vary modestly by month, we find that from the months of January to September (excluding August) of 2021, these datasets are similar along our core variables of interest, allowing us to append them into a large dataset of 13848 observations. Core variables of interest include categorical variables describing race, gender, income, marital status, highest education level, employment status, health insurance coverage, and vaccination status.

Several of these variables are potential observable omitted variables which we desire to take into account for our study. In particular, we expect that employment status would be a true determinant of COVID-19 vaccination, as many employers require vaccination, yet we expect that employment would also be strongly associated with insurance status, because many employers provide insurance if the employee has a full-time position. Thus, we create a binary variable called "fullemploy," which distinguishes those who are employed full-time from all others who are not. Controlling for full employment in our regression accounts for an important source of positive omitted variable bias.

We also expect that excluding income could be a source of omitted variable bias. Our income variable is unfortunately not continuous, but categorical. It consists of irregularly-incremented income tiers, like "Less than $20,000," "$75000 to less than $90,000" and "$100,000 or more." Thus, we include it as a control, but its coefficient is not meaningful, because it refers to a single-increment change which, by construction, varies in size. Our justification for including income to eliminate positive bias is that we expect that income level is a true determinant of a person's ability to receive COVID-19 vaccination, as the transportation, time, and information often required to receive the vaccine may exclude people of lower income statuses. Secondly, we expect income level to be strongly associated with insurance status, as health insurance is notably expensive in the United States. Furthermore, we would also reasonably expect income level and full employment status to be highly correlated.

Because these surveys are conducted over the phone, we include age as a control because anecdotally, older people are generally more responsive to phone surveys. We also control for race (separated into black, hispanic, and asian), because the study states that black and hispanic respondents were oversampled.

By appending these datasets together we are also able to control for unobservable variables with fixed effects for time. We control for time fixed effects because there have been changes in the national discourse and policy over time but have affected states similarly. For example, more people learned over time that they wouldn't have to pay for the vaccine or maybe found the chance to take a few days to take the vaccine and recover from the side effects. Both of these possibilities are associated with insurance status and also the likelihood of vaccination. Because the state of the pandemic and vaccine availability varied so widely even month-to-month, we tracked month status during the appending process and we indexed each month as a category under a fixed-effects framework.

Furthemore, we also control for states' fixed effects because there are various unobservable factors which cause bias and differ across states but stay constant over time, such as state policies around health care and the type of work which is common in a given state. Since state medicaid expansion differs across states but is not constant over time and differs over time but is not constant across states, our fixed effects don't account for the effects of this policy which is correlated with insurance status and might affect people's trust in the vaccine. A counter-argument for including this might be that it is already so related to a state's underlying politics that the state fixed effects do take care of it. However, we choose to include it regardless because it is quite an explicit, observable variable, and it is possible for states to react in unexpected, erratic ways during a pandemic.

Furthermore, we are also interested in how vaccination status may differentially impact demographic groups as mentioned earlier, and we particularly focus on how racialized medical malpractice like the Tuskegee vaccination experiments may have made mistrust a larger part of the calculus for Black people. For that reason, we interact race and insurance status on our most thorough regression which has the state and time fixed effects, demographic controls, and control for Medicaid expansion.

We run all of our above regressions once with insurance status as our primary explanatory variable. However, since we are also interested in whether public insurance has a greater impact or lesser impact than private insurance, we also run two extra regressions where our primary explanatory variable is public insurance and private insurance respectively. In both cases, our control is all people who are uninsured. This allows us to compare whether one of these is more impactful than the other. We have the following equations for our regressions with regards to insurance in general.

Regression 1: $VaccineStatus = \beta_0 + \beta_1 * Insured + \epsilon$

Regression 2: $VaccineStatus = \beta_1 * Insured + \beta_2 EmploymentStatus + \beta_3 * Age + \epsilon$

Regression 3: $VaccineStatus = \beta_1 * Insured_i + \beta_2 EmploymentStatus + \beta_3 * Age + \beta_4 * Black +$

$$\beta_5 * hispanic + \beta_6 * Asian + \epsilon$$

Regression 4: $VaccineStatus_{st} = \beta_1 * Insured_i + \beta_2 EmploymentStatus_{st} + \beta_3 * Age_{1,t} + \beta_4 * Black_{st} +$

$\beta_5 * hispanic_{1,t} + \beta_6 * Asian + \beta_7 * Black * Insured + \beta_8 * StateMedicareExpenditure + \gamma_t + \delta_s + \epsilon_{st}$

Finally, we have the following regressions with regards to firstly public insurance and secondly private insurance.

Regression 1: $VaccineStatus_{st} = \beta_0 + \beta_1 * publicins + \beta_2 EmploymentStatus_{st} + \beta_3 * Age_{1,t} + \beta_4 * Black_{st} +$

$\beta_5 * hispanic_{1,t} + \beta_6 * Asian + \beta_7 * Black * Insured + + \beta_8 * state_e xpenditure + \beta_9 * income + \gamma_t + \delta_s + \epsilon_{st}$

Regression 2: $VaccineStatus_{st} = \beta_0 + \beta_1 * privateins + \beta_2 EmploymentStatus_{st} + \beta_3 * Age_{1,t} + \beta_4 * Black_{st} +$

$\beta_5 * hispanic_{1,t} + \beta_6 * Asian + \beta_7 * Black * Insured + + \beta_8 * state_e xpenditure + \beta_9 * income + \gamma_t + \delta_s + \epsilon_{st}$

Furthermore, we have the following Logit regressions. This is because we are interested in knowing which variables of interest are most influential in increasing the vaccination status of our results.

Logistic Regression 1: $Pr(Vaccinestatus = 1 | Insured) = \frac{exp(\beta_0 + \beta_1 * Insured + \epsilon)}{1 + exp(\beta_0 + \beta_1 * Insured + \epsilon)}$

Logistic Regression 2: $Pr(Vaccinestatus = 1 | Insured, EmployStat, Age) = \frac{exp(\beta_0 + \beta_1 * Insured + ... + \beta_3 * Age)}{1 + exp(\beta_0 + \beta_1 * Insured + ... + \beta_3 * Age)}$

Logistic Regression 3:

$$Pr(Vaccinestatus = 1|Insured, EmployStat, Age, Black, Hispanic, Asian)$$
$$= \frac{exp(\beta_0 + \beta_1 * Insured + ... + \beta_6 * Asian)}{1 + exp(\beta_0 + \beta_1 * Insured + ... + \beta_6 * Asian)}$$

Results

1.1: Simple regression:

	(1) Simple Regression	(2) Multilinear regression with income, employment, and age	(3) Multilinear regression with age, income, full employment, and race	(4) Multilinear regression with fixed effects
insured	0.0298	0.0235	0.0255	0.0406
	(1.38)	(0.96)	(1.01)	(1.65)
income		-0.00659	-0.00645	-0.00498
		(-1.86)	(-1.76)	(-1.46)
fullemploy		0.0445^{*}	0.0464^{*}	0.0256
		(2.44)	(2.50)	(1.50)
age		0.00177^{***}	0.00177^{***}	0.000603
		(3.75)	(3.59)	(1.34)
black			0.00735	0.0493
			(0.38)	(1.03)
hispanic			0.0118	-0.0364
			(0.57)	(-1.74)

asian			-0.0226	-0.0260
			(-0.45)	(-0.52)
stateexp				0.0465
				(0.28)
insuredblack				-0.0663
				(-1.31)
Observations	3474	3060	2989	2989
R-squared	0.000515	0.00658	0.00693	0.221
F-stat	1.894	5.300	3.097	16.58

statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.2: Public and Private Insurance Regressions

	(1)	(2)
	Multilinear regression on public insurance with fixed effects	Multilinear regression on private insurance with fixed effect
public_ins	0.0409	
	(1.27)	
income	-0.0113*	-0.00498
	(-2.20)	(-1.04)

fullemploy	-0.00232	0.00349
	(-0.08)	(0.17)
age	-0.0000760	0.00142*
	(-0.11)	(2.20)
black	0.0596	0.0403
	(1.24)	(0.84)
hispanic	-0.0186	-0.0458
	(-0.64)	(-1.77)
asian	-0.0743	-0.0254
	(-0.83)	(-0.46)
stateexp	-0.284	0.0570
	(-0.62)	(0.80)
insuredblack	-0.0595	-0.0772
	(-1.09)	(-1.44)
private_ins		0.0546
		(1.89)
Observations	1447	1785
R-squared	0.285	0.229
F-stat	.	.

statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.3: Logistic Regression:

We ran the following three regressions for our logistic regressions. The log-likelihood ratio for the first regression was -2007.2098, for the second logistic regression was -1754.364, and for the third regression was -1713.8704.

	(1)	(2)	(3)
	Simple logistic regression	Multilinear logistic regression with income fixed effects, employment, and age	Multilinear logistic regression with age income fixed effects, employment, age, and race
vacc			
insured	0.157	0.132	0.140
	(1.34)	(0.98)	(1.01)
fullemploy		0.247*	0.258**
		(2.54)	(2.62)
age		0.00957***	0.00952***
		(3.76)	(3.64)
black			0.0357
			(0.35)
asian			-0.142
			(-0.47)
hispanic			0.0529
			(0.50)
_cons	-1.159***	-1.433***	-1.463***
	(-10.50)	(-7.81)	(-7.10)

Observations	3474	3060	2989

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Discussion

We start with a simple regression of vaccination status on insurance status and find a small effect of a .0298 increase in vaccination rate associated with coverage under insurance. Adding demographic controls decreases that effect, which is to be expected because the omission of our demographic variables causes a positive bias, as they have the same relationship (positive or negative) with the rate of vaccination and rate of insurance. Once we add state and time fixed effects, the effect jumps up to a .0406 increase in vaccination rate associated with coverage under insurance. This is to be expected because there are likely many unobservable variables which are associated with vaccination differently from insurance status and which are specific to states because of various different policies with regards to insurance. Furthermore, without the time-fixed effects, our result would have likely been quite biased because during the early pandemic, not everyone who wanted the vaccine could get one.

Our first, simple result of .0298 is a biased estimate. After adding controls and fixed effects, however, our finding of .0406 indicates that being insured is associated with a 4 percent greater likelihood of being vaccinated. This result is less biased, and depending on the comprehensivity of our controls, it may indicate a causal relationship of insurance on COVID-19 vaccination uptake. However, we should keep in mind that a t-value of 1.65 is not statistically significant.

We also run our regression controlling for demographic variables, fixed effects, and Medicaid expansion on public insurance and private insurance separately to see whether the impact is more pronounced in either case. In both cases, the control group is people who do not have any coverage. We find that, controlling for the other variables, coverage under public insurance is associated with a .00409 increase in the probability of receiving a vaccination, a result which is not significant at any standard level. Similarly, controlling for the other variables, coverage under private insurance is associated with a 0.0546 increase in the probability of receiving a vaccination. As such, our less-biased estimates indicate that private insurance has a greater effect on vaccination uptake than public insurance. However, not only are our results insignificant, but this is only our best guess for the unbiased estimate. We can imagine other omitted variables that we have not yet taken into account. For example, people who receive public insurance might have a different perception of big pharma and the government than people who receive private insurance, as people who receive public insurance are more likely to have low income and hence more negative experience with these institutions. However, we do not have access to these variables, and so this is only our approximation of an unbiased estimate.

In the logistic regressions, we found no statistically significant evidence for the positive correlation between insured status and the vaccination uptake. Nonetheless, we report a coefficient of 0.14 for our logistic regression with the most controls. While not meaningful for interpretation, this positive coefficient indicates that the effect of insurance coverage on vaccination uptake is positive. Age and fully-employed status had a positive correlation with vaccination status and the results were to some extent statistically significant, although these results are not relevant to our design and question. Beyond statistical inconclusivity, we are not sure if the results of these logistic regressions are truly interpretable because we were not able to include fixed effects in the logistic regression function.

Limitations

Across our results, it is important to note that due to missing values across all of our controls, the number of observations included in our regressions fell significantly from our original number of nearly 14,000 observations to about 3000. We don't believe that there was a systematic pattern to these excluded observations, so we don't believe that this biased our results. Nonetheless, factors here beyond our knowledge may be a source of limitation for our findings. Furthermore, the nature of the telephone interviews themselves could have imported bias into our data and thus our results. Namely, if there were systematic patterns to response, non-response, or early termination, our findings could be biased. We anticipated that age could be one such source of bias, and we know that Black and Hispanic respondents were oversampled, so we included these as controls. However, there could be other sources of systematic bias in data collection that were not measured or not considered in our analysis. Lastly, responses could have been biased towards over-reporting vaccination status due to respondents feeling embarrassment or discomfort in reporting non-vaccination.

Finally, we were limited in the scope of our controls with the available data. Income was categorical and irregularly-incremented; a continuous income variable could have provided more precision to our estimate. We limited our employment control to those who reported full employment, but we were not able to incorporate respondents who were married to or dependent on fully-employed individuals, because their access to health insurance and vaccination would likely be the same as that of their fully-employed spouse/caretaker.

Conclusion

If our estimate of a 0.0406 effect of insurance on vaccination status is true, then our finding is economically significant in that it would correspond to many people out of the millions of uninsured Americans being unvaccinated at a disproportionate rate to those who are insured. By extension, considering that vaccination is highly effective against serious disease, it would likely correspond with disproportionate deaths from COVID-19 among the uninsured than among the insured. This would be a matter of policy importance, as it could indicate that the structures of support for COVID-19 vaccination uptake for uninsured people is worse than for insured people.

To circumvent the data limitations, future studies could be conducted using data that is a verifiably random sampling of the population and that better verifies vaccination responses. Also, improvements could be made in our design through an improvement in the precision in the measurements of income and dependency status. While not a central question to this study, our exploration of the differential effects of private and public insurance on vaccination deserves more research, not just in the realm of COVID-19 vaccination, but also generally. Hopefully, further expansions in the literature on the support structures available to the insured and unavailable to the uninsured could more precisely identify the causes of disproportionate vaccination statuses beyond our binary identifier of simple insurance coverage.

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