Healthy Guardians and Utilization: Evidence from Covid-19 Vaccination and Veterinary Services Visits

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Abstract

Health is a durable capital stock which is heavily influenced by parents in adolescence. We identify the effect of parent health behavior on child service utilization in a context where fetal origins and genetics contribute nothing since they are impossible and insurance spillovers are highly unlikely to exist. We use county-level data on Covid-19 vaccination hesitancy, takeup, and visits to veterinary services stores and multiple identification strategies. We find that a 1 percentage point (pp) increase in vaccine takeup is associated with 4.01-4.13 additional veterinary services visits, holding income, race-specific popultion, poverty, and unemployment constant. Selection on unobservables would have to be at least .808 that of selection on the aforementioned variables to nullify this result. Furthermore, the results are inconsistent with reopening being the main driver and two-stage least squares (in which hesitancy is used to instrument for takeup) finds similar results.

Keywords: Utilization, Health Behavior, Vaccination, Vaccine Hesitancy, Veterinary Services

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1 Introduction

Pro-socialty is frequently associated with prosperous economies (Knack & Keefer, 1997). In recent times, preventative measures towards Covid-19, such as masking, vaccination, and distancing, has been the primary example of health-related social-mindedness. In addition to pro social behavior, healthy populations are another factor that underlies strong economies (Karlsson, Nilsson, & Pichler, 2014).

One context in which people frequently *care about* anothers' health is in familial relationships.[1] This is highly evident in child-parent relationships, since parents are the gatekeepers of child health (Case & Paxson, 2002). Parents provide the resources, labor, financial, and transportation, to enable their children to access health services. Beyond health behavior modeling, parents can affect child health in a number of ways such as insurance spillovers (Lipton, 2021; Sacarny, Baicker, & Finkelstein, 2022), fetal origins (Almond & Currie, 2011), and genetics (Thompson, 2014). Thus, it is generally challenging to estimate the separate mechanisms through which parents affect their children's health and, by extension, how parents affect their offspring's lifetime health capital.[2]

This paper asks two questions. First, does the health consciousness of ones' guardian affect anothers health utilization. We quantify health consciousness using county-level Covid-19 vaccination rate. We take a novel approach to measuring benefits to others' health by using county-level equilibrium visits to veterinary services as our outcome. In our setting, insurance is not common and fetal origins is impossible by definition. This makes this setting a unique laboratory for understanding the effect of a guardians' health behavior on "child" health utilization. Since early health matters for later in life outcomes, assessing this in a context free of common confounding factors could provide a deeper understanding of this important mechanism.

[1] There are many examples of where ones' behavior certainly affects others' health including: caring for elder parents (Van Houtven & Norton, 2004), drunk driving (Sloan, Eldred, & Xu, 2014), attacking someone (Lindo, Siminski, & Swensen, 2018), social media posts (Braghieri, Levy, & Makarin, 2022), undercooking a meal, etc.

[2] If it is challenging to theoretically sign the effect of one's behaviors on ones' own health (Grossman, 2000), then it is almost certainly challenging to estimate the effect of ones' behaviors on others' health. Such a theoretical model, with a family utility function and altruistic linkages is explored in Basu and Meltzer (2005).

We find a 1 percentage point increase in COVID-19 vaccination rate is associated with about 4 additional visits to veterinary services stores. This is roughly equal to an increase of $2,000 in median household income in a county. This provides a unique perspective to the literature which is concerned with how families and social networks influence health and health utilization. For instance, there are generally two channels through which a health shock can affect familial health behavior (Fadlon & Nielsen, 2019; Hodor, 2021). The behavioral channel holds that negative health shocks may lead one to behave differently by engaging in more or different healthy behaviors (Fadlon & Nielsen, 2019). The learning channel hypothesizes that negative family health shocks cause one to learn about treatment, payment, and behaviors (Hodor, 2021). Simply put, the family members in this empirical analysis have little control over altering their behavior and learning is likely to be negligent given species differences and the absence of insurance (which has been the focus of literature on learning). Thus, we see these results as suggesting an alternative channel through which better family health behaviors can increase ones' own utilization, it could be called the "pro-active guardian" channel. Though previously hypothesized in Case and Paxson (2002) as parents being health gate-keepers, this is the first evidence of this channel in a context free of many confounding factors found in human-human familial contexts.

This paper finds that human vaccination is also positively associated with veterinary services visits which also often lead to vaccination against various animal diseases such as rabies or bortadella. This is close in spirit to Bouckaert, Gielen, and Van Ourti (2020) who finds that flu vaccination campaigns for elders can cause their adult children to also vaccinate. Other familial spillovers have shown that workplace bans on smoking and drinking reduce spousal participation in the same activities (Fletcher & Marksteiner, 2017). Finally, the literature on health spillovers is not contained to families, with networks and peers also being found to have some importance. We add to this literature by being the first to show similar findings in a heretofore unexamined familial relationship (Debnath & Jain, 2020; Deri, 2005).

Though the results are insensitive to which month is used in the regression that includes controls (which are only available at the annual frequencies), we desire to ensure that our results are not driven by vaccination supply confounding. Thus, we also introduce county-level vaccine hesitancy, as variation in vaccine uptake, which is less likely to be driven by supply side factors. There is strong prior research that suggests that behaviors are influenced by beliefs, we find that this literature can be extended to hesitancy about COVID-19 vaccination and actual vaccination take-up in the United States. We document a strong association between COVID-19 vaccine hesitancy and COVID-19 vaccination take-up, specifically, a 1 percentage point increase in hesitancy is associated with a 1.234 percentage point reduction in COVID-19 vaccine take-up. Using vaccine hesitancy as an instrument for vaccine take up confirms our earlier results.

These results extend the literature on the influence of beliefs on behaviors. Within the health literature, beliefs about smoking affects propensity to smoke, in multiple contexts and across different devices (Lin & Sloan, 2015; Viscusi, 1991, 2020; Wang, 2014).[3] There is some evidence on COVID vaccine hestiancy and vaccine takeup (eg. Tagat et al., 2022), but most other findings focus on other types of vaccines (Carrieri, Madio, & Principe, 2019; Chang, 2018). We find evidence, in line with other vaccines and contexts, on the most damaging disease of the time within the US. Furthermore, Biroli, Boneva, Raja, and Rauh (2022) finds that parents beliefs about child behavior are predictive of health investments and outcomes, we extend this context to companion animals and a non-obesity related health behavior.

2 Data

The research question is how having a health-conscious guardian affects ones' own health services utilization? This requires observing both human health behavior, service utilization, and a linkage between guardian and guardee. Our measure of human health behavior is Covid-19 vaccine uptake.

[3]Beyond smoking, other health behaviors also depend on beliefs: such as risky drinking (Sloan, McCutchan, & Eldred, 2017). There are many examples outside of health, such as land values (McCluskey & Rausser, 2001).

This is a readily available measure and fits well with our utilization outcome- veterinary services visits. This fits, since a common reason for visiting veterinarians is for pets to receive vaccinations against common diseases such as rabies, lyme, etc. These outcomes are observed over the entire United States which gives the results the advantage of being valid for a geographically diverse sample.

SafeGraph patterns data collects a plethora of information at the firm-month level. Our interest is specifically in the number of veterinarian visits, a close proxy for the quantity of veterinarian services demanded. We filter this data to only businesses which have a North American Industry Classification System (NAICS) code of 541940- veterinary services. The total number of veterinary firms in the United States is 35,411, spanning 2,730 counties. The complete absence of veterinarians in some counties is a well-known fact in veterinary medicine and is likely more prevalent in rural areas with fewer companion animals.

Covid-19 vaccination rates comes from the Center for Disease Control (CDC). The county-level data records the percent of the population that has received at least 1 shot or both shots every week since the end of 2020 when vaccines first became available. We restrict the data to the earliest month being January 2021, because the vaccine is not widely available before then. Since pet ownership requires a minimum amount of resources for taking care of the animal, the rate that is used is the completed vaccines for those who are at least 18 years old.

Furthermore, while vaccine uptake is an observed health behavior, it may be equally important to understand how human health beliefs or sentiments are related to veterinary demand. To measure human health sentiment, the CDC provides data on Covid-19 vaccine hesitancy. This data comes from the Household Pulse Survey (HPS) which asks a nationally representative sample about their Covid-19 vaccination intentions. From this survey data, a county-level cross-section of vaccine hesitancy is created from individuals who took the survey from May 26 through July 7 using the American Community Survey. Three rates are available, including those who are hesitant or unsure, hesitant, or strongly hesitant. Our primary measure is those who are hesitant, although similar results are obtained when using the other definitions.

We take multiple approaches to estimate the causal impacts of healthy guardians on underling utilization. This requires slightly different samples. The first sample is a county-month level dataset, which enables county fixed effects to be included. The second sample is a county level dataset which enables several important covariates at the county level, which are only available at annual frequencies such as median household income and unemployment, to be included. The vaccinate hesitancy is also only a cross-section, necessitating the use of a cross-section to include in estimation.

2.1 Descriptive Statistics

The summary statistics are presented in Table 1. Panel A shows the sample over the first 10 months of 2021.[4] The average amount of veterinary services visits over this time is 339.87 and the median is 96 which indicates some positive skew. When one also includes stores that were not active in all 46 months, the average and median visit counts barely change, the average going from 339.87 to 351.7. Also, there are some counties that have 0 visits to veterinary services which is consistent with some counties not having any veterinarians. The two-shot Covid-19 vaccination rate for adults over 18 is 32.96% on average, with counties ranging from nearly completely vaccinated to some entirely unvaccinated. This demonstrates adequate variation in health behavior and veterinarian visits.

It may be informative to include covariates, but many of the ones that are likely to matter are not observed at a monthly frequency. To address this, Panel B subsets the data to only May, which is chosen because that is when the Household Pulse Survey, upon which the hesitancy data is based, was conducted. The vaccination rate and count of veterinary services visits are very similar to the

[4] Before 2021 is not shown, because vaccines were not available and October is the last month, since that was when the data was acquired.

numbers reported for the panel. As shown by Panels C and D, the average count of veterinary services visits is higher for counties with higher than average vaccinations. In counties with an above average vaccination rate, the average number of veterinary services visits is 503.55 while the average is only 322.22 in counties with a below average vaccination rate. While there may be other factors besides vaccination rate that matter for veterinarian visits that these unconditional means do not take into account, it does provide descriptive support that areas with less human health behavior also has less animal health behavior.

2.2 Bivariate Spatial Distributions

One might expect vaccination and vaccination hesitancy to be spatially clustered in rural areas. Similarly, there may be less veterinarian visits in rural areas due to lack of veterinarians. As such, a careful analysis requires examining the spatial distributions of both.

Figure 1 maps the bivariate distributions between vaccine rate and veterinary services visits and vaccine hesitancy and veterinary services visits. Each map breaks each variable into 3 even quartiles and colors each block of the resulting 3X3 matrix a different color. Figure 1a shows the spatial correlations between visits and vaccine rate. If healthy guardians are more likely to increase health service utilization, then clusters should form in the bottom left (skin colored square with $\leq$ 29.4% takeup and $\leq$ 70 visits) and in the top right (dark brown colored square with $\geq$ 40.7% takeup and $\geq$ 321 visits).

Indeed, this expectation is borne out in the spatial data. The two squares most consistent with this theory (skin, bottom left and dark brown, top right) are the most populated squares with 14 and 14.3% of counties respectively. There is a large cluster of tan squares (low takeup, low visits) in west Texas and Wyoming, while there is a large cluster of dark brown squares (high takeup, high visits) in Florida, the Northeast, and the west coast. There are small clusters of squares that do not align with expectations, such as the top left, medium blue (low takeup, high visits) in east Texas and near the Georgia-Alabama border. Nonetheless, these "unexpected clusters" only make up 8.6 and 9% respectively. While there appears to be a marginal amount of spatial autocorrelation, it doesn't appear to be strong enough to be concerned about the regression results.

Figure 1b shows the relationships between vaccine hesitancy and veterinary services visits. Here, we expect the opposite to be true, that higher hesitancy is associated with lower visits. This would correspond to the top left, medium blue and bottom right, orange squares being most frequent. Again, the spatial data are consistent with this expectation as the expected squares contain 24.4% of the counties, while the unexpected squares include only 19.9% of the data. There appears to be a higher amount of spatial autocorrelation, especially at state borders, but nonetheless a similar pattern emerges. Patterns driven purely by regions or state borders will be accounted for in the regressions using an extensive set of fixed effects, such as at the state or county level.

3 Methods

Two complementary strategies are used to estimate the effect of human health behaviors on veterinarian demand. First, two-way fixed effects (TWFE) regressions are estimated. These are specified as,

$$Vet\ Visits_{cm} = \beta_1 Human\ Vaccine\ Rate_{cm} + \mu_c + \gamma_m + u_{cm}, \tag{1}$$

in which c stands for county and m stands for month. The outcome, $Vet\ Visits_{cm}$, is the total number of visits to businesses that are classified as providing veterinarian services in county c in month m. The standard errors are clustered at the county level to account for correlated errors and some forms of mis-specification.

The coefficient of interest is β_1, which estimates the relationship between human health behavior, specifically Covid-19 vaccine takeup, and the equilibrium quantity of veterinarian visits.

County level fixed effects, mu_c, ensure that time-invariant characteristics of counties in 2021, such as farm land area, housing supply, or veterinarian supply, do not bias the estimated relationship between guardian health behavior and demand for underling veterinary services. Month fixed effects, γ_m, account for time trends in human vaccine rate. It is also possible that there are heterogeneous effects over time, because the relevant constraints on vaccine rate changes from capacity to willingness at some point, so effects are also reported separately by month.

In order to include potentially important covariates, such as population or income, it is necessary to reduce the data to a cross-section, since county-level income is observed at a yearly, instead of monthly, frequency. This approach is also taken to account for observable factors that could theoretically be correlated with both vaccine rate and veterinarian visits, but that are time-variant and not accounted for through unit fixed effects. This equation is specified:

$$Vet\,Visits_c = \beta_1 Human\,Vaccine\,Rate_c + \mathbf{X}_c\beta + \mu_s + \lambda_r + u_c, \tag{2}$$

and all the subscripts are similar. We remove the county fixed effects, since in a cross-section they are perfectly colinear, and add state fixed effects. These account for the sometimes stark differences at state borders that are shown in Figure 1. We still wish to account for sub-state factors which we accomplish by including a set of fixed effects (λ_r) for the Rural-Urban Continuum Codes (RUCC) developed by the USDA. Our preferred specifications interact the state fixed effects with the RUCC fixed effects to account for state-specific urbanicity. Obviously, we cannot also include month fixed effects in this equation since it is a single month so these are also removed.

The new county covariates are included in $\mathbf{X}_c$. The selection criteria for these variables are that they correlate with demand for veterinary services and may correlate with vaccination rates. The variables included are: median household income (Census Bureau Small Area Income and Poverty Estimates- SAIPE), poverty percent (SAIPE), unemployment (Bureau of Labor Statistics), and race-specific (black, white, other) population (SEER).

3.1 Interpretation

Our question is fundamentally causal, we would like to bestow a causal interpretation on β_1 in either equation.[5] As written, our approach appeals to unconfoundedness, particularly in Equation 2.[6] In other words, after conditioning on the most important determinants of veterinary service demand, income, population, poverty, and unemployment, and a regression highly saturated with state (50) by urbanicity (1-9) fixed effects, human vaccine takeup is as good as random with respect to veterinary services visits. With this set of covariates and interacted fixed effects, it is unlikely that there other factors that are much more important than these.

While we have gathered the most important variables, there certainly could be other omitted variables. If they are only correlated with veterinary services visits, then not including them only reduces precision, reducing our chances of finding statistically significant results. We will provide sensitivity estimates that can be used to assess the fragility of the results to unobserved confounding and use a separate identification strategy. Under unconfoundedness, the interpretation of β_1 is an average treatment effect. Practically, it matters very little whether county fixed effects (Equation 1) or covariates (Equation 2) or are used to account for other factors as both find very similar results.

3.2 Incorporating Vaccine Hesitancy

Our alternative identification strategy relies on variation in vaccine takeup that arises due to variation in vaccine hesitancy. Vaccine hesitancy is likely to be a strong predictor for vaccine takeup. Furthermore, using hesitancy as a source of variation ensures that our the variation in health behaviors are driven by a demand side factor and not the supply side. It is unlikely that hesitancy causes

[5] Sometimes research with similar variables proceeds under a parallel trends assumption. This requires converting the continuous variable, vaccine rate, into a binary treatment variable. We do not think that there is an obvious way to do that in this context. In this context, vaccination rate covers 99.9% of it's possible values and we can not include covariates in our monthly regressions since there was only 10 months of data.

[6] Some may notice that this is the assumption for propensity score matching. If we were to do that, it would also require dichotomizing the continuous treatment of vaccination rate. Furthermore, we have 3,142 counties which could make matching not work well. The primary benefit would be more careful weighting, but that would still depend on an arbitrarily chosen cutoff and may not work well computationally.

vaccine availability. To assess the relationship between hesitancy and utilization, regressions are specified as:

$$(3) \qquad Vet\ Visits_c = \beta_2 Human\ Vaccine\ Hesitancy\ Rate_c + \mu_s + \lambda_r + e_c,$$

in which the subscripts are the same as Equation 1. Higher human health hesitancy is likely to be negatively associated with child utilization, thus we expect that β_2 is negative.

We also confirm the relationship between vaccine hesitancy and vaccine takeup. This first-stage relationship is estimated:

$$(4) \qquad Human\ Vaccine\ Rate_c = \phi Human\ Vaccine\ Hesitancy\ Rate_c + \mu_s + \lambda_r + \varepsilon_c,$$

in which all subscripts are the same. We expect that hesitancy about vaccination reduces vaccination rates, thus we expect ϕ to be negative.

One can interpret β_2 as an average treatment effect of vaccine hesitancy on child health utilization or an intent-to-treat, with vaccine takeup, effect on child health utilization. Both interpretations require that vaccine hesitancy is as good as random with respect to service utilization, conditional on income, poverty, employment, population, and state-specific urbanicity. Under additional assumptions, one can scale β_2 by ϕ ($\frac{\beta_2}{\phi}$) to produce a local average treatment effect (LATE). These assumptions are that: vaccine hesitancy predicts vaccine rate with adequate strength ($\phi < 0$), vaccine hesitancy affects veterinarian visits only through vaccine takeup (conditional exclusion), increases in vaccine hesitancy do not increase vaccine takeup (weak monotonicity), and the stable unit treatment value assumption (SUTVA) (Angrist, Imbens, & Rubin, 1996; Imbens & Angrist, 1994). This is not our main identification strategy, so we do not belabor the assumptions, but we believe that they are reasonable.

4 Results

Our results begin by estimating the relationship between human health behavior and animal health behavior by using two-way fixed effects. As shown by Panel A of Table 2, every 1 pp increase in human Covid-19 vaccination rate is associated with 4.13 more visits to veterinarian services clinics. This is statistically significant at 99% using county-clustered robust standard errors.

The two-way fixed effects from Panel A, column 1 control for time-invariant county-level factors and time trends. One might nevertheless be concerned that some places differ in some other way that is not able to be captured by the fixed effects. For example, income is likely to correlate with the treatment and outcome, but perhaps is not time-invariant over this time period. In this case, the estimate would be biased away from the true effect. To address this possibility, Panel B of Table 2 re-estimates the effects using a single-month cross-section of counties. In column 1, only state fixed effects are included and the estimate becomes larger than the TWFE estimate. In column 2, including rural-urban code continuum fixed effects reduces the effect to 8.16.

It is possibly the case that incorporating state and urbanicity fixed effects separately ignores the way that urban and rural areas can differ by state. If this misspecification exists, then these coefficients may be biased. To adjust for state-specific differences in urban and rural areas, column 3 interacts the state fixed effects with rural urban indicators. The estimated effect hardly changes and remains statistically significant.

Finally, one may be concerned that basic classic determinants of demand are different across high and low vaccination areas. In order to address this, column 4 includes median household income, race-specific population, poverty percent, and unemployment.[7] Holding these factors constant, a 1 pp increase in adult vaccination rate is associated with 4.01 additional veterinarian visits and this is statistically significant at 99% confidence. Notice that this coefficient is very

[7]We allow population to be race-specific to account for potential differences in health and pet health behaviors across different races.

similar to the TWFE estimates in Panel A, suggesting a robust positive association between human and animal health.

The causal interpretation of the estimates relies on the selection on observables assumption. While this is not directly testable, the inclusion of observables can shed light on whether this assumption is appropriate. In general, if the coefficient is relatively stable with the inclusion of observables, then it suggests that selection on unobservables is also not very threatening. By the time fixed effects are added the coefficient goes from 15.23 to 4.01 which is somewhat unstable. However, these fixed effects and controls explain much of the variation in veterinary services visits with the R-squared rising from 0.117 to 0.701 by the time all controls and fixed effects are included. Using the methods detailed in Oster (2019), selection on unobservables would have to be 0.808% of the selection on income and population for the 95% confidence interval to include 0.[8] It is unlikely that other unobservables explain as much of the variation in demand for veterinarian services household income, population, poverty percent, and unemployment rate which suggests these estimates can be interpreted as more than just correlation.

Next, additional context on the size of the effect of human health behavior on animal health behavior is provided. A one-sixteenth of a standard deviation increase in vaccination rate leads to 0.005% of a standard deviation in vet visits increase. Simplified, a 1 standard deviation increase in vaccination rate leads to a 8% of a standard deviation increase in veterinary services. Income provides another useful benchmark. The point estimate on median household income is 2.53 times larger than the effect of vaccination, suggesting increasing vaccination rate by 2.53 pp has about the same effect on equilibrium veterinary services vistis as median household increasing by $1,000.

[8] This method requires an r-squared max for an input, which Oster (2019) suggests using 1.3*r-squared, because this is the r-max at which 90% of experimental results survive. This results in a reasonable r-squared max of .9113.

4.1 Re-opening Versus Behavior Spillovers

While we would like to interpret these results as a "spillover" from a health conscious guardian increasing ones' own healthcare utilization, another possible interpretation is that Covid-19 vaccination rate is positively associated with re-opening and thus the results are actually driven by re-opening decisions. Both stories would produce positive coefficients in theory. We address these concerns in two ways. First, we estimate the effect separately for each month, since there is variation in re-opening across months. If there is no difference in the coefficients, despite different months having different levels of re-opening, then that provides evidence against re-opening.

As shown by Figure 2a, the vaccination rate over time grows somewhat rapidly until about May when it begins to grow less quickly. Despite the difference in the growth of vaccination rate, Figure 2b shows that the estimates are statistically significant and similarly sized in every month. Given there is variation in reopening over these months and the estimates do not change, we do not think it is reasonable to interpret the results as being sensitive to differences in reopening.

4.1.1 Falsification

Another empirical way to adjudicate between reopening and health behavior spillovers interpretations is to check if vaccination rates correlate with foot traffic in non-health industries. We source our industries from Goolsbee and Syverson (2021), where a list of most and least Covid-19 affected industries (in terms of foot traffic) are provided. We notice that veterinary services are among the least affected industries and pull similarly affected industries from this list. Our method will be to estimate Equation 2, using other industries' foot traffic as the dependent variable. If the health behavior spillover story is the correct interpretation, then Covid-19 vaccination rate will be uncorrelated with industries unrelated to health.

First, we perform a sanity check using foot traffic to pharmacies. It is likely that vaccination uptake and pharmacy visits are positively correlated, because vaccines are literally a drug which are sold by pharmacies and sometimes Covid-19 vaccinations were performed in pharmacies. Row 1 of Figure 3 shows that a 1 pp increase in vaccination rate is associated with 46.05 additional veterinary services visits.

In the Rows 2-6 of Figure 3, we regress Covid-19 vaccination rate on non-health industries. These industries, in order, are: automobile parts, hardware, outdoor power equipment, gas stations, and home and garden wholesalers. Of these 5 alternative industries, only one produces a statistically significant association. This industry (row 3) is hardware; however, the standard error is large enough that it may not be statistically different from the same coefficient when the dependent variable is veterinary services visits. This falsification exercise, in combination with the stability of the coefficient in different months, provides strong evidence that reopening behavior is not the reason that Covid-19 vaccination rate is positively associated with veterinary services visits.

4.2 Robustness and Heterogeneity

Next, we provide results that assess robustness and heterogeneity. Our first check involves making a slight altercation to the dependent variable of veterinary services foot traffic. In the original specifications, this variable is composed of only locations that were observed every single month of the sample (i.e. all 46 months from 1/2018 to 10/2021). Given that the pandemic lead to some closing of veterinary services offices, this may lead to some non-negligible error in the dependent variable. As shown in Panel A of Table 3, this altercation makes nearly no difference to our results as the coefficient changes from 4.01 to 4.255.

Next, we recognize that our outcome, veterinary services visits, is a discrete, count variable. This can lead to issues with OLS, so we estimate Poisson models which explicitly account for the discrete outcome. As shown in Panel B of Table 3, this does not have a concerning effect on the results. The coefficients are the same sign, statistically significant at 99% confidence, and are of reasonable magnitudes. In column 2 of Panel B, a 1 pp increase in Covid-19 vaccination rate is associated with 1.6% higher veterinary service foot traffic. From the average foot traffic of 426.8, this implies an additional 6.82 visits which is actually a little larger than the OLS results.

Finally, there are stark differences in animal population across urban and rural areas, with the latter much more likely to engage in raising food animals. Thus, we are interested in whether there are the effect of Covid-19 vaccination on veterinary services visits varies across urban versus rural areas. To subset the data, we use the USDA definition of urban by designating any RUCC code from 1-3 as urban and the rest (4-9) as rural. As shown in Panel C of Table 3, the finding is driven by urban areas and there is no effect in rural areas. In column 1 of Panel C, an increase of vaccination rate by 1 pp is associated with 9.149 additional veterinary services visits in urban areas. In column 2 of Panel C, the rural areas subsample, the effect of Covid-19 vaccination is essentially 0. This further reinforces that the results are driven by companion animals and not food animals.

4.3 Vaccine Hesitancy

It may be difficult to believe that time and cross-sectional variation in vaccination uptake is as good as random, conditional on many relevant fixed effects and controls, with respect to veterinarian services visits. However, health beliefs are less likely endogenous than health behaviors. For example, health beliefs are less likely to be correlated with vaccine distribution compared to uptake. This addresses concerns from health behavior supply side confounding, since health beliefs are solely health behavior demand.

Figure 4 shows binned scatter plots with vaccine hesitancy on the x-axis, since these correspond to the upcoming regression analyses. The first row plots Covid-19 vaccination rate on the y-axis. As Figure 4a shows, there is barely any visible association between vaccine hesitancy and vaccination rate when state fixed effects are not accounted for. This is likely because there is there is little across-state variation in vaccination rates and because state fixed effects were used in the creation of the vaccine hesitancy measurement. Figure A.1 shows considerable within-state variation in the association between vaccine hesitancy and vaccination rates.

When correcting for state specific factors, Figure 4b shows that there is a precise, negative correlation between Covid-19 vaccination hesitancy and Covid-19 vaccination rate. This negative correlation is expected, since more hesitant counties have lower vaccination uptake. This provides initial support for the first stage assumption, since there is a strong, precise relationship (once state fixed effects are added). The direction of this relationship, hesitancy is negatively correlated with uptake, is also in the expected direction. These visualizations also support the weak monotonoicity assumption, since covid-19 vaccination rate does not increase with hesitancy anywhere in the range of hesitancy.

Since vaccine hesitancy is associated with vaccination rate and vaccination rate is associated with veterinarian visits, it could be expected that vaccine hesitancy could be correlated with veterinarian visits. Even without controlling for differences across states, Figure 4c shows that counties which are more vaccine hesitant also have less visits to veterinary services. While the relationship is less precise without state fixed effects, Figure 4d shows adjusting for across state variation makes the relationship much more precise which could be expected if vaccination hesitancy only predicts vaccination take up when state fixed effects are included.

Next, the 2SLS estimates provide magnitudes and explicit estimates of uncertainty under different specifications. As shown by Panel A of Table 4, an increase of 1 pp hesitant individuals is associated with 22.5 less veterinary services visits and this is statistically significant at 99% confidence. However, as shown by column 2, there is no detectable across-state relationship between vaccine hesitancy and vaccine takeup without state fixed effects. This lack of a first stage leads to uncertainty which swamps the magnitude of the second stage estimates.

As shown by Panel B, adding state fixed effects has noticeable consequences. Using within-state variation, a 1 pp increase in vaccine hesitancy is associated with 246.01 less veterinary services visits which is 10 times larger than the unconditional association. This is also probably too large, given the mean of visits is approximately 426.

One possible reason that the magnitude grows is due to the now statistically significant and large first stage. A 1 pp increase in vaccine hesitancy is associated with a 1.95 pp reduction in vaccine takeup. As shown in column 3, the F-statistic that this coefficient is 0 now equals 30.58 which makes vaccine hesitancy have enough predictive power for vaccine uptake that second stage coefficients will be minimally biased (Stock & Yogo, 2002). The second stage estimate suggests higher vaccination rates are associated with more veterinary services visits. Furthermore, the weak-instrument efficient, Anderson-Rubin confidence intervals show that this estimate is also statistically significant. When it comes to inference, the AR intervals are likely to be even more conservative than recently refined inferential approaches for IV estimates (Lee, McCrary, Moreira, & Porter, 2022).

The estimates above seem large relative to the mean of veterinary services visits (426) and a reason for that could be that the exclusion of urbanicity is causing omitted variable bias. To address this concern, Panel C adds urbanicity indicators and all 3 coefficients become smaller, particularly the reduced form and second stage coefficients, yet all remain statistically significant. Panel D adjusts for the same variables as earlier, including household income, race-specific population, poverty, and unemployment, and the coefficients again become smaller, yet are still statistically significant at 99% confidence.

After several controls and fixed effects, the effects of vaccine hesitancy and vaccine uptake are larger than OLS, yet still reasonably sized. For instance, the reduced form finds a 1 pp increase in vaccine hesitancy is associated with 49.841 less veterinary services visits. Thus, a one-quarter of a standard deviation change in hesitancy leads to a one-sixteenth of a standard deviation change in veterinary services visits.

Furthermore, a 1 pp increase in hesitancy is associated with 1.34 pp lower vaccination uptake. The second stage estimates find that a 1 pp increase in vaccination rate is associated with 37.18

additional veterinary services visits. Panel E uses state-specific urbanicity indicators and the results only become slightly larger. Finally, as shown by Table A.2 and Table A.3, the results which use either strongly hesitant or hesitant or unsure are similar with strongly hesitant having larger effects and hesitant or unsure having similar or smaller effects.

The OLS and 2SLS results are in the same direction and both are statistically signifcant. The magnitudes diverge slightly which could be for a number of reasons. First, the instrument may be correcting for a downward bias due to endogeneity of vaccine uptake. Second, the effect may be different for counties whose vaccine takeup is affected by vaccine hesitancy (the compliers). Recent work finds that other reasons can be different weights placed on treatment levels or covariates (Ishimaru, 2022).

5 Conclusion

Parents matter for their offspring's health and this affects their entire lifetime stock of health capital. There are many ways that parents and families could matter, including: genetics, fetal origins, insurance spillovers, learning, and behavioral aspects. However, it is difficult to distinguish if a different mechanism, the imposition of a parent's health preferences on their offspring is important. In our setting, the only channel through which parents affect their underlings utilization is through imposing their health preferences, because companion animals do not choose their health behaviors (diet, exercise, etc.), they are a different species which cannot learn, they are not genetically related or given birth to be their human "parents", and workplace health insurance does not extend to animals like it does to humans in the family.

We document a robust relationship between human health beliefs, behaviors, and underling health utilzation using data on Covid-19 vaccine hesitany and uptake and veterinary services visits at the county level. We rule out that the results are driven by a reopening story through falsification and monthly subsampling. We back up the causal interpretation by showing the results are not very sensitive to omitted confounders and by using an alternative identification strategy. This result is the first to show that living beings in the stead of a guardian increase their health utilization if that guardian is also inclined to practice healthy behaviors, in the absence of all other commonly recognized confounding factors.

There are some limitations that are worthy of discussion. First, our result uses data aggregated to the county level. It would be most appropriate to have human-animal linked health data; however, there are no known sources of this at the time of this writing.

Table 1: Summary Statistics

Panel A: Panel (2021)	Mean	Median	SD	Min	Max	Count
Count of Visits	339.87	96.00	712.70	0.0	11646.00	37704
Visit Counts, Closing Included	351.70	101.00	737.92	0.0	11914.00	37704
2 Shot C-19 Vaccination Rate	32.96	35.81	23.33	0.0	99.90	37704

Panel B: Cross-Section (May)	Mean	Median	SD	Min	Max	Count
Count of Visits	426.80	162.00	796.95	0.0	11481.00	3142
Visit Counts, Closing Included	437.24	169.00	814.31	0.0	11769.00	3142
2 Shot C-19 Vaccination Rate	32.76	35.11	16.27	0.0	99.90	3142
Vaccine Hesitant or Unsure	19.14	19.01	5.35	5.0	32.33	3142
Vaccine Hesitant	13.26	13.18	4.63	2.7	26.70	3142
Vaccine Hesitant, Strongly	8.67	8.49	3.29	1.9	18.24	3142
RUCC Code (2013)	5.01	6.00	2.71	1.0	9.00	3140
RUCC Code (2013) Above 4	0.63	1.00	0.48	0.0	1.00	3140
Population (10,000s)	10.45	2.58	33.36	0.0	1003.91	3140
Real GDP (Billions)	5.96	1.07	22.06	0.0	639.23	3087
Median Household Income (thousands)	58.93	56.63	15.26	25.7	153.72	3140
Unemployment Rate	4.66	4.40	1.76	0.9	19.90	3140
Poverty Percent, All Ages	14.61	13.60	5.66	2.9	43.90	3140

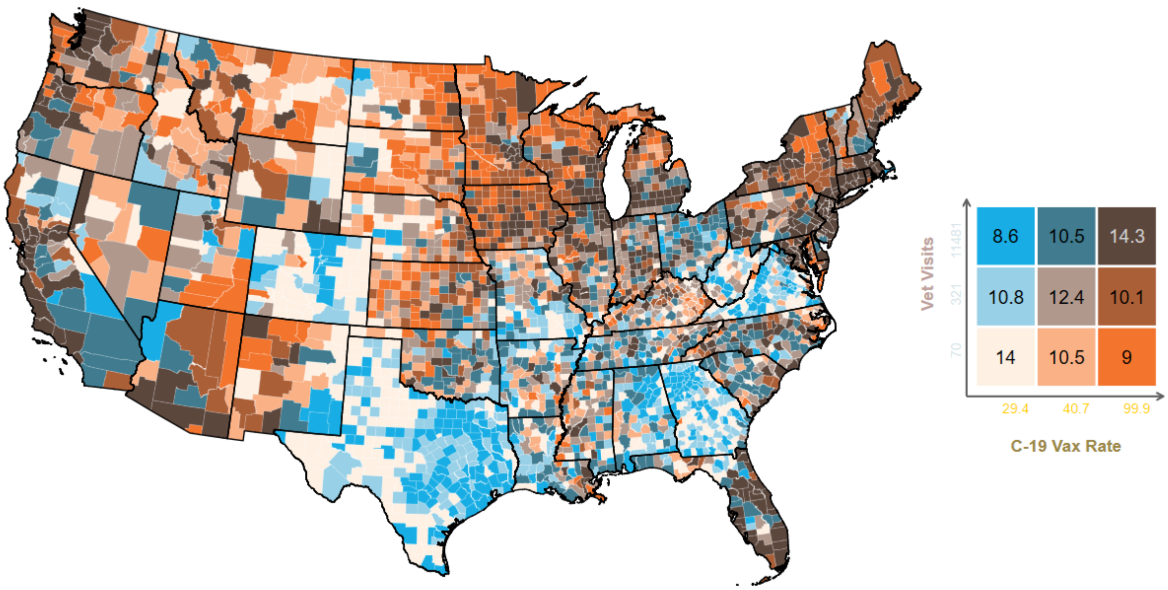
Panel C: May, Above Mean Vax	Mean	Median	SD	Min	Max	Count
Count of Visits	503.55	202.00	849.55	0.0	10664.00	1812
Visit Counts, Closing Included	516.65	208.50	869.24	0.0	10859.00	1812
2 Shot C-19 Vaccination Rate	43.70	42.35	8.17	32.8	99.90	1812
Vaccine Hesitant	12.91	12.85	4.67	3.7	26.70	1812

Panel D: May, Below Mean Vax	Mean	Median	SD	Min	Max	Count
Count of Visits	322.22	117.00	706.12	0.0	11481.00	1330
Visit Counts, Closing Included	329.06	122.00	719.23	0.0	11769.00	1330
2 Shot C-19 Vaccination Rate	17.85	22.52	12.21	0.0	32.76	1330
Vaccine Hesitant	13.73	13.80	4.55	2.7	26.70	1330

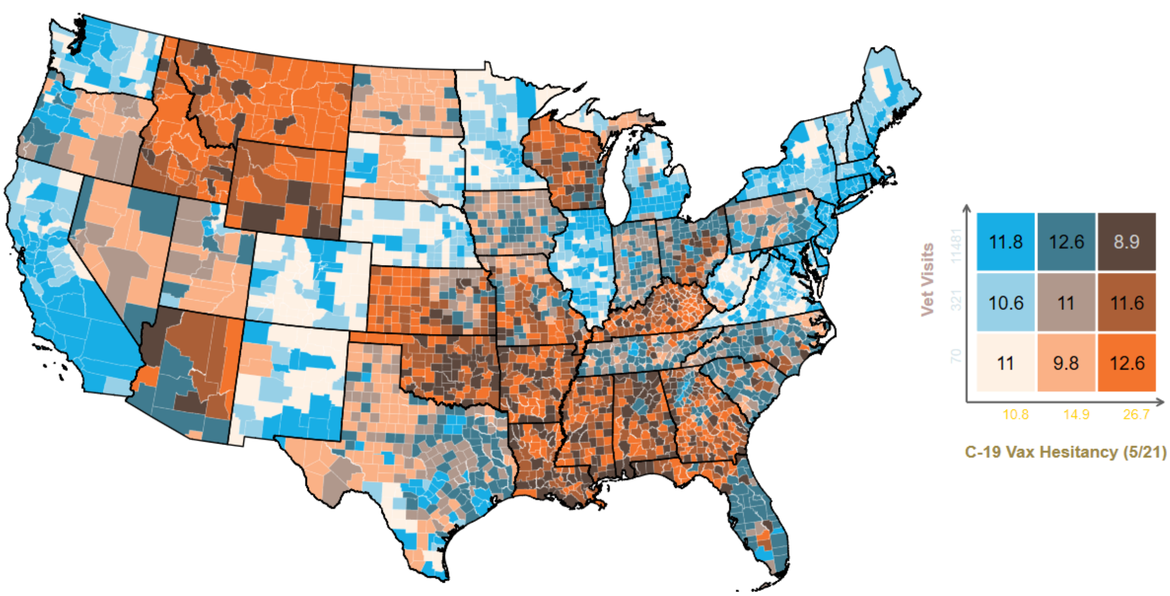
Note: Panel A reports summary statistics for the all months in 2021. Panel B reports summary statistics for May 2021. Panel C reports summary statistics for May 2021 for counties with above mean vaccination rate in May 2021. Panel D reports summary statistics for May 2021 for counties with below mean vaccination rate in May 2021. Count of visits is visits to veterinary services locations and this comes from SafeGraph Patterns data. 2-shot C-19 Vaccination Rate comes from the Center for Disease Control (CDC). It is the percent of the population, that is above the age of 18, that has received at least 2 Covid-19 shots. Vaccine hesitancy comes from the Household Pulse Survey from May 26-June 7. RUCC stands for Rural-Urban Continuum Code which comes from the United States Department of Agriculture (USDA) and the Office of Management and Budget. Population comes from the United States Census Bureau and is measured in 2020. Real GDP comes from the Bureau of Economic Analysis (BEA) and is measured in 2020. Median household income and poverty percent comes from the US Census Bureau's Small Area Income and Poverty Estimates. The Unemployment Rate is from the Bureau of Labor Statistics, Local Area Unemployment Statistics.

Figure 1: Spatial Relationships Between Vaccine Hesitancy, Vaccination Rate, and Veterinarian Visits

(a) Vaccine Rate and Vet Visits



(b) Vaccine Hesitancy and Vet Visits



Note: Maps show the association of vaccine hesitancy, vaccine uptake, and veterinary services visits. The sample is May 2021. Each variable is broken into three quartiles and the resulting 3X3 matrix is shown to the right of the figure. The percent of counties is shown inside the respective square. Figure (a) shows the relationship between Covid-19 vaccination rate (x-axis) and veterinary services visits (y-axis). Figure (b) shows the relationship between Covid-19 vaccine hesitancy (x-axis) and vet visits (y-axis). For the relationship between vaccine hesitancy and vaccine takeup, see Figure A.1.

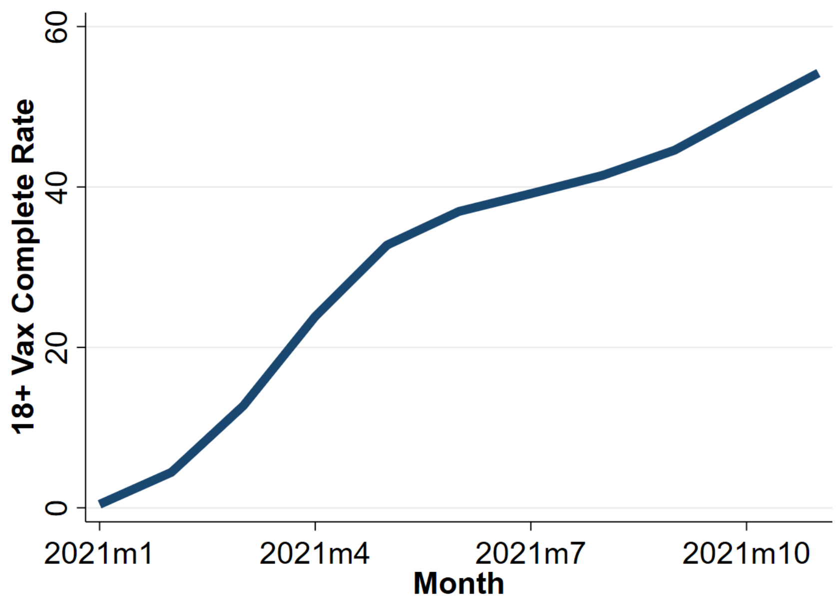
Table 2: OLS Estimates of Human Covid-19 Vaccination Rate and Veterinarian Visits

Panel A: Panel (1/2021-10/2021)				
	(1)			
2 Shot Covid-19 Vaccination Rate (18+)	4.13***			
	(0.85)			
Observations	37704			
County FEs	X			
Month FEs	X			
SEs Robust or Cluster	County			
Panel B: Cross-Section (May 2021)				
	(1)	(2)	(3)	(4)
2 Shot Covid-19 Vaccination Rate (18+)	15.23***	8.16***	10.36***	4.01***
	(2.99)	(1.93)	(2.39)	(1.12)
Median Household Income				10.15***
				(2.71)
Unemployment Rate				-22.33***
				(6.99)
Poverty Percent, All Ages				9.62**
				(4.29)
Adult White Population (1000's)				3.98***
				(0.77)
Adult Black Population (1000's)				1.96
				(1.69)
Adult Other Population (1000's)				-8.62***
				(1.61)
Observations	3142	3140	3140	3136
R-Squared	0.117	0.307	0.410	0.701
State FEs	X	X	-	-
RUCC FEs	-	X	-	-
State X RUCC FEs	-	-	X	X
Cluster Level	State	State	State	State
Unobservable Selection Proportion for Null Effects				0.808

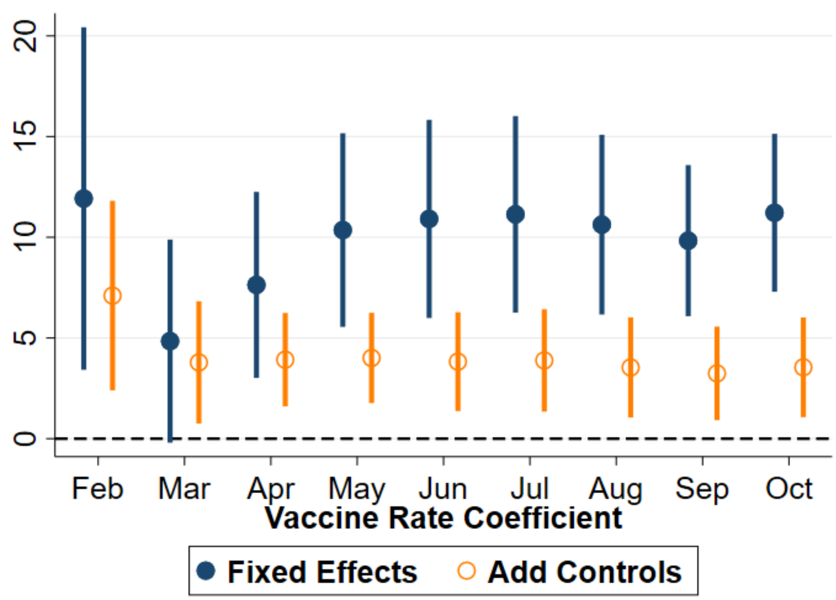
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by county (Panel A) or state (Panel B), in parentheses. All regressions estimated by OLS. The independent variable is the two-shot Covid-19 vaccination rate for those who are 18 or older. Panel A uses two-way fixed effects on a county-year panel. Panel B uses a cross-section of counties in May 2021. Column 1 of Panel B includes state fixed effects. Column 2, Panel B includes state and urbanicity, from the USDA's 2013 (the most recent version) Rural-Urban Continuum Codes (RUCC), fixed effects. Column 3, Panel B includes interacted state and RUCC fixed effects. Column 4 adds population, income, and black population as controls. The Unobservable Selection Proportion for Null Effects is from Oster (2019). It is the proportion of selection on unobservable variables, compared to observable variables, that would be required for the 95% confidence intervals to include 0. Calculating this requires inputting an r-squared max, which Oster (2019) suggests being 1.3*r-squared. For details, see Oster (2019). For details on the methodology, see Section 3.

Figure 2: How Vaccination and Estimates Vary by Month of 2021

(a) Cumulative Vaccination Rate Over Time

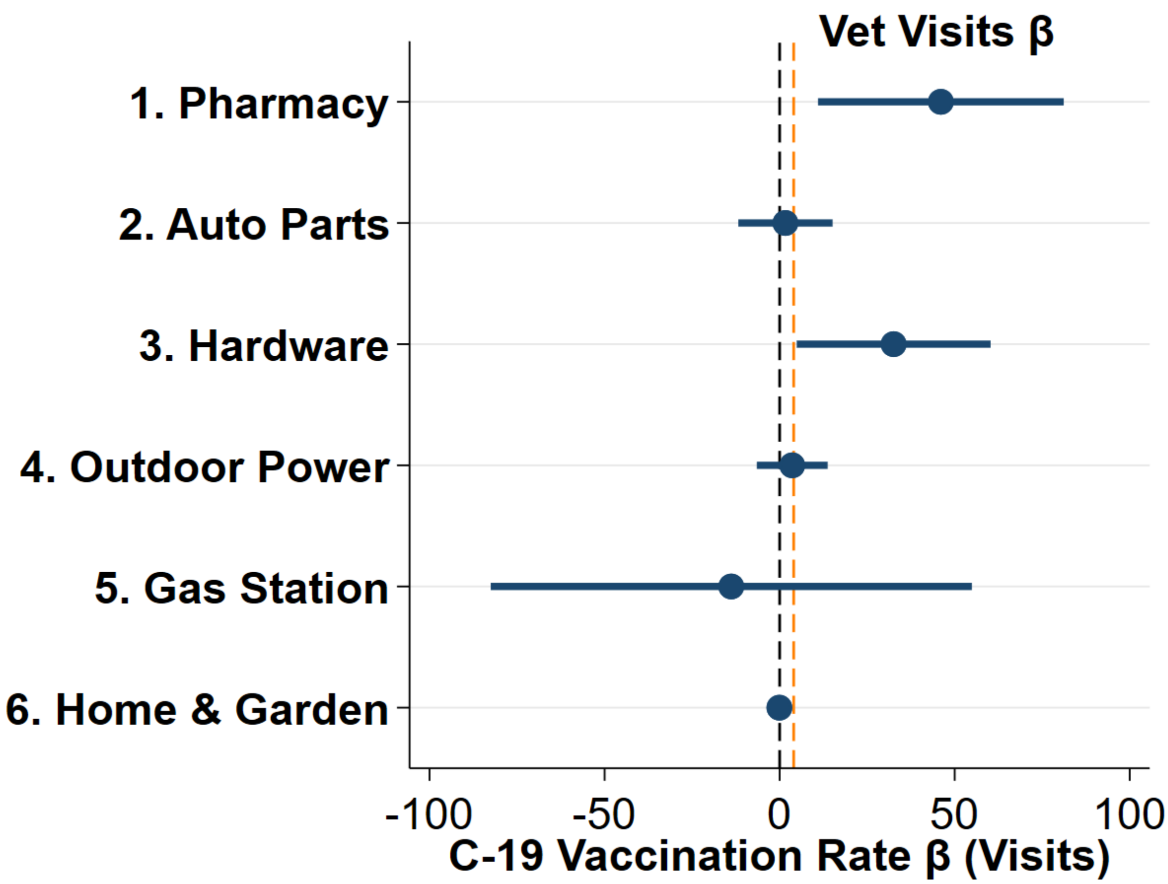


(b) OLS Estimates By Month



Note: (a) shows the average county-level Covid-19 vaccination rate by month. It is the percent of the 18 and over population that has received 2 shots. (b) shows OLS estimates that are subsampled by month. The estimating equation is Equation 2 which is the same as column 4, Panel B of Table 2. Filled-in navy dots are estimates from OLS with state X RUCC fixed effects. Open orange dots are estimates from OLS with state X RUCC fixed effects and controls for median household income, race-specific population, unemployment, and poverty percent. January point estimate is reported in Table A.1.

Figure 3: Falsification: The Effect of Vaccination Rate on Other Industries



Note: Figure shows the vaccination rate coefficient estimates. Each row is a different dependent variable, store visits for different industry codes. The whiskers represent 95% confidence intervals with state-clustered standard errors. The estimating equation is Equation 2. The point estimate with veterinary services visits (the main specification) is shown by the orange dashed line. The NAICS codes are as follows: 1. 446110, 2. 441310, 3. 444130, 4. 444210, 5. 447190, 6. 811411.

Table 3: The Effect of Vaccination Rate on Veterinary Services Visits, Including Closed Stores, Using Poisson, and Subsampling by Urban-Rural

Panel A: Including Closed Stores	(1)	(2)
2 Shot Covid-19 Vaccination Rate (18+)	10.688***	4.255***
	(2.471)	(1.190)
Median Household Income (thousands)		10.051***
		(2.832)
Unemployment Rate		-23.872***
		(7.394)
Poverty Percent, All Ages		9.403**
		(4.439)
Adult White Population (1000's)		4.106***
		(0.797)
Adult Black Population (1000's)		1.932
		(1.716)
Adult Other Population (1000's)		-8.955***
		(1.681)
Observations	3140	3136
R-Squared	0.412	0.704

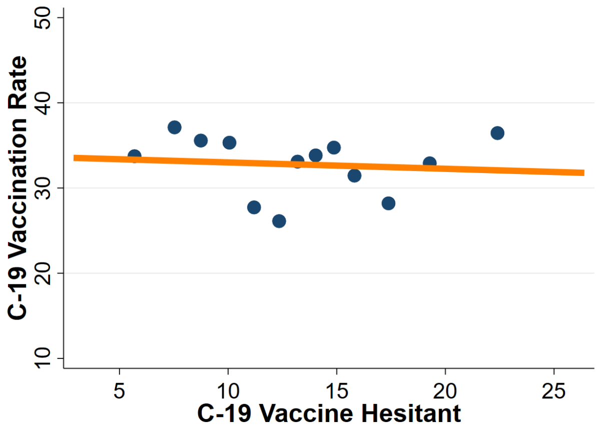
Panel B: Poisson	(1)	(2)
2 Shot Covid-19 Vaccination Rate (18+)	0.027***	0.016***
	(0.005)	(0.004)
Median Household Income (thousands)		0.016***
		(0.003)
Unemployment Rate		-0.035*
		(0.021)
Poverty Percent, All Ages		0.008
		(0.010)
Adult White Population (1000's)		0.002***
		(0.000)
Adult Black Population (1000's)		0.001
		(0.001)
Adult Other Population (1000's)		-0.005***
		(0.001)
Observations	3140	3136
Psuedo R-Squared	0.587	0.684

Panel C: Urban and Rural	(1) Urban	(2) Rural
2 Shot Covid-19 Vaccination Rate (18+)	9.149***	-0.061
	(3.227)	(0.442)
Median Household Income (thousands)	13.969***	-0.781
	(4.745)	(0.573)
Unemployment Rate	-42.454**	-12.234***
	(20.376)	(3.957)
Poverty Percent, All Ages	15.163	-2.787**
	(11.718)	(1.056)
Adult White Population (1000's)	3.897***	9.916***
	(0.711)	(0.812)
Adult Black Population (1000's)	2.244	6.442*
	(1.679)	(3.507)
Adult Other Population (1000's)	-8.656***	2.570*
	(1.608)	(1.423)
Observations	1164	1972
R-Squared	0.644	0.623

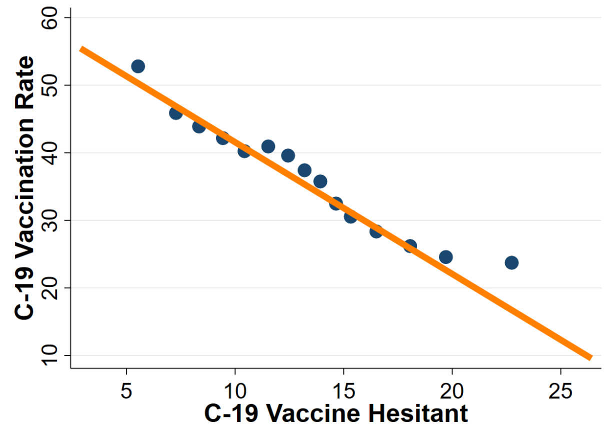
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The independent variable is the two-shot Covid-19 vaccination rate for those who are 18 or older. All panels use May 2021 data. All panels include state X RUCC interacted fixed effects, in which RUCC is an urban-rural continuum code from 1-9. Panel A modifies the dependent variable by including stores that were not present over the whole length of the panel. Panel B estimates the equations by Poisson regression, because veterinary services visits are a count variable. Panel C subsamples to urban counties in column 1 and rural counties in column 2.

Figure 4: Binned Scatterplots for Instrumental Variable Regressions

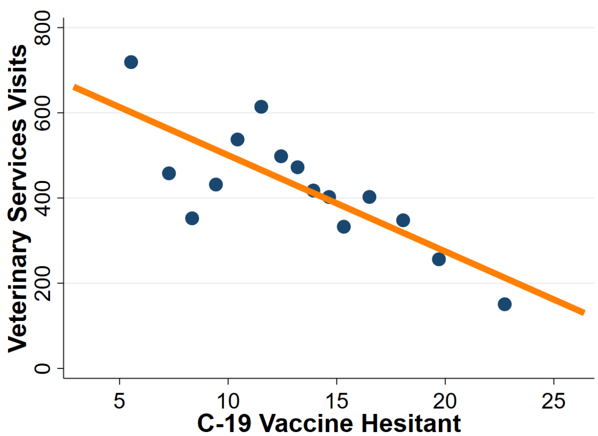
(a) First Stage



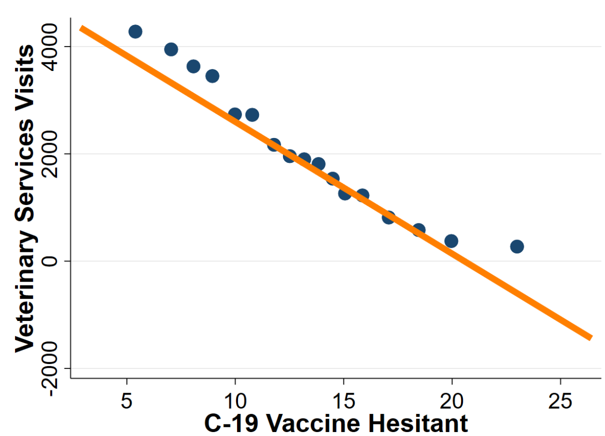
(b) First Stage, State Fixed Effects



(c) Reduced Form



(d) Reduced Form, State Fixed Effects



Note: Sample is counties in May 2021. All bins contain same number of counties. All figures use the optimal number of bins, in terms of trading out variance and bias (Cattaneo, Crump, Farrell, & Feng, 2019). Fixed effects differ across columns. Column 2 uses a semi-parametric adjustment for state fixed effects (Cattaneo et al., 2019).

Table 4: 2SLS Estimates of Relationship Between Vaccination and Vet Visits, Hesitant or Unsure

Dep Var. Panel A: Single Independent Variable	(1) Reduced Form Vet Visits	(2) First Stage Vaccination Rate	(3) Second Stage Vet Visits
Vaccine Hesitant	-22.582*** (7.859)	-0.075 (0.399)	
2 Shot Covid-19 Vaccination Rate (18+)			302.685 (1578.624)
Observations	3142	3142	3142
Kleibergen-Paap F			0.0350
Panel B: Add State FE			
Vaccine Hesitant	-246.016*** (29.107)	-1.950*** (0.353)	
2 Shot Covid-19 Vaccination Rate (18+)			126.132*** (22.273)
Observations	3142	3142	3142
Kleibergen-Paap F			30.58
A-R 95% Confidence Set			[89.97, 192.27]
Panel C: Add RUCC FE			
Vaccine Hesitant	-146.702*** (22.008)	-1.739*** (0.343)	
2 Shot Covid-19 Vaccination Rate (18+)			84.365*** (16.325)
Observations	3140	3140	3140
Kleibergen-Paap F			25.63
A-R 95% Confidence Set			[56.56, 132.84]
Panel D: Add Controls			
Vaccine Hesitant	-49.841*** (18.308)	-1.340*** (0.336)	
2 Shot Covid-19 Vaccination Rate (18+)			37.188*** (13.590)
Observations	3136	3136	3136
Kleibergen-Paap F			15.95
A-R 95% Confidence Set			[14.04, 81.85]
Panel D: State X RUCC FEs			
Vaccine Hesitant	-60.937*** (19.984)	-1.234*** (0.314)	
2 Shot Covid-19 Vaccination Rate (18+)			49.371*** (15.654)
Observations	3136	3136	3136
Kleibergen-Paap F			15.42
A-R 95% Confidence Set			[22.71, 98.33]

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of veterinary services visits on Covid-19 vaccination rate, using hesitant or unsure rate as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. Panel A includes no other variables. Panel B adds state fixed effects. Panel C adds urbanicity fixed effects. Panel D adds control variables, specifically race-specific adult population, median household income, poverty percent, and unemployment rate. Panel E replaces the additive state and urbanicity fixed effects with state-specific urbanicity fixed effects. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews, Stock, and Sun (2019) for just-identified structural equations.

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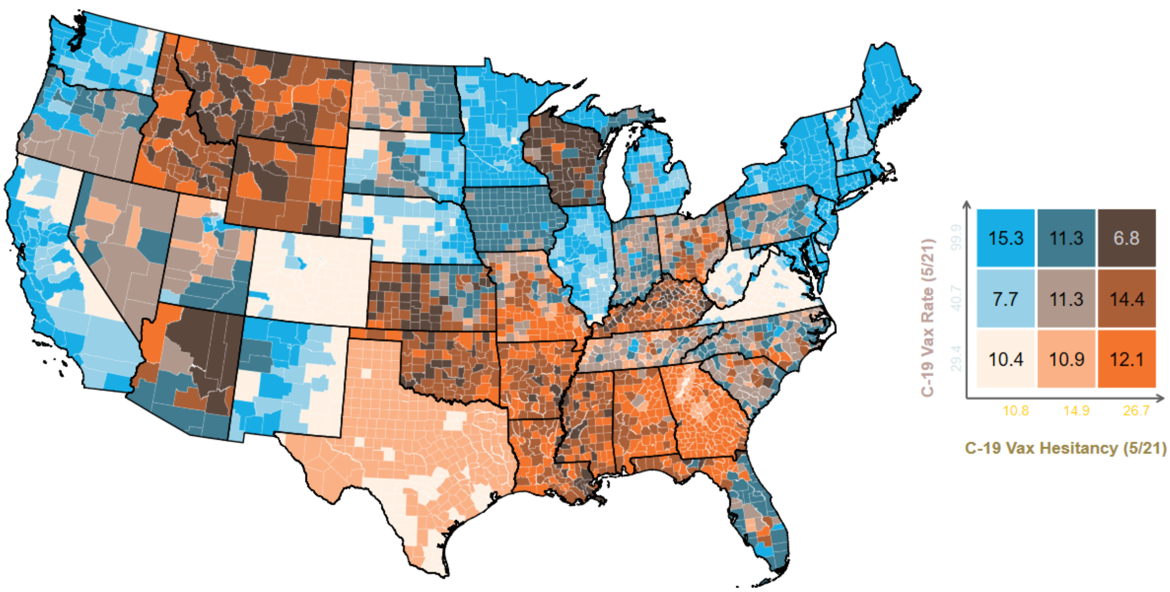
Online Appendix

A Additional Tables and Figures

Figure A.1: Spatial Relationship Between Human Vaccine Hesitancy and Human Vaccination Rate



Note: Map shows the association of vaccine hesitancy and vaccine uptake, the so-called first stage. The sample is May 2021. Each variable is broken into three quartiles and the resulting 3X3 matrix is shown to the right of the figure. The percent of counties is shown inside the respective square.

Table A.1: OLS Estimates of Human Covid-19 Vaccination Rate and Veterinarian Visits, January

	(1)
2 Shot Covid-19 Vaccination Rate (18+)	66.67**
	(25.49)
Observations	3136
R-Squared	0.712

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state (Panel B), in parentheses. The regression is estimated by OLS. The independent variable is the two-shot Covid-19 vaccination rate for those who are 18 or older. The sample is a cross-section of counties in May 2021. The specification includes interacted state and RUCC fixed effects. Column 4 adds population, median household income, poverty, and unemployment rate as control variables.

Table A.2: 2SLS Estimates of Relationship Between Vaccination and Vet Visits, Hesitant or Unsure

Dep Var.	(1) Reduced Form Vet Visits	(2) First Stage Vaccination Rate	(3) Second Stage Vet Visits
Panel A: Single Independent Variable	(1)	(2)	(3)
Estimated hesitant or unsure	-21.228***	-0.273	
	(6.810)	(0.322)	
Completely Vaxxed, 18 Plus			77.623
			(88.467)
Observations	3142	3142	3142
Kleibergen-Paap F			0.721
Panel B: Add State FE	(1)	(2)	(3)
Estimated hesitant or unsure	-161.046***	-1.230***	
	(20.211)	(0.237)	
Completely Vaxxed, 18 Plus			130.880***
			(24.965)
Observations	3142	3142	3142
Kleibergen-Paap F			26.89
A-R 95% Confidence Set			[90.3514, 208.972]
Panel C: Add RUCC FE	(1)	(2)	(3)
Estimated hesitant or unsure	-89.837***	-1.078***	
	(14.581)	(0.235)	
Completely Vaxxed, 18 Plus			83.353***
			(18.726)
Observations	3140	3140	3140
Kleibergen-Paap F			20.96
A-R 95% Confidence Set			[52.9538, 143.41]
Panel D: Add Controls	(1)	(2)	(3)
Estimated hesitant or unsure	-30.702***	-0.775***	
	(11.146)	(0.250)	
Completely Vaxxed, 18 Plus			39.639**
			(16.339)
Observations	3136	3136	3136
Kleibergen-Paap F			9.603
A-R 95% Confidence Set			[14.4074, ...]
Panel D: State X RUCC FEs	(1)	(2)	(3)
Estimated hesitant or unsure	-36.715***	-0.726***	
	(12.376)	(0.240)	
Completely Vaxxed, 18 Plus			50.577***
			(18.539)
Observations	3136	3136	3136
Kleibergen-Paap F			9.144
A-R 95% Confidence Set			[20.4814, ...]

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of veterinary services visits on Covid-19 vaccination rate, using hesitant or unsure rate as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. Panel A includes no other variables. Panel B adds state fixed effects. Panel C adds urbanicity fixed effects. Panel D adds control variables, specifically race-specific adult population, median household income, poverty percent, and unemployment rate. Panel E replaces the additive state and urbanicity fixed effects with state-specific urbanicity fixed effects. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) for just-identified structural equations.

Table A.3: 2SLS Estimates of Relationship Between Vaccination and Vet Visits, Strongly Hesitant

Dep Var. Panel A: Single Independent Variable	(1) Reduced Form Vet Visits (1)	(2) First Stage Vaccination Rate (2)	(3) Second Stage Vet Visits (3)
Estimated strongly hesitant	-31.392***	-0.178	
	(10.908)	(0.513)	
Completely Vaxxed, 18 Plus			176.101
			(495.466)
Observations	3142	3142	3142
Kleibergen-Paap F			0.121
Panel B: Add State FE			
	(1)	(2)	(3)
Estimated strongly hesitant	-352.253***	-2.684***	
	(41.669)	(0.460)	
Completely Vaxxed, 18 Plus			131.245***
			(22.654)
Observations	3142	3142	3142
Kleibergen-Paap F			34.12
A-R 95% Confidence Set			[92.6745, 196.724]
Panel C: Add RUCC FE			
	(1)	(2)	(3)
Estimated strongly hesitant	-213.322***	-2.374***	
	(32.358)	(0.446)	
Completely Vaxxed, 18 Plus			89.869***
			(16.816)
Observations	3140	3140	3140
Kleibergen-Paap F			28.31
A-R 95% Confidence Set			[61.237, 139.807]
Panel D: Add Controls			
	(1)	(2)	(3)
Estimated strongly hesitant	-76.202***	-1.855***	
	(28.019)	(0.430)	
Completely Vaxxed, 18 Plus			41.071***
			(14.886)
Observations	3136	3136	3136
Kleibergen-Paap F			18.65
A-R 95% Confidence Set			[15.7257, 88.8148]
Panel D: State X RUCC FEs			
	(1)	(2)	(3)
Estimated strongly hesitant	-89.223***	-1.721***	
	(30.352)	(0.400)	
Completely Vaxxed, 18 Plus			51.832***
			(16.178)
Observations	3136	3136	3136
Kleibergen-Paap F			18.51
A-R 95% Confidence Set			[23.007, 99.8744]

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cluster-robust standard errors, by state, in parentheses. The table displays 2SLS regressions of veterinary services visits on Covid-19 vaccination rate, using strongly hesitant as an instrument. Columns 1, 2, and 3 display the reduced form, first stage, and second stage respectively. Panel A includes no other variables. Panel B adds state fixed effects. Panel C adds urbanicity fixed effects. Panel D adds control variables, specifically race-specific adult population, median household income, poverty percent, and unemployment rate. Panel E replaces the additive state and urbanicity fixed effects with state-specific urbanicity fixed effects. All panels show the Kleibergen-Paap first stage F-statistic for historic hogs. All panels show the corresponding Anderson-Rubin 95% confidence sets for the IV estimate, which are efficient for potentially weak instruments, as suggested by Andrews et al. (2019) for just-identified structural equations.