

COVID-19 Vaccinations, Business Activity, and Firm Value

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Abstract

Using establishment-level data, we show that COVID-19 vaccinations boost business activity and firm performance in the US. A ten percent increase in vaccination rates results in approximately six percent increase in customer visits. At the firm level, vaccinations increase sales and earnings, impact expansion decisions, and decrease probability of default and firm risk, but the benefits vary across businesses. We document the channels through which vaccinations increase store visits, and the limits to the effect of vaccines on business activity. Vaccinations create economically significant private benefits to firms, their shareholders and employees, in addition to their intended public health benefits.

1. Introduction

The COVID-19 pandemic presented the most significant risk to overall public health and economic activity since the Spanish flu epidemic in 1918. As initial fear and concern over the public health consequences of COVID increased, states, counties, and businesses adopted various non-pharmaceutical interventions with a public health focus on reducing the transmission rate of the virus. These include business closures, mask mandates, state-at-home orders, along with numerous other personal and business restrictions. Spiegel and Tookes (2021, 2022) document that some of the interventions helped reduce COVID-19-related fatalities.

In addition to its dramatic effect on public health, COVID-19 also had a significant negative effect on business activity. For example, Goolsbee and Syverson (2021) and Bizjak, Kalpathy, Mihov, and Ren (2022) document that foot traffic to retail establishments declined between 60 and 70 percent during the early onset of the pandemic in March and April of 2020. Kim, Parker, and Schoar (2020) show that both revenues of small businesses and the consumption spending of their owners declined by roughly 40% at the onset of COVID-19. The drop in economic activity led to a substantial increase in unemployment and precipitous drop in GDP in the US. By May of 2020, unemployment rose to 13% and in the second quarter of that same year GDP declined by 9%.

While the early government interventions can mitigate the fear and the spread of COVID-19, they can also adversely affect business activity. In response to the detrimental effect that the virus was having on public health and business activity, there was an unprecedented push both in government and the private sector to rapidly develop a vaccine that would be effective in combatting the adverse consequences of COVID-19. When the results from Phase 3 clinical trials of the COVID-19 vaccine were first announced by Pfizer-BioNTech on November 9, 2020 (and

soon after by Moderna), they were greeted with optimism that vaccines would lower the spread of the virus, reduce the health consequences associated with COVID-19, and reverse the impact of the virus on the economy.¹ As evidence of the optimism that the vaccines brought, there was a positive stock market reaction to the announcement of the success of the first clinical trials (Acharya, Johnson, Sundaresan, and Zheng (2021)). Therefore, the expectation was that the introduction of the COVID-19 vaccines would boost economic business activity.

While perhaps the conventional wisdom was that the implementation of vaccines would reduce anxiety associated with virus transmission without the negative economic effects of the initial government policies, there are a number of reasons why the effect of the introduction of vaccines on both public health and business activity are not clear cut. There were opposing and contentious viewpoints surrounding the COVID-19 vaccine.² Concerns about the safety and side effects, a lack of unanimity among medical professionals in recommending vaccines, and mis- and dis-information on the topic of vaccinations affected individual attitudes towards the virus and whether to get vaccinated.³ There was also a divide in the business community whether or not to promote vaccination. Many firms required their employees to get vaccinated before they could work in-person while many others were opposed to such requirements.^{4,5} At the government level, the Federal mandate of private employers requiring their employees to get vaccinated was blocked

¹ Subsequent approvals through Emergency Use Authorizations (EUA) allowed the formal administration of the vaccines. The authorization dates are December 11, 2020 for Pfizer-BioNTech, December 18, 2020 for Moderna, and February 27, 2021 for Johnson and Johnson. <https://www.fda.gov/emergency-preparedness-and-response/mcm-legal-regulatory-and-policy-framework/emergency-use-authorization>.

² Evidence from surveys and academic research points to an ideological divide on the decision of an individual to get vaccinated. (Agarwal, Dugas, Ramaprasad, and Gao (2021), Kaiser Family Foundation surveys, (2021)).

³ See a report by McKinsey on the challenges related to vaccinations, <https://www.mckinsey.com/industries/life-sciences/our-insights/covid-19-vaccines-meet-100-million-uncertain-americans>.

⁴ <https://www.nbcnews.com/business/business-news/here-are-companies-mandating-vaccines-all-or-some-employees-n1275808>.

⁵ A poll conducted by Willis Towers Watson reported that more than a third of the large companies included in the survey were not intending to impose such vaccine requirements for their employees.

by the US Supreme Court. States differed in their policies relating to vaccines. Some states imposed vaccine mandates (for example, for state employees, frontline and health care workers, teachers and school staff), while others passed legislation or executive orders banning such mandates.^{6,7} Individual attitudes towards the vaccine along with business and public policies make it unclear how vaccine rates in the US would evolve over time, whether herd immunity can be achieved, and whether vaccine rates ultimately would have a beneficial effect on both public health and overall business activity. Another potential limitation on understanding the effect of vaccinations on business activity is the structural change in individual shopping and work behavior such as online shopping and work-from-home.

The contributions of our study are as follows. First, we establish the magnitude of the economic benefits of a pharmaceutical intervention, COVID-19 vaccinations, and its value as a public good. While it might be expected that vaccines would have positive economic effects, given the tensions discussed above regarding acceptance and implementation of the vaccines, it is important to quantify the economic magnitude of the effect of vaccines. Second, we document the mechanisms through which the benefits are accrued. To the best of our knowledge, our study is the first to identify the channels through which vaccinations lead to economic benefits. While several studies document the medical efficacy of vaccines, our focus is on their economic effect.⁸ We study the role that COVID-19 vaccinations play in expanding activity in business establishments, and how that affects firm operating and market performance. Finally, we identify and measure the limitations of these benefits.

⁶ <https://www.aarp.org/politics-society/government-elections/info-2020/coronavirus-state-restrictions.html>.

⁷ <https://www.nytimes.com/2022/01/31/business/texas-florida-vaccine-mandate.html>.

⁸ See Harris (2022), Vilches et al. (2022), Watson et al. (2022).

We use establishment-level customer foot traffic as a measure of business activity following the introduction of vaccinations in the US. With respect to economic magnitude, our findings indicate that a ten percent increase in vaccination rates results, on average, in a 6 percent increase in establishment visits. These findings demonstrate that vaccinations had a significant economic benefit at the establishment level. The increase in visits associated with higher vaccination rates impacts firm performance. Specifically, the increased vaccination rates and visits to the establishment translate into higher sales and earnings for the parent firm. We also find a lower probability of default and stock return volatility, signifying a reduction in firm risk overall. Firms make strategic decisions to expand operations in response to the increased vaccination rates. Firms experience a higher sensitivity in establishment visits to vaccinations rates when there is a greater initial loss of foot traffic at the onset of COVID-19, when firms are in non-essential industries, and when firms have a sharp decline in financial performance during the last three quarters of 2020. The stock market reaction to the initial announcement of successful vaccine trials indicates higher abnormal returns for firms which had greater initial loss of foot traffic during the initial onset of the pandemic, and among firms that witnessed the sharpest decline in financial performance.

Our findings indicate the primary channels through which vaccinations influence business activity include reduced threat of the virus, increased vaccination rates of customers, the relaxing of local government restrictions in response to rising vaccination rates, and higher employment in the establishments. We note that these channels are not mutually exclusive, and they reflect both demand-side as well as supply-side effects that drive up business activity.

Our analysis suggests there are limitations on the benefits of vaccinations to business activity. The “delta” variant in summer of 2021 presents an external shock that demonstrates that

the original vaccines have limits in terms of their medical efficacy as illustrated by the surge in COVID-19 cases. Insofar as customers' shopping behavior responds to the safety of the environment, we find a diminished effect of vaccination rates on foot traffic during this period. The primary economic benefits occur before cumulative vaccination rates reach 15%-37%, depending on the specification, after which the effect plateaus. This is much lower than the scientifically proposed level of 70% required to achieve herd immunity.⁹ An important insight from our paper is that the rate of vaccination required from a public health standpoint differs significantly from that required to achieve economic benefits.

A potential competing explanation for the effect of vaccination rates on business activity is that some states relaxed restrictions contemporaneously with the introduction of vaccinations. Spiegel and Tookes (2021, 2022) find that business restrictions, particularly with respect to high-risk businesses, resulted in lower fatalities. It is unclear, however, whether loosening of restrictions would affect economic activity. On the one hand, by design, many of these restrictions (e.g., stay-at-home orders, gym closures, capacity constraints on restaurants) can lower retail activity and physical foot traffic to establishments. On the other hand, as shown in Correia, Luck, Verner (2022), non-pharmaceutical health interventions during the 1918 flu pandemic reduced mortality rates but did not adversely impact business activity. Such non-pharmaceutical interventions (e.g., mask wearing, social distancing) can slow that virus' spread and help restore economic activity. The introduction of vaccinations can serve as a substitute to such interventions by increasing customers' confidence and willingness to go out. An empirical challenge in assessing the rebound in economic activity is attributing the role of vaccinations vis-à-vis the role of relaxing restrictive orders. We address this challenge by incorporating detailed data on county-level COVID

⁹ <https://www.who.int/news/item/23-12-2021-achieving-70-covid-19-immunization-coverage-by-mid-2022#:~:text=%5B4%5D%20These%20targets%20were%20then,population%20coverage%20by%20mid%2D2022.>

restrictions in the US (Spiegel and Tookes (2021)) in our main tests, as well as similar data at the province level in Canada. While we find that loosening of prior restrictions increases business activity, vaccines continue to play a vital role.

We recognize that the choice to get vaccinated is endogenous and directly related to an individual's disposition toward the virus and social distancing measures. Individuals with *laissez faire* attitudes towards the pandemic are less likely to stay at home (and more likely to attend business establishments) while also less likely to get vaccinated. On the contrary, individuals exercising abundant caution might have avoided visiting stores despite being fully vaccinated. Therefore, any test using observed vaccination rates potentially biases downward the effect of vaccines on business activity. In addition to using establishment, and establishment and time fixed effects, we also use another identification strategy that relies on a difference-in-differences approach by comparing US states that border Canadian provinces which introduced vaccinations with a notable lag relative to the US. We find a greater increase in traffic to an establishment in a US state compared to an establishment of the same brand in a bordering province in Canada during a period when there is increased vaccination in the US compared to Canada. A third identification strategy involves the use of instrumental variables. We continue to find a positive effect of vaccination rates on customer foot traffic. Overall, our evidence suggests that the effect of vaccinations on business activity is causal in nature.

Our paper is most closely related to the following studies. Acharya et al. (2021) examine the ex-ante anticipatory effect of COVID-19 vaccine development on asset prices, and show that financial markets anticipate increased economic activity with vaccine introduction. Our paper, on the other hand, complements their study by documenting the ex-post realization of benefits of vaccine introduction using customer behavior, consistent with the market reaction that they

document. Our paper is also related to contemporaneous studies in the economics literature that examine how vaccines impact the economy at the county, state, national or international level (Deb et al. (2021), Hansen and Mano (2021), Gagnon et al. (2022), Gibson (2022), Tito and Sexton (2022)). In contrast to the above studies, we use establishment-level visits to understand and quantify the effect of vaccinations on economic activity. Unlike aggregate economic data, typically available at a quarterly or annual frequency, the weekly establishment visits capture the economic effects in almost real time providing a cleaner and more direct inference less subject to confounding effects. By using establishment fixed effects for our main tests, we are also able to account for confounding factors that could be present if economic activity is aggregated at the county, state or higher levels. For some of our tests, we are able to measure the geographical source of customer visits at a granular level (Census Block Group (CBG) or ZIP code) which allows us to connect vaccination rates of customers to visits more tightly.¹⁰

In addition to the above contributions of our work, our research provides evidence on the important role that vaccines play as a public good and its influence on economic and business activity. Non-pharmaceutical interventions such as lockdowns are controversial and have both costs and benefits (see Aum, Yoon and Shin (2021) and Spiegel and Tookes (2021)). Our study shows that a pharmaceutical intervention, namely COVID-19 vaccines, helped reverse the deleterious impact that the pandemic had on business activity. Our findings suggest that immunizations, a public good, create economic benefits for firms, their shareholders, and employees, beyond their intended public health benefits.

¹⁰ Our primary tests rely on county-level vaccination rates. Given the heterogeneity in vaccination rates within a county, we also use more granular data from California using ZIP code level vaccination rates to validate our primary results.

2. Empirical design and data

2.1. Identifying assumptions

A key econometric issue in our empirical analysis is establishing causality in the effect of vaccines on economic activity. For example, as Bizjak et al. (2022) note, there was a high degree of politicization of the virus and the business responses to containing its transmission. Similarly, Agarwal et al. (2021) and Kaiser Family Foundation surveys (2021) document that political partisanship is one of the strongest predictors of the decision to get vaccinated. In light of this evidence, individuals with *laissez faire* attitudes towards the pandemic are more likely to attend business establishments while also less likely to get vaccinated. Alternatively, individuals exercising an abundance of caution are likely to stay home even after getting vaccinated. This could cause the coefficient on the cross-sectional effect of the vaccination rate on business activity to be biased downward. We address this issue in three main ways. One, we use cross-sectional identification using an establishment (or establishment and time) fixed effects model.¹¹ By using store fixed effects for our primary tests, we are able to account for confounding factors at the county, state or higher levels. In other words, we account for latent factors that could drive establishment traffic that are time-invariant in nature, while allowing foot traffic and vaccination rates to vary week by week. We estimate the following baseline panel regression specification:

$$LNVISITS_{i,t} = \alpha + \beta_1 VRATE_{i,t} + X_i + Y_i + \varepsilon_{i,t} \quad (1)$$

where $LNVISITS_{i,t}$ is the logarithm of the visits to establishment i during week t , X_i stands for the lagged firm-level or demographic control variables, Y_i refers to the industry, state, county, establishment or time fixed effects.

¹¹ Additional specifications include the use of controls for firm characteristics, and industry, state, county or firm fixed effects.

Second, we address causation using the staggered introduction of vaccines in the US relative to Canada. Canada and the US demonstrated significantly different vaccination rates between late December of 2020 (the beginning of vaccination in the US) through May of 2021. Exploiting the difference in vaccination rates between the two countries to address causality, we perform a difference-in-differences (DiD) analysis comparing US states and Canadian border provinces after vaccines were introduced in the US but not yet in Canada. We explicitly account for whether the states and provinces are contiguous to each other, and only include establishments belonging to firms or brands that operate in both countries in those states and provinces. This analysis relies on the assumption of parallel trends in these contiguous states and provinces before the introduction of the vaccines. The US border states and Canadian border provinces are similar in industrial development, commerce, political system, culture and climate, along with other factors that may jointly affect store visits. Furthermore, Canada effectively closed its border with the US during our sample period, thus the visits on each side of the border reflects strictly local traffic. We estimate a regression specification of the following form:

$$LNVISITS_{i,t} = \alpha + \beta_1 US_i + \beta_2 Post + \beta_3 US_i * Post + Y_i + \varepsilon_{i,t} \quad (2)$$

where $LNVISITS_{i,t}$ is the natural logarithm of weekly visits to an establishment i during week t ; US_i is an indicator variable equal to 1 if the establishment i is in a US border state, and 0 if in a Canadian border province; $Post$ is an indicator variable taking the value of 1 during March 1, 2021-April 26, 2021, and 0 during the period June 1, 2020-December 7, 2020; and Y_i stands for brand, contiguousness, or brand-contiguousness fixed effects.

Third, we employ an instrumental variables (IV) approach to address identification concerns. In the first stage (equation 3 below) we predict $VRATE$ using instruments, and in the second stage (equation 4 below), we regress $LNVISITS$ on the instrument $VRATE$.

$$VRATE_{i,t} = \alpha + \beta_1 Instrument_{i,t} + Y_i + \varepsilon_{i,t} \quad (3)$$

$$LNVISITS_{i,t} = \alpha + \beta_1 \widehat{VRATE}_{i,t} + Y_i + \varepsilon_{i,t} \quad (4)$$

We provide a detailed description of the instruments in subsection 4.2.

2.2 Data and summary statistics

We use the *SafeGraph* database to collect data on establishment-level foot traffic. *SafeGraph* identifies physical visits to millions of points-of-interests (POIs) by collecting GPS data from mobile phone applications and provides detailed information on visits and (anonymized) visitors to establishments. The establishments cover millions of POIs and thousands of distinct brands, including public and private companies in industries such as restaurants, grocery stores, retail stores, hotels, banks, movie theaters, etc.

We identify brand establishments and link them to their parent firms in the US. In *SafeGraph*, the variable “brand” reflects an establishment (e.g., Taco Bell, Pizza Hut, or KFC) that ultimately belongs to a corporate parent entity (Yum! Brands). We drop establishments belonging to private firms thereby restricting our sample to publicly traded firms in order to examine the effect of vaccinations on firm performance. We exclude financials (two-digit SIC codes 60-63). The final sample, after obtaining firm characteristics from Compustat and CRSP, consists of 327,259 unique establishments belonging to 249 public firms. We calculate the number of the visits each week ($VISITS$) in each establishment. Bizjak et al. (2022) show that firm characteristics help explain changes in store traffic, in addition to other variables. Therefore, we add firm controls measured as of 2019 for all of our observations (2020-2021), except when we use firm/brand fixed

effects or establishment fixed effects, where these controls are not needed. Firm characteristics are obtained from Compustat and CRSP.

We use several sources for vaccination rates. First, we use weekly data at the county level from the Center for Disease Control (CDC) for all US states. Since data for Texas is not included in the CDC data, we obtain the data from the Texas Department of State Health Services (DSHS). For our DiD analysis, we obtain Canadian vaccination data from the Public Health Agency of Canada. Finally, for some of our tests we obtain data on vaccinations and local policies from the California Department of Public Health. Throughout the analyses, we use the percentage of fully vaccinated individuals as our explanatory variable.¹²

We obtain demographic data from *SafeGraph* Open Census. We obtain from the New York Times county-level data on COVID-19 cases and county-level 2020 Presidential election voting results.

Our final sample consists of 327,259 establishments owned by 249 public firms operating in 2,770 counties during the period December 28, 2020-June 28, 2021. Table 1 presents the summary statistics for our sample. The average number of visits to an establishment in a week is 100.6 with a median of 63. The average vaccination rate during the period in a county is 16.6% with a median of 11.9%.

In Figure 1, we plot the distribution of cumulative vaccination rates per capita across time in the US, and the natural logarithm of visits in our sample. As we observe in the figure, visits to establishments exhibit a notable increase in the beginning of 2021 which coincides in time with the introduction of vaccinations.

¹² We define vaccination rates as the total number of fully vaccinated individuals (two doses of Pfizer-BioNTech or Moderna or one dose of Johnson and Johnson vaccines) divided by the county's population. Our results are robust when we use the first dose only.

3. Main results

3.1 Vaccination rates and store visits

Table 2 reports our baseline regression results. We regress *LNVISITS*, the dependent variable, on vaccination rates, control variables, and different types of fixed effects. In model 1, we include state and industry fixed effects; in model 2 we include an exhaustive set of firm and demographic control variables as well as state and industry fixed effects; in model 3 we include firm controls and county and industry fixed effects (county fixed effects fully absorb the demographic characteristics). In model 4, we include establishment fixed effects. The establishment fixed effects fully absorb all observable and unobservable time-invariant factors that influence foot traffic. In this specification, which is the tightest of all the models, we compare week-by-week foot traffic as a function of vaccination rates for the same store. Across the first four models, we observe that a 10 percent increase in vaccination rates is associated with 5.2 to 6.6 percent increase in foot traffic. Given the average weekly change in visits of 5.6 percent in our sample, the point estimates we obtain are economically quite large. In model 5, we include time (monthly) fixed effects in addition to establishment fixed effects. The coefficient estimate is much lower, indicating that a 10 percent increase in vaccination rates is associated with 1.4 percent increase in foot traffic. The time fixed effects estimate an average effect at each point in time and assume that the same average effect for all establishments (and by extension, all counties in which they operate) which is a strong assumption. The time fixed effects also remove the time-series variation in vaccination rates, and the test becomes a cross-sectional comparison of two counties, for example Dallas County versus Los Angeles County at a given point in time, which is a weaker inference compared to model 4.

3.2 *Vaccinations, COVID restrictions, and business activity*

As discussed previously, it is unclear what effect business restrictions play on economic activity. Spiegel and Tookes (2021, 2022) find that restrictions resulted in lower fatalities. Similarly, Correia, Luck, Verner (2022), find that non-pharmaceutical health interventions during the 1918 Flu pandemic reduce mortality rates but do not adversely impact business activity. By design, many of these restrictions (e.g., stay-at-home orders, gym closures, capacity constraints on restaurants) can lower retail activity and physical foot traffic to establishments. To the extent that many states and counties had started relaxing some of these constraints contemporaneously with the introduction of vaccinations, the challenge is to disentangle the effect of vaccination vis-à-vis the role of relaxing restrictive orders. We address this issue by incorporating detailed data on county-level COVID restrictions in the US. We acquire the Yale COVID Restrictions Database (based on the Spiegel and Tookes (2021) and extended thereafter). The data contain state- and county-level restrictions such as stay-at-home orders, business closures for gyms, spas, and restaurants, capacity restrictions, mask requirements, restrictions on gatherings, among others.

In order to account for the conditions at state and county levels with respect to the openness of the economy, we construct dummy variables (*OPEN_1*, *OPEN_2*, *OPEN_3*, *OPEN_4*) for the level of openness based on the levels of businesses in the four categories of risk as defined in the database that are open or closed. These variables are identical to variables “Risk levels 1-4 closed” defined in Spiegel and Tookes (2021), except for exposition purposes we construct them to measure openness. Similar to Spiegel and Tookes (2021), we also define indicator variables for closure of restaurants, gyms, spas, mask mandates, state of emergency, no nursing home visits, limitations on gatherings, and others. Formally, the variables are defined in the Appendix.

In Table 3, models 1-5, we observe that the coefficients on *VRATE* remain economically and statistically significant, albeit slightly lower than those in the baseline table 2 regressions. We also observe that levels 2 and 3 of openness are significantly related to visits in some specifications.¹³ In models 6-10 of the Table, we include an exhaustive set of restriction dummy variables described above. We observe that controlling for the overall set of restrictions in place, the coefficients on *VRATE* remain economically and statistically significant at similar levels. Our main baseline specification (establishment fixed effects, model 9) indicates that a 10% increase in visits results in 6.0% increase in foot traffic, compared to 6.6% without accounting for restrictions in model 4 of Table 2. Thus, opening up the economy explains part of the increase in business activity, while the effect of vaccinations remains relatively unchanged.

In Internet Appendix (IA) Table 1, we repeat the endogeneity test in Spiegel and Tookes (2021) by removing the five most populous counties in each state. The authors hypothesize that state policies are often designed with the largest cities and counties in mind. To the extent that restrictions were the tightest in the biggest cities (and populous counties) and the vaccination uptake was also highest in those locales, this may cause a bias in our tests. After removing those five most populous counties in each state, we observe similar results with respect to the effect of *VRATE* on business activity.

Finally, in IA Table 2, we run models using county-time (models 1 and 2), and county-industry-time (models 3 and 4), fixed effects, where time is at monthly frequency. For a given county, we are holding constant the prevalent conditions (including restrictions) in a certain month, or in a month for a given industry, in the restaurant sector, for example, and seeing whether weekly vaccination rates in the county can explain the variation in store traffic in establishments in that

¹³ The coefficient on variable *OPEN_I* cannot be estimated because, for our sample period, no county had complete closure of the lowest risk businesses.

county. This test aims to complement the evidence from the COVID Restrictions Database. As we see in IA Table 2, while restrictions play a role in business activity, vaccination rates continue to be strongly related to visits.

3.3 The Interdependence of vaccinations and business restrictions

While our results indicate that vaccination rates influence business activity after we account for county and state restrictions, it is conceivable that vaccination rates and restrictive policies are not independent of each other - it is possible that both vaccination and policy restrictions affect business activity. We observe that the coefficients on *VRATE* are slightly weaker with the inclusion of COVID restrictions. Admittedly, it is very difficult to disentangle the effects of the two since restrictions likely respond to vaccination rates, but lifting of restrictions, which is likely to increase business activity, can coincide in time with the introduction of vaccinations. We do not claim that we can resolve this issue fully, but in this subsection, we provide evidence on the interdependence of the two, as well as some evidence on the role that vaccination rates play in lifting of restrictions.

First, to illustrate the interactive effects of the two sources of potential increase in business activity, we interact the openness dummies with *VRATE*. In IA Table 3, we observe that vaccination rates have a stronger effect at lower level of openness than at higher levels of openness of the economy, consistent with the idea that the two forces play a complementary role in fostering business activity.

Second, we study the lifting of local restrictions in California. The state instituted a color-coded rank system for counties with four tiers ranging from 1 (purple) having the most stringent restrictions to 4 (yellow) having minimal restrictions, with the status updated weekly.¹⁴ In Table

¹⁴<https://emd.sacounty.gov/EMD-COVID-19-Information/Documents/California-Color-Coded-Tier-System--en.pdf>

4, Panel A, we show that the vaccination rate is positively associated with higher tier (fewer restrictions) for a county. In terms of economic significance, a 10 percent increase in vaccination rates corresponds to an improvement in the county status (and the associated lifting of restrictions) by more than one half of a tier. We obtain similar results when we examine changes in tier status. The evidence points to a channel through which vaccination rates can drive up traffic, by removing or relaxing government restrictions on businesses.

In Table 4, Panel B, we extend this analysis to all the counties in the US. Specifically, for each week in each county, we count the total number of COVID restrictions in place. Admittedly, this is a parsimonious approach that gives the same weight to different restrictions, but nonetheless this is an informative measure of the change in the strength of restrictions at a given time. We calculate the change in the number of total restrictions week-to-week, and classify these changes as an increase, a decrease, or no change categories. We run a multinomial logit model with the no change category as the normalized alternative. We observe that vaccinations rates are positively related to lifting of restrictions, and negatively related to an increase in restrictions. This evidence is largely consistent with our prior analysis from California.

3.4. Robustness tests

We perform a battery of tests to check for the robustness of our baseline results. First, in order to address potential concerns about non-stationarity in visits and vaccination rates, we use percentage change in visits relative to the same calendar month, pre-COVID in 2019. In IA Table 4, we report the results using both weekly vaccination rates (models 1 and 2) as well as cumulative vaccination rates (models 3 and 4) and observe that our main inferences on the effect of vaccinations on store traffic remain unchanged. Second, we address concerns of specifying a log-linear model with count variables by re-examining our main results under a Poisson model (Cohn,

Liu, and Wardlaw (2022)). We present these results in IA Table 5. The coefficient estimates from models 1 and 2 indicate that a ten percent increase in vaccine rates translates into a 6 percent ($e^{0.059}-1$) and 1.3 percent ($e^{0.013}-1$) increase in visits, respectively. These estimates are very close to the ones obtained from models 4 and 5 in Table 2. Third, in IA Table 2, we use higher-dimension fixed effects to account for shocks clustered using firm fixed effects and county fixed effects at a point in time, as well as shocks clustered within a county at a point in time for a brand. Our results are qualitatively the same. In IA Table 6, we present additional robustness tests when we use the first dose of COVID-19 vaccines and account for state-level allocations of vaccinations. We find that our main results on the effect of vaccinations on store traffic remain unchanged.¹⁵

4. Causal inferences

As discussed earlier, an important econometric issue with our empirical analysis is assessing causality in the effect of vaccines on business activity. Vaccination rates are likely not exogenous and could depend on omitted factors correlated with both vaccination rates as well as store traffic. We address this issue using difference-in-differences (DiD) and instrumental variables (IV) approaches.

4.1. Difference-in-differences approach

We use the staggered nature of the introduction of vaccinations in the US (the treated group) relative to Canada (the untreated group) to perform a DiD analysis. As Figure 2 shows, there is a distinct lag between the introduction of the vaccines in the two countries.

We identify as pre-vaccinations the period from June 2020 to December 7, 2020, before vaccinations were administered. We define as post-vaccinations the period starting in March 1,

¹⁵ In unreported robustness analysis, we exclude politically polarizing firms (based on the 2019 Axios-Harris survey of partisan orientation of a firm's customers) and politically polarized counties (top and bottom 5% based on the 2020 Presidential voting results). We find that our results remain unchanged.

2021 and ending in the last week of April 2021, during which period the US ramped up vaccinations significantly, but Canada did not yet. We exclude the period January 1 to February 28, 2021 during which the difference in vaccination rates between the bordering states in the US and provinces in Canada was quite small. As of March 1, the difference in vaccination rates was greater than 5%. We note that Canada had much lower vaccination rates (as opposed to being strictly “untreated”), and the US had higher vaccination rates (as opposed to being fully “treated”).

This set up allows us to draw inferences of the effect of vaccine introduction on foot traffic, as the two countries generally have similar economic and political systems, and the same retail store brands. This set up also ensures that the control group (Canada) remains “untreated” since Canada had closed its border with the US. Our identification is strong because we account for the change in traffic (pre- vs. post) for establishments of the same brand, but across different vaccination regimes. We include US state and Canadian provinces that are on the border as illustrated in Figure 2, Panel B, in order to account for latent cultural, social, political, climatic, and other factors based on shared geography. In other words, we compare, for example, a store in Seattle with one in Vancouver of the same brand as opposed to comparing a store in Miami with one in Montreal.¹⁶ Of particular importance are two issues: seasonality and government restrictions. By using contiguous states and provinces, for example, Washington State in the US and British Columbia in Canada, we account for any patterns in in-person shopping that may be caused by seasonality.

We present the results in Table 5. In model 1, we include fixed effects for brand and contiguousness simultaneously; in other words, we compare the traffic for stores of the same brand in a US state to the traffic of stores of the same brand in an adjacent Canadian border province. In

¹⁶ We exclude the Canadian province of Yukon, which had vaccination rates similar to the US bordering states.

model 2, we include brand fixed effects and contiguousness fixed effects independently. In model 3, we include brand fixed effects only. We find that the coefficient associated with the post period in the US is positive and significant, indicating that the visits in US border states are higher by 38 percent relative to contiguous Canadian border provinces after the introduction of vaccinations in the US, across all three models. Figure 3 presents the DiD weekly coefficient plot, along with the 95% confidence intervals. We observe a sharp increase in the coefficient (indicating higher visits in the treated group, US), starting in March of 2021. The average coefficient in the pre-period is 9.5 percent indicating a higher traffic in the US relative to Canada pre-vaccinations. Importantly, for the DiD assumptions of parallel trends, we do not observe any trends in the coefficients in the pre-period. The coefficient increases sharply in the post-period with an average of 43.4 percent.

To address the differences in government policies (likely more stringent in Canada than the US as a whole), we repeat the DiD analysis by comparing Canadian provinces to only those border states in the US that have tight restrictions. For this test, we only include the U.S. border states with policies that are stricter than the median state (i.e., the states with more stringent restrictions). We use the Wallethub.com rankings of states based on COVID-19 restrictions as of January 2021 to measure the restrictiveness of COVID-19 state policies. The states that are dropped (having looser restrictions than the median) are Alaska, Idaho, Montana, New Hampshire, and North Dakota. The remaining states are Maine, Michigan, Minnesota, Ohio, Pennsylvania, New York, Vermont, and Washington. Our methodology excludes states like Montana, for example, which lifted the majority of its restrictions in January while still having negligibly low vaccination rates (and thus, could attribute the differences to vaccinations as opposed to lifted restrictions). In model 4, we report the results with the strictest identification (brand-

contiguosness fixed effects). We observe similar results – the coefficient on *US*POST* is similar to that in model 1.

Finally, we obtain detailed COVID-19 restrictions data from Canada.¹⁷ The Canadian restrictions data contain indices for specific types of restrictions such as school closings, workplace closings, stay-at-home requirements, gym closings, restrictions on indoor gatherings, etc. For each of these restrictions, the restriction index ranges from 0 to 100. Notwithstanding the differences in how policies may have been put in place in Canada vis-à-vis the US, we match restriction variables that are common between Canada and the US. Specifically, we identify stay-at-home orders, restaurant closings, gym closings, spa closings, and restrictions on indoor gatherings.¹⁸ In model 5 of the Table, we include these restriction variables both for US counties and Canadian provinces at the weekly interval, using the most restrictive brand-contiguosness fixed effect specification. We observe that restrictions generally lower physical foot traffic, as expected. Accounting for restrictions lowers the effect of vaccination of business activity, but the coefficient on *US*POST* remains statistically and economically significant, indicating that the US experienced a 30% increase in visits relative to Canada after vaccines were introduced in the US. Collectively, these results point to vaccinations having a causal effect on increase in store visits.

4.2. Instrumental variables approach

In addition to the DiD analysis, we also use an instrumental variables (IV) framework to obtain casual estimates on the effect of vaccination rates on store visits. The IV approach addresses the concern that there is likely to be self-selection in terms of who gets vaccinated more. Our choice of instruments is driven by both the relevance condition (i.e., being highly correlated with

¹⁷ <https://www150.statcan.gc.ca/n1/pub/36-28-0001/2022008/article/00002-eng.htm>

¹⁸ In the US data, “spas closed” is defined as “personal care services, such as barbershops, salons, and related services closed to all indoor activities.” In Canada, the respective variable is “hair salons and barbershop closures.”

COVID-19 vaccinations) as well as the exclusion condition (i.e., affect store traffic exclusively through the COVID-19 vaccination channel). We use two different instruments in the first stage of the IV analysis. Our first instrument accounts for eligibility criteria based on pre-existing health conditions for COVID-19 vaccinations. We use county-level data on the proportion of the population with comorbidities (cancer, obesity, and diabetes). We calculate an indicator variable equal to one if a county is in the top quintile of any of the above criteria, and zero otherwise. The second instrument is based on a given county's prior experience in vaccinating its population against the flu. Unlike COVID-19, flu vaccinations were historically less influenced by political considerations. We define an indicator variable equal to one if a county is in the top quintile in flu vaccination rates per capita, and zero otherwise. We measure all the variables described above as of 2019. We expect our instruments to be directly related to vaccination rates (instrument relevance), but not directly related to store visits (other than through the vaccine channel), thereby satisfying the exclusion condition. Our instrument related to comorbidities/eligibility meets the exclusion criterion since people with higher risk of infection are not more likely to visit retail stores in-person except for the immunity provided by the vaccination. As for the instrument related to flu vaccinations, we expect the variable to be highly related to the propensity to get COVID-19 vaccination but, a priori, we do not expect the instrument to be directly related to store visits (exclusion condition). The 2020-21 flu season was characterized by a very low incidence of the flu virus and thus the flu vaccine, in and of itself, is less likely to alleviate people's concerns of going shopping in-person.¹⁹

We report the results in Table 6. In Panel A, we report the second stage results. We observe that *LNVISITS* is highly related to the instrumented *VRATE*. We note in Panel B of the table that

¹⁹ <https://www.cdc.gov/flu/season/faq-flu-season-2020-2021.htm>

our instruments are highly correlated with vaccination rates. The F -statistic for the excluded instruments and the Kleibergen-Paap rK statistic are highly significant confirming the relevance of the chosen instruments. Overall, our instrumental variables approach bolsters our main results from the OLS models.

5. Firm-level effects of vaccinations

Our findings so far indicate that vaccination rates positively influence establishment level foot traffic. In this section, we investigate their impact at the firm level.

5.1. Effect on firm performance and risk

In Table 7, Panel A, we regress the natural logarithm of a firm's quarterly sales for the first two quarters of 2021 (in models 1-4), and the natural logarithm of a firm's quarterly EPS (earnings per share) obtained from COMPUSTAT, on the predicted store visits.²⁰ We calculate the sum of the weekly visits to all establishments of the same firm to obtain the firm-level visits for the first two quarters of 2021. In the first stage of a 2SLS, we regress weekly store visits on vaccination rates along with fixed effects. From this regression, we estimate a firm's average instrumented store visits for each week and calculate the time series average of the firm's instrumented store visits for the second stage analysis. In the second stage, we regress the quarterly sales or EPS on the instrumented store visits from the first stage. By design, the first stage is run at the establishment level, and the second stage at the firm level. Our analysis shows that vaccinations benefit firms by increasing their sales and earnings through customers' visits to the firm's establishments.

²⁰ We add a constant equal to the minimum EPS observation to ensure that there are no negative values resulting in loss of observations when taking the logarithm. As an alternative approach, we calculate the percentile rank of all variables and rerun the same regression. We obtain similar results.

In Panel B of Table 7, we study how vaccines influence corporate decision to expand or close stores. We examine corporate decisions pertaining to strategic expansion at the extensive margin as a function of vaccination rates. Specifically, we calculate the number of stores for each firm in each county per month for the period January-June 2021. We compare this to a firm's total number of stores per month in a county for the period between June, 2020 and November 2020, prior to vaccinations. We estimate a multinomial logit model with the following outcomes: no change (the normalized alternative); increase in number of stores; decrease in number of stores. Results indicate that vaccination rates positively influence the likelihood of store openings and negatively influence the likelihood of store closures. Overall, we find that firms incorporate the new business environment post-vaccination in their strategic decisions relating to store expansion or contraction.

One potential channel through which vaccination rates can increase business activity is by the removal of restrictive measures by the firms themselves through their store policies (e.g., relaxing social distancing measures, removing limits of number of customers at a time, lifting of mask requirements). While we do not have available data to examine this channel directly, the evidence presented in this subsection does not rule out the possibility of firms taking into consideration the changing environment after vaccines are introduced. The store expansion and the labor market increased participation that we document in the next section point to supply-side channels that drive up business activity, in addition to the demand-side channel arising from customer vaccinations.

At the onset of the COVID-19 pandemic, there were significant concerns about financial distress and viability of businesses. In response to these concerns, the government enacted various fiscal and monetary policies in 2020 with the goal of preserving jobs, preventing bankruptcies, and

strengthening the economy overall. By the time the vaccinations were introduced, it was unclear whether vaccinations would have had any additional role in lowering default risk. The effects on earnings and sales discussed earlier indicate a positive effect at the mean. However, it remains to be seen whether there are any significant effects at the tails.

To answer this question, we calculate a probability of default using the naïve measure described in equations (8) through (13) in Bharath and Shumway (2008). This measure translates the distance to default into a default probability, based on a firm's market value of equity, stock return volatility, and level of debt. We calculate the monthly default probability and regress this in a panel regression against the instrumented visits as in the analysis discussed earlier in subsection 5.1. This analysis includes the period January – June 2021.²¹ We present the results in Table 8. We observe that the increase in visits (influenced by vaccination rates) significantly lowers a firm's probability of default (models 1-4). These results indicate that vaccinations have an incremental role to play in reducing the likelihood of financial distress, in addition to measures put in place by the US government through the various fiscal and monetary policies. Lower default risk translates to reduced cost of financial distress and lower cost of debt for firms thereby facilitating capital raising to finance investments. We also observe a significant reduction in stock return volatility (models 5-8). Reduced volatility is likely to lead to higher firm value by improving investment efficiency (Stulz (1990) and Minton and Schrand (1999)) and reduction in the shareholder-debtholder conflicts (Myers (1977)).

5.2. Market response to vaccine announcement

We examine the stock market reaction to the initial announcement of successful vaccine trials. On November 9, 2020, Pfizer-BioNTech announced successful phase 3 trials for their

²¹ The number of observations in Table 8 is three times those in Table 7, Panel A, due to the frequency of the dependent variable (monthly vs. quarterly).

COVID-19 vaccine. Our tests capture whether the announcement effects are greater for those firms that were more severely affected during the pandemic. In Table 9, we report regressions of cumulative abnormal stock returns (*CAR*) on firm characteristics. *CARs* are calculated using a market adjusted model, in Panel A, and relative to the Fama-French three-factor model, in Panel B. We use the CRSP value-weighted index as the market portfolio. The estimation period is 252 trading days ending 30 trading days before the event. We cumulate the *CARs* over days (0,1) relative to the event.²²

Overall, we observe greater *CARs* for firms of non-essential nature, those that experience greater initial drop of foot traffic, or perform poorly during the last three quarters of 2020 based on sales, earnings, free cash flows, or risk-adjusted stock returns. These results reflect the ex-ante anticipation of increased business activity, particularly for the firms hit the hardest by COVID-19.

6. Channels driving store traffic

In this section, we document the specific channels through which increased vaccination rates translate into store traffic. Specifically, we examine the following channels: 1) the mitigation of initial concerns of the threat posed by COVID-19 by vaccinations; 2) increased vaccination rates among customers (which we study by using visits by senior citizens, more granular evidence on vaccinations at the ZIP code level from California, and by comparing the effect on visits by vaccinated versus unvaccinated individuals); 3) the effect of vaccinations on increased employment at the retail establishments.

²² The five industries with the highest *CARs* are Nursing and Personal Care Facilities (43.17%), Motion Picture Theaters (40.07%), Paper and Paperboard Products (Party City's industry, 34.55%), Eating and Drinking Places (28.66%), and Apparel and Accessory Stores (21.28%). The five with the lowest *CARs* include Gold and Silver Ores (-11.00%), Building Materials (-8.25%), Household Furniture (-7.53%), Miscellaneous General Merchandize Stores (-7.32%), and Computer and Software Stores (-7.21%).

6.1 Threat of the virus

One of the primary channels through which vaccination rates increase business activity is by alleviating the threat of the virus. In this analysis, we include county transmission rates and fatalities to account for the severity of the threat of the virus and how it affects people's attitudes and propensity to shop in person. To the extent that the vaccines are effective in reducing transmission rates and fatalities, thereby lowering the threat of the virus, we expect that higher uptake of the vaccine should increase confidence and store visits by customers. In Figure 4, we show that the introduction of vaccines corresponds in time with a sharp drop in COVID-19 transmission rates and fatalities at the county level for our sample.

In Table 10, Panel A, we specify an OLS model of store visits. Consistent with the threat of the virus, we observe that transmission rates and fatalities are negatively related to customer visits. Importantly, vaccination rates are positively related to store visits. The economic magnitudes are similar to our baseline results in Table 2. In Panel B, to account for the correlation between store visits and transmission rates, we specify a seemingly unrelated regression (SUR) model, where in the first equation we model store visits (similar to Panel A, model 1), and in the second equation, we model county-level transmission rates. The results (reported in Panel B) are unchanged. In (unreported) additional analysis, we replace transmission rates with fatalities and obtain similar results. Overall, we find that store visits increase in vaccinations rates even after we account for the threat posed by COVID-19 in terms of transmission and fatalities.

6.2. Vaccination rates among customers

6.2.1 Visits by seniors

Early eligibility criteria gave priority for vaccination to seniors (along with individual with certain medical conditions). We obtain the age distribution for the Census Block Group (CBG) in

which each establishment is located (in models 1 and 2 of Table 11), as well as that the primary CBG where customers come from (in models 3 and 4).²³

We define *HIGH_AGE* as an indicator variable equal to 1 if the CBG is in the top quintile of age, 0 otherwise. In Table 11, we interact *HIGH_AGE* with *VRATE* to examine the incremental effect of individuals that are more likely to be vaccinated on store traffic. We note that store traffic is decreasing in *HIGH_AGE*, indicating that, on average, older individuals are less likely to shop in person. The interaction variable is positively related to store traffic, suggesting that the effect of vaccination rates on store traffic is amplified when the traffic is driven by senior customers who are more likely to be vaccinated.

6.2.2 ZIP code-level evidence from California

We employ the disclosure of vaccination rates on ZIP code level by the state of California. There is a high level of heterogeneity in vaccination within a county. However, ZIP codes reflect a higher homogeneity in demographics and attitudes towards vaccination. This allows us to proxy for the vaccination status of the individuals going to the store more precisely.²⁴ In Table 12, Panel A, we repeat our Table 2 models 4 and 5 (establishment or establishment and time fixed effects) with vaccination rates measured at the ZIP code level. In models 1 and 2 we measure the vaccination rate at the store ZIP code, while in models 3 and 4 we measure it from the ZIP code from which the majority of the customer traffic comes from. We continue to find economically large and statistically significant coefficients of vaccination rates on traffic. This analysis provides more direct evidence that the increased store traffic is driven by vaccinated customers.

²³ *SafeGraph* reports the CBGs from which the customers come from. We identify the primary CBG from which customers come to an establishment. When multiple customer CBGs are tied as primary, we break the tie randomly.

²⁴ We ensure that the inferences that we draw from California data can be generalized. In IA.7, we replicate our results from Table 2 for California and compare them to the rest of the country. Generally, the coefficients are of similar magnitude, and we are unable to reject that they are statistically different pairwise, with the exception of those in models 5.

We obtain additional evidence based on the source of traffic to the stores by examining ZIP codes with the high and low vaccination rates in California. For each establishment in each week, *SafeGraph* provides the number of visitors from various CBGs. We classify each customer CBG into the top or bottom quintile based on its vaccination rate measured at the corresponding ZIP code. Next, we calculate the ratio of number of visitors coming from the highest or the lowest quintile to total store visitors for each establishment in each week (*PCT_VISITOR*). In Table 12, Panel B, we regress *PCT_VISITOR* on the store ZIP code *VRATE* separately for the lowest (in models 1 and 2) and the highest (in models 3 and 4) quintiles. We observe that as the vaccination rate for the store area goes up, a greater fraction of customers come from highly vaccinated areas, and a lower fraction from low vaccinated areas. This finding is consistent with the idea that the store traffic is driven by vaccinated individuals, and is inconsistent with the alternative idea that unvaccinated customers may go out more and contribute to traffic as vaccination rates increase in an area.

6.3 Labor market effects

The last channel that we examine is how vaccination rates can boost business activity by increased employment. *SafeGraph* provides a variable related to foot traffic that likely indicates the presence of an employee measured by the “dwell time” that an individual spends at a store at prolonged intervals of time. In Table 13, we regress the natural logarithm of number of store employees (*LN_EMP*) on *VRATE*, on weekly basis. A ten percent increase in vaccination rate is associated with around 2.7% increase in employment at the establishment. This provides another mechanism through which vaccination rates can enhance business activity by increased labor market participation.

7. Limits to the benefits of vaccinations on business activity

While COVID had a devastating effect on business activity, not all businesses fared equally. For some, the effect was much worse, and some actually benefited from the effect of the pandemic (Goolsbee and Syverson, 2021). In this section, we examine the differential effects of the introduction of vaccinations across establishment and firm characteristics.

In Table 14, we examine the effect of vaccinations on establishments or firms that were particularly negatively affected by COVID compared to those that were not. In Table 14, Panel A, models 1 and 2, we define an indicator variable equal to 1 if the establishment was in the highest quintile of decrease in visits in March 2020, or 0 otherwise. We interact that variable with *VRATE*, and show that the establishment that lost greater traffic benefit the most from increase in vaccination rates.²⁵

We also examine the essential or non-essential nature of the establishment business. Using data from CDC we classify establishments as essential or non-essential and create an indicator variable equal to 1 if the businesses were non-essential and 0 otherwise.²⁶ In models 3 and 4, we interact the non-essential dummy variable with *VRATE*, and observe much higher incremental effect of vaccination on foot traffic for non-essential businesses.

We use data from *SafeGraph* to determine the percentage of sales that come from online orders on establishment level. We create an indicator variable (*LOW_ONLINE*) equal to 1 if the establishments are in the lowest quintile of online sales, 0 otherwise. In models 5 and 6, we interact *LOW_ONLINE* with *VRATE* and find higher differential effect for businesses with low percentage of online sales.

²⁵ We find similar results if we aggregate the initial drop in visits at the firm level.

²⁶ <https://www.cdc.gov/vaccines/covid-19/categories-essential-workers.html>.

In Table 14, Panel B, we examine the effect of vaccinations on firms that were particularly adversely affected by COVID-19 compared to those that were not. We use several measures of performance to examine this adverse effect – sales, earnings, free cash flow, and stock returns over the last three quarters of 2020. We classify if a firm is in the lowest quintile in each of these four characteristics, and interact its poor performance status with *VRATE*. Across all eight models we observe firms that had the worst performance across these categories benefited the most in terms of increase in foot traffic as it relates to vaccinations. Our cross-sectional tests show that the introduction of vaccinations benefits firms differently. While firms that did poorly during the onset of the pandemic benefit more, firms that were of essential nature, had higher percentage of online sales, or otherwise performed well do not benefit as much. Overall, the stock market reaction to the news of the vaccines that we documented earlier is validated by the ex-post realization reflected in higher foot traffic to the establishment of firms of similar characteristics.

In order to shed light into other dimensions of the vaccine limitation on business activity, we examine a period (the “delta” surge in summer of 2021) where the originally developed vaccines were not nearly as medically effective towards the new variant. Insofar as customers’ shopping behavior responds to the safety of the environment, we study the effect of vaccination rates on foot traffic during this period. In Table 15, we define an indicator variable, *DELTA_VARIANT*, equal to one during July-September, 2021 (the delta variant surge), 0 otherwise. We interact the variable with *VRATE*. The interacted variable is negative and significant, indicating a lower impact of vaccination rates on customer traffic during the delta surge.

Further, we show that the effect of vaccination rates on business activity is non-linear, with higher benefits achieved at lower levels of vaccination, and the benefits diminishing at higher

vaccination rates. In IA Table 8, we report results where we model the vaccination rate under a quadratic, cubic, and piece-wise linear frameworks. We observe that the benefits accrue faster at relatively lower levels of vaccination rate, after which the benefits diminish, as shown in IA Figure 1. Depending on the specification for *VRATE*, we observe much higher slopes before vaccination rate reaches 15%-37% (much lower than the medically-suggested 70% level for herd immunity), after which the effect plateaus. These findings indicate that the benefits accrue faster at relatively lower levels of vaccination rate, after which the benefit diminishes. We note that the average vaccination rate at the end of our sample is in the mid-30s (35.5) percent. Structural changes such as online shopping and work-from-home that COVID-19 accelerated can potentially explain the constraints on how much vaccinations can boost in-person economic activity. As vaccination rates evolve further, it remains to be seen how the effect may change at higher levels of vaccination, and at what level the benefits plateau.

8. Conclusion

We study how COVID-19 vaccines impact business activity, firm performance and value. Using granular data on store level foot traffic, and county or ZIP code level vaccination rates, we show that customer foot traffic is increasing in vaccination rates with significant economic effects both at the establishment level as well as at the corporate level in terms of increased firm sales, earnings, reduced default risk, and positive announcement stock returns. Our evidence suggests that this effect is causal in nature. We also find that firms incorporate the new business environment post-vaccination in their strategic decisions to expand or close stores.

We document the primary channels that influence the effect of vaccinations on increased business activity are: reduced threat of the virus, traffic driven by vaccinated individuals, lifting of local government restrictions in response to higher vaccination rates, and higher employment rates

at the establishments as a function of vaccination rates. These channels are not necessarily mutually exclusive, reflecting both demand-side as well as supply-side factors that influence increased economic activity.

We examine both the ex-ante market anticipation at the vaccine announcement and the ex-post realization in terms of customer foot traffic once vaccines are introduced. The benefits we document are not uniform across all firms or establishments. The benefits are concentrated among firms that perform poorly at the onset of COVID-19, firms that rely less on online sales, and firms that are of non-essential nature. Nonetheless, there are limitations on the positive effect of vaccinations on business activity. The effect is reduced during the “delta” variant surge in COVID infections in the summer of 2021, among retail establishments that are essential in nature, and among establishments with higher levels of online sales. We also find that the economic effects of vaccinations are non-linear and accrue early on at lower levels of vaccinations and diminish later on at higher levels.

By studying a major government intervention that has economy-wide implications, our paper sheds light on the effects of public health policies on a firm’s business activity. Similar to prior evidence on the positive effects of public health interventions during the 1918 flu pandemic, our findings have implications beyond the COVID-19 pandemic. A key takeaway from our study is that the provision of a public good aimed at improving public health can also create private economic benefits to firms and their shareholders by boosting economic activity.

Appendix - Variable Definitions

<i>BEACHES OR PARKS CLOSED</i>	Equals to 1 if beaches or parks are completely closed to the public, and 0 otherwise
<i>CAR</i>	Cumulative abnormal return based on either market-adjusted returns or the Fama-French three factors
<i>CASH</i>	<i>Compustat</i> item CH/ <i>Compustat</i> item AT
<i>DEBT</i>	<i>Compustat</i> item DLTT+ <i>Compustat</i> item DLC)/ <i>Compustat</i> item AT
<i>ELIGIBILITY</i>	Equals to 1 if a county is in the top quintile in (cancer, diabetes, or obesity per capita), and 0 otherwise
<i>EMPLOYEES MASKS</i>	Equals to 1 if mandatory or recommended face coverings for employees
<i>EPS</i>	<i>Compustat</i> item EPSFXQ
<i>FATALITIES</i>	The weekly change in total COVID-related fatalities is calculated as the difference between current week total confirmed fatalities and prior week total confirmed fatalities
<i>FCF</i>	$(\text{Compustat item IB} - \text{Compustat item TXT} + \text{Compustat item DP} - \text{Compustat item CAPX}) / \text{Compustat item AT}$
<i>FLU_VRATE</i>	Equals to 1 if a county's flu vaccination rate (per capita) is in the highest quintile, and 0 otherwise
<i>GATHERINGS LIMITED TO 10</i>	Equals to 1 if gatherings are limited to 10 people, and 0 otherwise
<i>GYMS CLOSED</i>	Equals to 1 if gyms are closed, and 0 otherwise
<i>HIGH DROP</i>	Equals to 1 if the establishment was in the top quintile of decrease in visits in March 2020, and 0 otherwise
<i>LNINCOME</i>	Log of median household income measured at the county level
<i>LOW ONLINE SALE</i>	Equals to 1 if the establishments were in the bottom quintile of online sales in November 2020, and 0 otherwise
<i>MASKS RECOMMENDED</i>	Equals to 1 if mandatory or recommended face coverings anywhere, and 0 otherwise
<i>MKTBOOK</i>	$[\text{Compustat item AT} + (\text{Compustat item CSHO} * \text{Compustat item PRCC_F}) - \text{Compustat item CEQ}] / \text{Compustat item AT}$
<i>NI</i>	<i>Compustat</i> item NI

<i>NO ELECTIVE PROCEDURES</i>	Equals to 1 if any elective medical procedures (medical procedures including dental and eye) are prohibited, and 0 otherwise
<i>NON-ESSENTIAL</i>	Equals to 1 if an industry is defined as essential-work industry by Center for Disease Control and Prevention, and 0 otherwise https://www.cdc.gov/vaccines/covid-19/categories-essential-workers.html
<i>NO NURSING HOME VISITS</i>	Equals to 1 if nursing home visitors are prohibited, and 0 otherwise
<i>OPEN 2</i>	Equals to 1 if high- risk businesses are open, and 0 otherwise
<i>OPEN3</i>	Equals to 1 if higher- and high-risk businesses are open, and 0 otherwise
<i>OPEN4</i>	Equals to 1 if highest-, higher-, and high-risk businesses are open, and 0 otherwise
<i>P_DEFAULT</i>	The naïve measure of probability of default presented in equations (8)-(13) in Bharath and Shumway (2008).
<i>PBLACK</i>	The share of the Black population measured at the county level. We aggregate census block group (CBG) data from <i>SafeGraph Open Census</i> at the county level
<i>PLATINO</i>	The share of the Latino population measured at the county level. We aggregate CBG data from <i>SafeGraph Open Census</i> at the county level
<i>POPULATION_DENSITY</i>	Number of individuals living per square kilometer measured at the county level
<i>PVISITS</i>	Percentage change in weekly visits to stores relative to the visits in the same calendar month in 2019, pre-COVID
<i>REOPENINGS REVERSED</i>	Equals to 1 if reopenings are reversed, and 0 otherwise
<i>RESTAURANTS CLOSED</i>	Equals to 1 if restaurants closed with the possible exception of takeout services, and 0 otherwise
<i>RETURNS</i>	Cumulative abnormal return based on market-adjusted returns for the period between April, 2020 and November, 2020
<i>ROA</i>	<i>Compustat</i> item EBITDA/ <i>Compustat</i> item AT
<i>SALES</i>	<i>Compustat</i> item SALE
<i>SIGMA</i>	The annualized standard deviation of daily stock returns over the prior 12 months
<i>SPAS CLOSED</i>	Equals to 1 if spas are closed, and 0 otherwise

<i>STAY-AT-HOME ORDER</i>	Equals to 1 if “Stay-at-home order” issued by the state or county government is effective, and 0 otherwise
<i>STATE OF EMERGENCY</i>	Equals to 1 if “State of emergency” issued by state or county government is effective, and 0 otherwise
<i>TRANSMISSIONS</i>	The weekly change in total COVID-related cases is calculated as the difference between current week total confirmed cases and prior week total confirmed cases
<i>TRUMP_BIDEN_2020</i>	Trump share of the presidential 2020 vote at the county level
<i>VISITS</i>	Weekly visits to stores
<i>VRATE</i>	Cumulative number of fully vaccinated (second dose for Pfizer-BioNTech or Moderna, single dose of Johnson and Johnson) individuals divided by the population of the county

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Figure 1. Store Visits and Vaccination Rates in the US Across Time

The figure presents, for each week in our sample, the mean of the natural logarithm of weekly store visits obtained from *SafeGraph*, measured on the left vertical axis, and the number of individuals fully vaccinated in the US as a percentage of a county's population, measured on the right vertical axis.

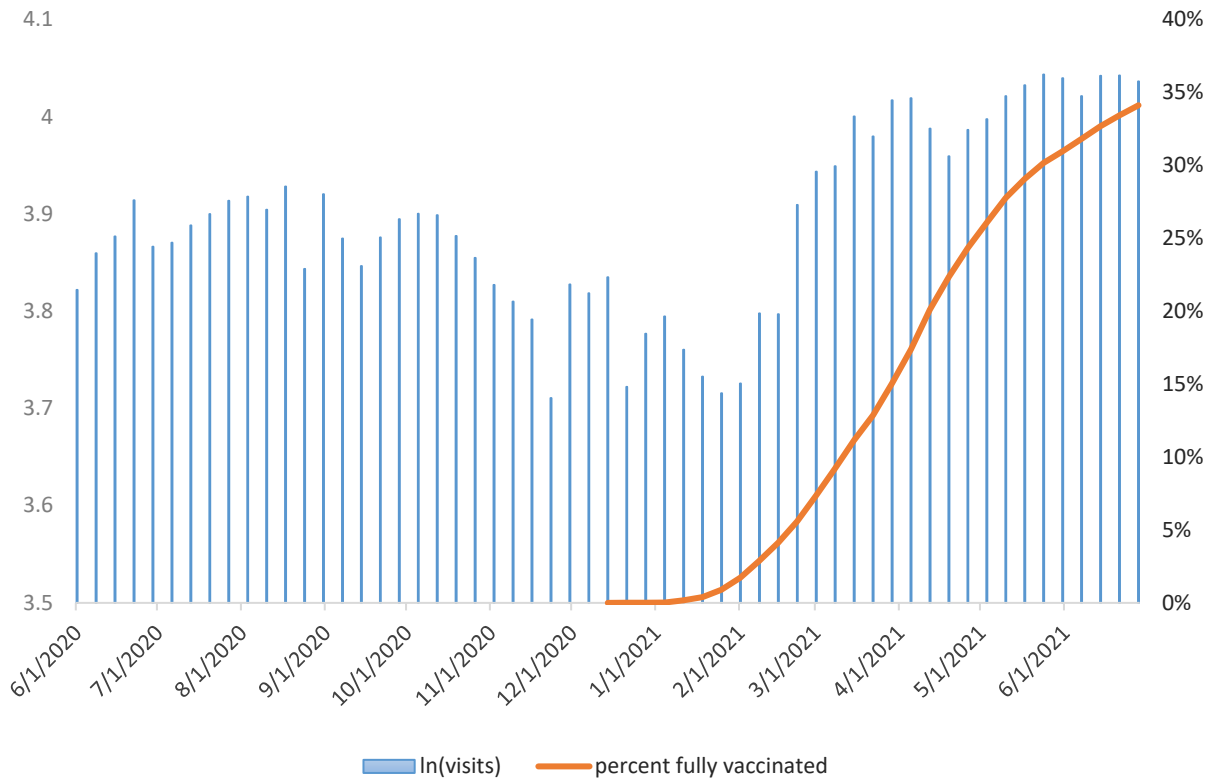
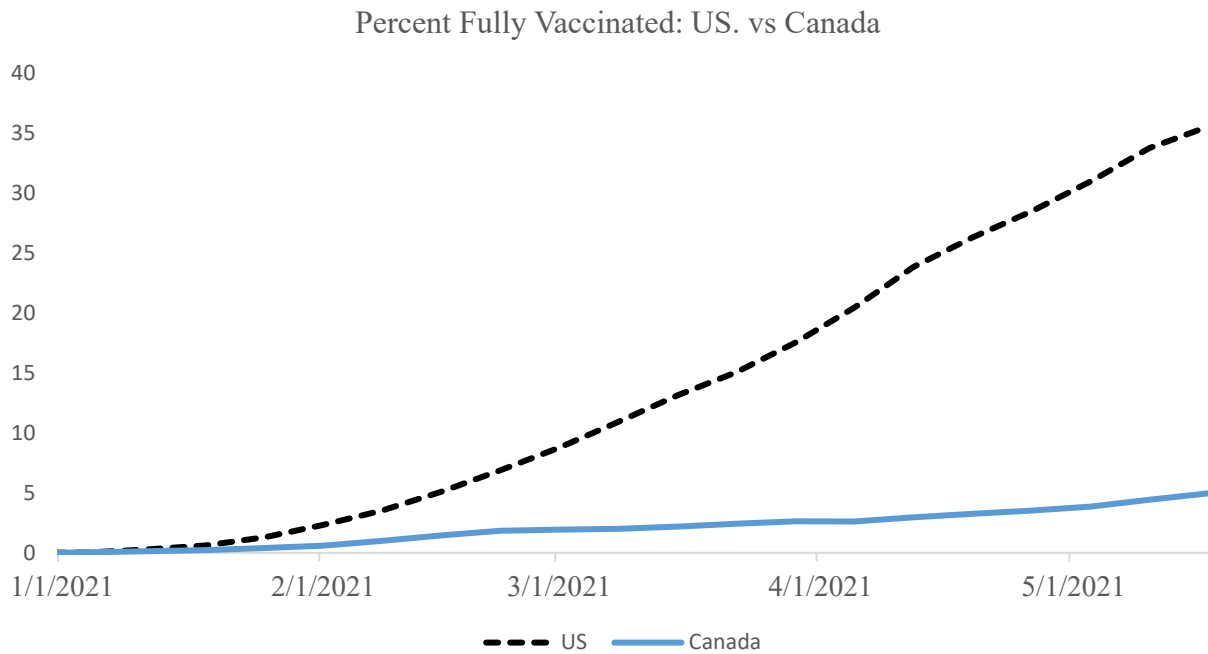


Figure 2. Vaccination Rates in the US and Canada

The figure presents the percentage fully vaccinated individuals in the US and Canada from the January 1, 2020 through May, 17, 2021, in Panel A. The vaccination rate data is based on the US states and Canadian provinces on the US-Canada border, shown in Panel B. Source for the figure in Panel B is DOI: 10.1007/978-3-540-46266-8_9

Panel A: Vaccination Rates



Panel B: States and Provinces on the US-Canada Border



Figure 3. Difference-in-Differences Coefficient Time Plot

The figure displays the weekly coefficients from our Difference-in-Differences (DiD) analysis on the comparison between the US (the treated group) and Canada (the untreated group) along with their 95% confidence intervals. The pre-vaccination period is June 1-December 7, 2020. The post-vaccination period is March 1 – April 26, 2021. The figure also displays the average coefficient in the pre-period (9.53%) and the average coefficient for the post-period (43.36%).

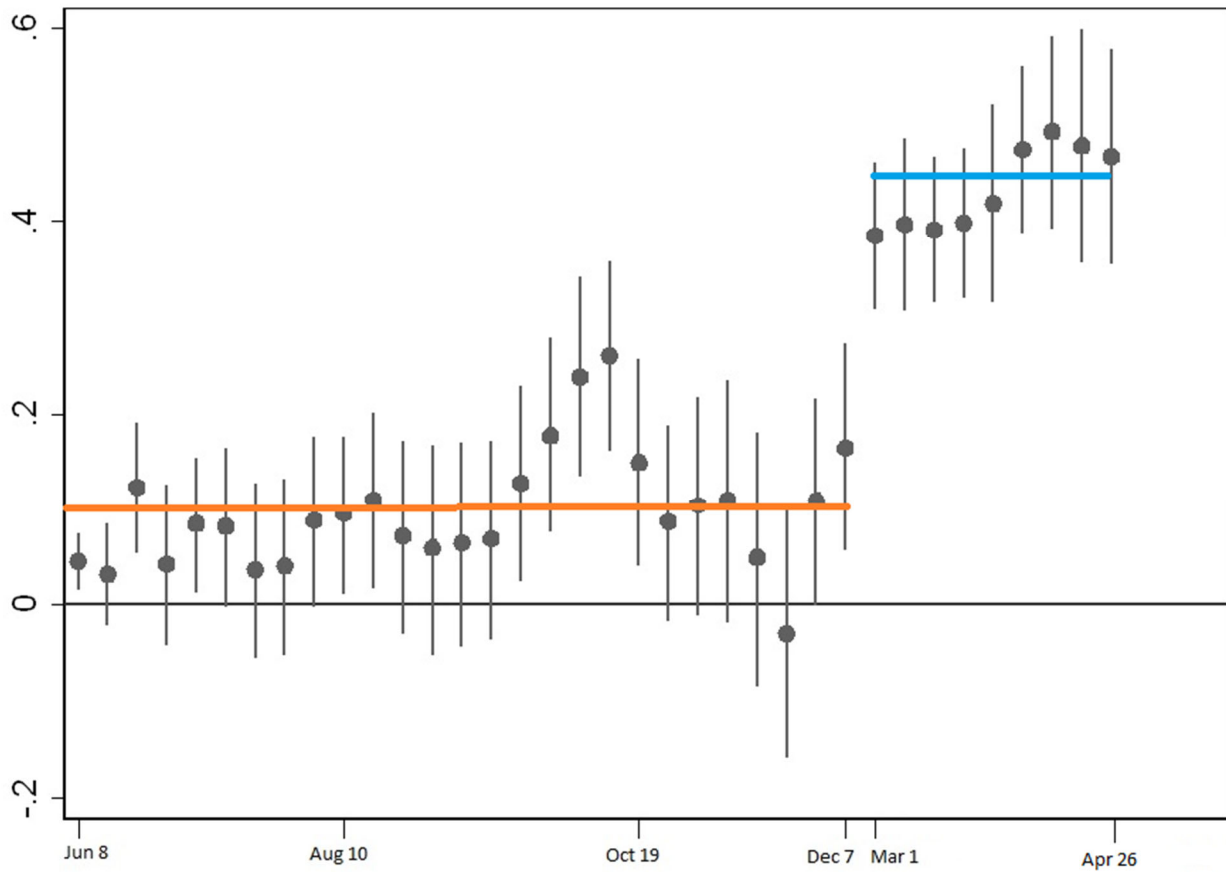


Figure 4. Vaccination Rates and COVID-19 Cases and Fatalities

The figure presents, for each week in our sample, the weekly COVID-19 related cases in a county per million people (Panel A) and fatalities in a county per million people (Panel B) measured on the left vertical axis, and the number of individuals fully vaccinated in the US as a percentage of a county’s population, measured on the right vertical axis.

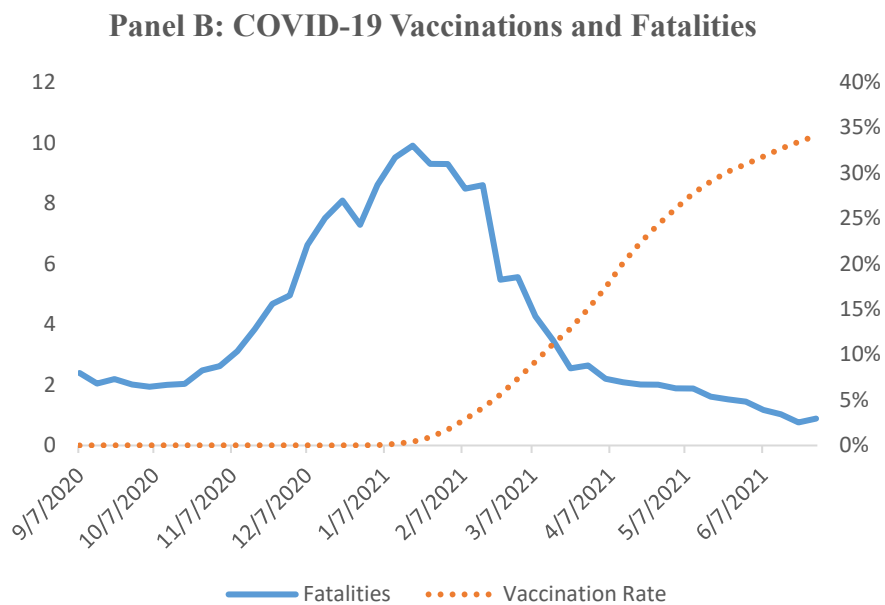
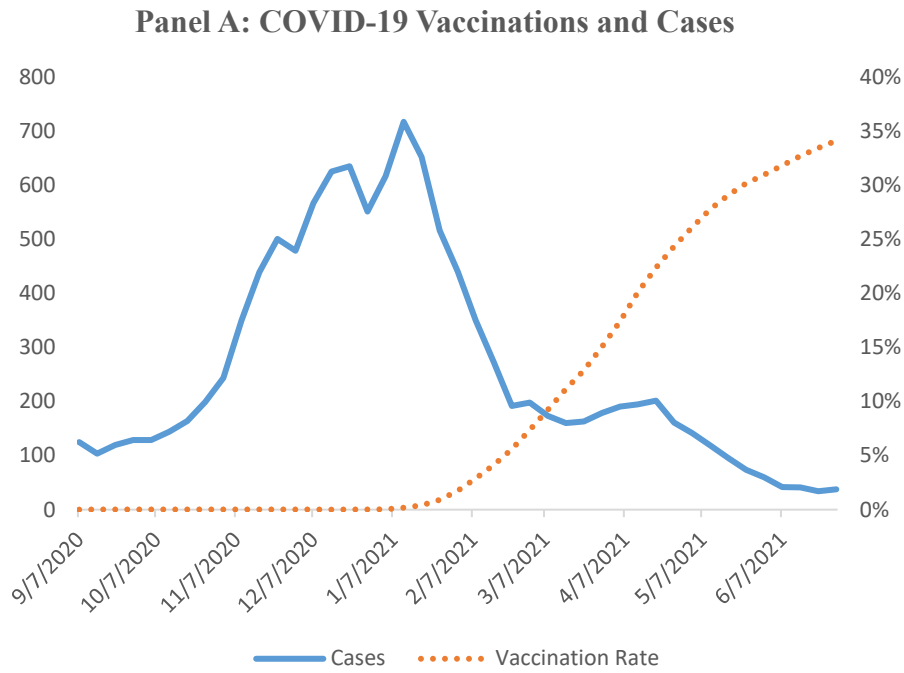


Table 1. Descriptive Statistics

This table presents descriptive statistics across establishment-week observations for a sample of 327,259 establishments owned by 249 firms for the period December 28, 2020-June 28, 2021, with available firm-level data, and *SafeGraph* data on store visits. *VISITS* are calculated at the establishment level on a weekly basis, *VRATE* is calculated at the county level measured at weekly frequency. Demographic characteristics are on the county level, and firm characteristics are as of the year preceding COVID, i.e., 2019. Variable definitions are provided in the Appendix.

Variable	N	MEAN	SD	P25	P50	P75
<i>VISITS</i>	8,287,701	100.579	119.210	26	63	126
<i>VRATE</i>	8,287,701	0.166	0.160	0.017	0.119	0.293
<i>SALES (in \$ mil.)</i>	8,287,701	61,302	96,113	4,627	16,039	72,148
<i>DEBT</i>	8,287,701	0.539	0.250	0.352	0.512	0.666
<i>MKTBOOK</i>	8,287,701	2.861	2.482	1.286	1.739	3.765
<i>ROA</i>	8,287,701	0.162	0.101	0.101	0.124	0.204
<i>CASH</i>	8,287,701	0.059	0.064	0.018	0.036	0.080
<i>PBLACK</i>	8,287,701	0.139	0.144	0.030	0.086	0.202
<i>PLATINO</i>	8,287,701	0.134	0.137	0.039	0.082	0.185
<i>TRUMP_BIDEN_2020</i>	8,287,701	0.482	0.165	0.369	0.461	0.605

Table 2. Vaccination Rates and Store Visits

The table presents regression of the natural logarithm of weekly store visits at establishment level, *LNVISITS*, on county-level cumulative vaccination rates, *VRATE*, and control variables for the period December 28, 2020-June 28, 2021. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(4) <i>LNVISITS</i>	(5) <i>LNVISITS</i>
<i>VRATE</i>	0.5183*** (0.0145)	0.5728*** (0.0127)	0.6199*** (0.0115)	0.6598*** (0.0118)	0.1392*** (0.0186)
<i>LNSALES</i>		0.2722*** (0.0036)	0.2754*** (0.0035)		
<i>DEBT</i>		0.0670*** (0.0218)	0.0604*** (0.0206)		
<i>MKTBOOK</i>		-0.0817*** (0.0036)	-0.0785*** (0.0036)		
<i>ROA</i>		-0.4407*** (0.0603)	-0.4989*** (0.0584)		
<i>CASH</i>		2.0508*** (0.1089)	2.0055*** (0.1074)		
<i>PBLACK</i>		0.2242*** (0.0822)			
<i>PLATINO</i>		0.1963 (0.1258)			
<i>TRUMP_BIDEN_2020</i>		0.8758*** (0.0841)			
Observations	8,287,701	8,287,701	8,287,701	8,287,701	8,287,701
Adjusted R-squared	0.3166	0.3762	0.3963	0.9377	0.9404
State FE, Industry FE	YES	YES			
County FE, Industry FE			YES		
Store FE				YES	
Store FE, Time FE					YES

Table 3. Vaccination Rates, Restrictions, and Store Visits.

The table presents regression of the natural logarithm of weekly store visits at establishment level, *LNVISITS*, on county-level cumulative vaccination rates, *VRATE*, and control variables, including restrictions, for the period December 28, 2020-June 28, 2021. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>
<i>VRATE</i>	0.5042*** (0.0198)	0.5646*** (0.0149)	0.6200*** (0.0129)	0.6600*** (0.0134)	0.1048*** (0.0224)	0.3381*** (0.0325)	0.4673*** (0.0229)	0.5594*** (0.0155)	0.5968*** (0.0161)	0.0830*** (0.0209)
<i>LNSALES</i>		0.2714*** (0.0037)	0.2746*** (0.0036)				0.2715*** (0.0037)	0.2746*** (0.0036)		
<i>DEBT</i>		0.0699*** (0.0226)	0.0621*** (0.0214)				0.0697*** (0.0225)	0.0620*** (0.0214)		
<i>MKTBOOK</i>		-0.0809*** (0.0037)	-0.0777*** (0.0037)				-0.0809*** (0.0037)	-0.0777*** (0.0037)		
<i>ROA</i>		-0.4320*** (0.0622)	-0.4874*** (0.0603)				-0.4326*** (0.0622)	-0.4873*** (0.0603)		
<i>CASH</i>		1.9949*** (0.1123)	1.9473*** (0.1107)				1.9947*** (0.1126)	1.9472*** (0.1107)		
<i>PBLACK</i>		0.2398*** (0.0898)					0.2203** (0.0882)			
<i>PLATINO</i>		0.1869 (0.1270)					0.2094* (0.1269)			
<i>TRUMP_BIDEN_2020</i>		0.8495*** (0.0895)					0.8133*** (0.0835)			
<i>OPEN2</i>	0.1643** (0.0695)	0.0696 (0.0446)	0.0757*** (0.0185)	0.0994*** (0.0167)	-0.0047 (0.0120)	0.1383* (0.0716)	0.0569 (0.0463)	0.0348 (0.0247)	0.0578** (0.0241)	-0.0227* (0.0127)
<i>OPEN3</i>	0.0720 (0.0457)	0.0720*** (0.0266)	0.0349*** (0.0114)	0.0396*** (0.0121)	0.0227** (0.0104)	0.0633 (0.0464)	0.0622** (0.0265)	0.0121 (0.0152)	0.0120 (0.0163)	0.0238** (0.0110)
<i>OPEN4</i>	-0.0030 (0.0173)	-0.0183* (0.0101)	-0.0239*** (0.0059)	-0.0263*** (0.0061)	0.0050 (0.0093)	-0.0077 (0.0182)	-0.0214* (0.0112)	-0.0273*** (0.0056)	-0.0301*** (0.0059)	0.0024 (0.0085)
<i>STAY-AT-HOME ORDER</i>						-0.0368*** (0.0105)	-0.0476*** (0.0088)	-0.0487*** (0.0082)	-0.0528*** (0.0086)	0.0135** (0.0053)
<i>STATE OF EMERGENCY</i>						-0.0387** (0.0151)	-0.0262* (0.0140)	0.0008 (0.0061)	0.0034 (0.0063)	-0.0127** (0.0053)
<i>NO NURSING HOME VISITS</i>						-0.0067 (0.0317)	0.0016 (0.0288)	-0.0157 (0.0139)	-0.0236* (0.0143)	0.0053 (0.0092)
<i>EMPLOYEES MASKS</i>						0.0231 (0.0502)	0.0431 (0.0547)	-0.0399** (0.0174)	-0.0370** (0.0182)	-0.0320** (0.0128)

<i>MASKS RECOMMENDED</i>						-0.0663 (0.0508)	-0.0446 (0.0548)	0.0503*** (0.0170)	0.0496*** (0.0178)	0.0434*** (0.0125)
<i>BEACHES OR PARKS CLOSED</i>						0.0460 (0.0373)	0.0420 (0.0391)	0.0018 (0.0534)	-0.0012 (0.0476)	-0.0029 (0.0426)
<i>NO ELECTIVE PROCEDURES</i>						-0.0870 (0.0901)	-0.0494 (0.0774)	-0.0512*** (0.0099)	-0.0554*** (0.0103)	-0.0213*** (0.0066)
<i>RESTAURANTS CLOSED</i>						0.0478 (0.0365)	0.0252 (0.0294)	0.0445* (0.0242)	0.0491* (0.0273)	0.0243** (0.0120)
<i>GYM CLOSED</i>						-0.0397*** (0.0154)	-0.0294** (0.0145)	-0.0287*** (0.0107)	-0.0328*** (0.0113)	-0.0109* (0.0058)
<i>SPAS CLOSED</i>						0.0911*** (0.0228)	0.0709*** (0.0178)	0.0255 (0.0194)	0.0271 (0.0213)	-0.0188* (0.0097)
<i>GATHERINGS LIMITED TO 10</i>						-0.1179*** (0.0140)	-0.0839*** (0.0121)	-0.0628*** (0.0152)	-0.0659*** (0.0160)	-0.0264*** (0.0060)
<i>REOPENINGS REVERSED</i>						-0.1035*** (0.0133)	-0.0798*** (0.0100)	-0.0582*** (0.0070)	-0.0622*** (0.0072)	-0.0160*** (0.0046)
Observations	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850
Adjusted R-squared	0.3161	0.3750	0.3949	0.9373	0.9399	0.3171	0.3755	0.3953	0.9377	0.9399
State FE, Industry FE	YES	YES				YES	YES			
County FE, Industry FE			YES					YES		
Store FE				YES					YES	
Store FE, Time FE					YES					

Table 4. Vaccination Rates and Lifting of Restrictions

Panel A of the table presents regressions of the California county rank on vaccinations rates and control variables. The rank represents a color-coded tier system for counties with four tiers ranging from 1 (purple) having the most stringent restrictions to 4 (yellow) having minimal restrictions updated weekly. Panel B presents regressions of US county-level changes in restrictions on vaccinations rates and control variables. We count the number of restrictions in a county in a given week and observe if they increased, decreased, or did not change (the normalized alternative). *TRANSMISSIONS* is the weekly number of COVID-19 cases per capita in a county. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

Panel A: California

VARIABLES	(1) <i>RANK</i>	(2) <i>RANK</i>	(3) <i>RANK</i>
<i>VRATE</i>	5.7107*** (0.2192)	5.2656*** (0.2369)	5.7353*** (0.2177)
<i>TRANSMISSIONS</i>		-65.5418*** (9.5118)	
<i>PBLACK</i>	-0.3982 (1.1329)	-0.3043 (1.1727)	
<i>PLATINO</i>	0.2712 (0.1784)	0.3420* (0.1833)	
<i>TRUMP_BIDEN_2020</i>	0.3508 (0.3198)	0.3403 (0.3282)	
Observations	1,250	1,250	1,250
Adjusted R-squared	0.7660	0.7779	0.8057
County FE	NO	NO	YES

Panel B: US (Multinomial Logit)

VARIABLES	DECREASE	INCREASE	DECREASE	INCREASE	DECREASE	INCREASE
	(1)	(1)	(2)	(2)	(3)	(3)
<i>VRATE</i>	1.0811*** (0.1069)	-0.4886* (0.2543)	1.1021*** (0.1146)	-0.4660* (0.2728)	1.3066*** (0.1189)	-0.8656*** (0.2761)
<i>TRANSMISSIONS</i>			-0.4062 (0.5553)	-0.2652 (1.2225)		
<i>PBLACK</i>	-1.6082*** (0.1392)	-0.3419 (0.2794)	-1.5888*** (0.1432)	-0.3234 (0.2876)		
<i>PLATINO</i>	0.4789*** (0.1574)	0.8440** (0.3452)	0.5000*** (0.1614)	0.8848** (0.3524)		
<i>TRUMP_BIDEN_2020</i>	-0.7939*** (0.1135)	0.6249** (0.2629)	-0.7644*** (0.1221)	0.6245** (0.2792)		
Observations	74,667	74,667	74,667	74,667	74,667	74,667
County FE	NO	NO	NO	NO	YES	YES
Pseudo R-squared	0.0089	0.0089	0.0089	0.0088	0.1140	0.1140

Table 5. Difference-in-Differences Analysis: US versus Canada

The table displays the results from a DiD analysis comparing visits in the US (the threatened group) vs Canada (the untreated group) following the introduction of vaccinations in the US. We identify the pre-vaccination period as June 1, 2020 to December 7, 2020, before vaccinations started being administered. Contiguous fixed effects are based on an indicator variable taking the value of 1 if for a Canadian province i (e.g., British Columbia) a US state j is bordering it (e.g., Washington State), 0 otherwise. The full list of border states and provinces are shown in Figure 2, Panel B. We define as post-vaccinations the period from March 1, 2021 to April 26, 2021. We report coefficient estimates with standard errors in parentheses. In model 4, we exclude the US states with restrictions below the median based on the Wallethub study as of January 2021. In model 5, we include indicator variables for common restrictions both for the US and Canada. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(4) <i>LNVISITS</i>	(5) <i>LNVISITS</i>
<i>US*POST</i>	0.3838*** (0.0272)	0.3829*** (0.0272)	0.3826*** (0.0272)	0.3597*** (0.0252)	0.3034*** (0.0334)
<i>US</i>	1.3448*** (0.0646)	1.3360*** (0.0573)	1.3160*** (0.0638)	1.3442*** (0.0683)	1.1348*** (0.0617)
<i>POST</i>	-0.2715*** (0.0268)	-0.2709*** (0.0267)	-0.2705*** (0.0267)	-0.2831*** (0.0234)	-0.1865*** (0.0318)
<i>STAY-AT-HOME ORDER</i>					-0.1307*** (0.0165)
<i>RESTAURANTS CLOSED</i>					-0.1129** (0.0443)
<i>GYM CLOSED</i>					-0.0067 (0.0705)
<i>SPAS CLOSED</i>					-0.1141** (0.0489)
<i>GATHERINGS LIMITED</i>					0.0312 (0.0302)
Observations	2,831,391	2,831,391	2,831,391	2,182,492	2,831,391
Adjusted R-squared	0.5865	0.5747	0.5723	0.5893	0.5834
Brand - Contiguous FE	YES			YES	YES
Brand FE, Contiguous FE		YES			
Brand FE			YES		

Table 6. Instrumental Variable (IV) Analysis

The table displays the results from an IV analysis examining the effects of vaccination rates on store traffic. We report coefficient estimates with standard errors in parentheses. In Panel A, we report the second stage of the estimation. In Panel B, we report the first stage and instrument diagnostics. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

Panel A: Second Stage

	(1) <i>LNVISITS</i>
<i>VRATE</i>	0.8873*** (0.0201)
Observations	8,283,489
Store FE	YES

Panel B: First Stage

	(1) <i>VRATE</i>
<i>ELIGIBILITY</i>	0.1982*** (0.0150)
<i>FLU_VRATE</i>	0.1294*** (0.0106)
Observations	8,283,489
Store FE	YES
<i>F</i> -test of excluded instruments:	249.29***
Stock-Yogo 5% critical value	13.91
Kleibergen-Paap <i>rk</i> Statistic	166.83***

Table 7. Vaccination Rates and Firm Performance

Panel A presents regressions of the natural logarithm of a firm's quarterly sales or EPS (earnings per share) for the first two quarters of 2021, obtained from COMPUSTAT, on predicted store visits. *VRATE* is used to predict store visits in the first stage. In Panel B, we present the results from a multinomial logit model with the following outcomes: no change (the normalized alternative); increase in number of stores; decrease in number of stores as a function of *VRATE*. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. We report coefficient estimates with robust standard errors in parentheses. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

Panel A: Effect of Predicted Store Visits on Firm Quarterly Sales and Earnings Per Share

VARIABLES	(1) <i>LN_SALES</i>	(2) <i>LN_SALES</i>	(3) <i>LN_SALES</i>	(4) <i>LN_SALES</i>	(5) <i>LN_EPS</i>	(6) <i>LN_EPS</i>	(7) <i>LN_EPS</i>	(8) <i>LN_EPS</i>
<i>PREDICTED_LNVISITS</i>	3.1355*** (0.0741)	2.9383*** (0.0816)	3.6165*** (0.0399)	3.5263*** (0.0462)	0.1365*** (0.0281)	0.1310*** (0.0343)	0.2011*** (0.0296)	0.2068*** (0.0359)
<i>DEBT</i>			-0.3423*** (0.0954)	-0.2457** (0.0977)			-0.0353 (0.0707)	-0.1270* (0.0753)
<i>MKTBOOK</i>			0.3307*** (0.0154)	0.3181*** (0.0151)			0.0499*** (0.0085)	0.0545*** (0.0088)
<i>ROA</i>			1.4895*** (0.3230)	1.4072*** (0.3070)				
<i>CASH</i>			-7.4285*** (0.2545)	-6.7233*** (0.2986)			-0.4598** (0.1889)	-0.4288* (0.2316)
Observations	471	470	471	470	470	469	470	469
Adjusted R-squared	0.7923	0.8618	0.9493	0.9627	0.0459	0.2196	0.1070	0.2821
Industry FE	NO	YES	NO	YES	NO	YES	NO	YES

Table 7, Panel B: Probability of Increase or Decrease in the Number of Stores (Multinomial Logit)

VARIABLES	(1)		(2)		(3)		(4)	
	DECREASE	INCREASE	DECREASE	INCREASE	DECREASE	INCREASE	DECREASE	INCREASE
<i>VRATE</i>	-0.8526*** (0.0449)	2.5454*** (0.0686)	-0.9274*** (0.0466)	2.6415*** (0.0703)	-1.0692*** (0.0451)	2.2607*** (0.0684)	-1.1617*** (0.0470)	2.3266*** (0.0700)
<i>LNSALES</i>					0.0292*** (0.0060)	0.2229*** (0.0105)		
<i>DEBT</i>					1.1598*** (0.0428)	0.0770 (0.0850)		
<i>MKTBOOK</i>					-0.0441*** (0.0063)	0.2142*** (0.0078)		
<i>ROA</i>					3.8854*** (0.1253)	-0.9359*** (0.2127)		
<i>CASH</i>					-0.3033*** (0.1139)	-2.1238*** (0.2446)		
<i>PBLACK</i>					-0.7889*** (0.0793)	-0.6953*** (0.1377)	-0.8391*** (0.0826)	-0.8177*** (0.1393)
<i>PLATINO</i>					1.6034*** (0.0736)	1.8727*** (0.1237)	1.8616*** (0.0777)	2.0521*** (0.1271)
<i>TRUMP_BIDEN_2020</i>					-4.5043*** (0.0651)	-3.4029*** (0.1107)	-5.1426*** (0.0694)	-3.8968*** (0.1133)
Observations	564,458		564,458		564,458		564,458	
Pseudo R-squared	0.173		0.267		0.216		0.304	
State FE, Firm FE			YES				YES	
State FE, Industry FE	YES				YES			

Table 8. Effect of Vaccination Rates on Firm Risk

Panel A presents regressions of default probability ($P_DEFAULT$) (Bharath and Shumway (2008)) and standard deviation of equity stock returns ($SIGMA$) on predicted store visits. $VRATE$ is used to predict store visits in the first stage. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. We report coefficient estimates with robust standard errors in parentheses. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	(1) <i>P_DEFAULT</i>	(2) <i>P_DEFAULT</i>	(3) <i>P_DEFAULT</i>	(4) <i>P_DEFAULT</i>	(5) <i>SIGMA</i>	(6) <i>SIGMA</i>	(7) <i>SIGMA</i>	(8) <i>SIGMA</i>
<i>PREDICTED_LNVISITS</i>	-0.0670*** (0.0089)	-0.0966*** (0.0102)	-0.2143*** (0.0158)	-0.2165*** (0.0150)	-0.1656*** (0.0169)	-0.1327*** (0.0176)	-0.1572*** (0.0278)	-0.1465*** (0.0244)
<i>LNSALES</i>			0.0542*** (0.0052)	0.0564*** (0.0055)			-0.0316*** (0.0093)	-0.0209** (0.0091)
<i>DEBT</i>			0.0150 (0.0257)	0.0061 (0.0288)			0.2703*** (0.0452)	0.2975*** (0.0471)
<i>MKTBOOK</i>			-0.0232*** (0.0042)	-0.0204*** (0.0045)			-0.0394*** (0.0074)	-0.0273*** (0.0073)
<i>ROA</i>			-0.0683 (0.0895)	-0.0776 (0.0939)			-1.3342*** (0.1554)	-1.3588*** (0.1512)
<i>CASH</i>			0.5433*** (0.0751)	0.2692*** (0.0910)			0.5054*** (0.1301)	0.3369** (0.1435)
Observations	1,412	1,412	1,412	1,412	1,418	1,418	1,418	1,418
Adjusted R-squared	0.0381	0.1400	0.1164	0.2055	0.0626	0.3052	0.2592	0.4314
Industry FE	NO	YES	NO	YES	NO	YES	NO	YES

Table 9. Market Response to Vaccine Announcements

The table presents regressions of cumulative abnormal stock returns (*CAR*) on firm characteristics. *CARs* are calculated using a market adjusted model, in Panel A, and relative to the Fama-French three-factor model, in Panel B, using value-weighted (VW) *CRSP* index as the market portfolio, with estimation period of 252 trading days ending 30 trading days before the event. The event date is the announcement of Pfizer-BioNTech of successful phase 3 clinical trials on November 9, 2020. The *CARs* are calculated during days (0,1) relative to the event. We report coefficient estimates with robust standard errors in parentheses. Variable definitions are provided in the Appendix. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

Panel A: Market-Adjusted CARs	<u>Non-essential</u>		<u>High Drop</u>		<u>Low Net Income</u>		<u>Low Sales</u>		<u>Low Returns</u>		<u>Low FCF</u>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<i>VARIABLE</i>	0.0484*** (0.0156)	0.0404 (0.0287)	0.0791*** (0.0181)	0.0589*** (0.0180)	0.1208*** (0.0153)	0.0750*** (0.0165)	0.1150*** (0.0158)	0.0788*** (0.0148)	0.0161 (0.0164)	-0.0174 (0.0173)	0.0923*** (0.0149)	0.0550*** (0.0183)
<i>LNSALES</i>	-0.0031 (0.0036)	0.0036 (0.0040)	-0.0035 (0.0034)	0.0023 (0.0037)	-0.0035 (0.0031)	0.0009 (0.0035)	-0.0024 (0.0030)	0.0018 (0.0035)	-0.0056* (0.0033)	0.0050 (0.0037)	-0.0054* (0.0032)	0.0020 (0.0038)
<i>DEBT</i>	0.0682* (0.0348)	0.0279 (0.0325)	0.0538* (0.0303)	0.0250 (0.0304)	0.0595** (0.0301)	0.0314 (0.0303)	0.0660** (0.0291)	0.0337 (0.0291)	0.0581* (0.0331)	0.0103 (0.0307)	0.0639** (0.0307)	0.0251 (0.0305)
<i>MKTBOOK</i>	-0.0164*** (0.0043)	-0.0163*** (0.0044)	-0.0171*** (0.0043)	-0.0133*** (0.0039)	-0.0183*** (0.0048)	-0.0151*** (0.0046)	-0.0148*** (0.0038)	-0.0136*** (0.0039)	-0.0178*** (0.0041)	-0.0157*** (0.0044)	-0.0193*** (0.0049)	-0.0167*** (0.0050)
<i>ROA</i>	0.0290 (0.1105)	0.0139 (0.1043)	0.0870 (0.1023)	0.0138 (0.0997)	0.1062 (0.1034)	0.0441 (0.1072)	0.0944 (0.0947)	0.0553 (0.0981)	0.0751 (0.1054)	0.0333 (0.1058)	0.0871 (0.1061)	0.0405 (0.1087)
<i>CASH</i>	0.0569 (0.0726)	0.0456 (0.0782)	0.0985 (0.0734)	0.0115 (0.0832)	0.0962 (0.0674)	0.0732 (0.0793)	0.0513 (0.0569)	0.0231 (0.0720)	0.0849 (0.0694)	0.0026 (0.0784)	0.0978 (0.0690)	0.0676 (0.0799)
Observations	235	229	245	239	245	239	245	239	245	239	245	239
Adj. R-squared	0.0950	0.4114	0.1440	0.4389	0.2768	0.4633	0.2589	0.4782	0.0539	0.4003	0.1770	0.4324
Industry FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Panel B: FF CARs	<u>Non-essential</u>		<u>High Drop</u>		<u>Low Net Income</u>		<u>Low Sales</u>		<u>Low Returns</u>		<u>Low FCF</u>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<i>VARIABLE</i>	-0.0007 (0.0135)	0.0117 (0.0241)	0.0341** (0.0155)	0.0247* (0.0144)	0.0832*** (0.0139)	0.0620*** (0.0141)	0.0636*** (0.0150)	0.0404*** (0.0133)	0.0630*** (0.0113)	0.0278 (0.0169)	0.0658*** (0.0133)	0.0510*** (0.0157)
Observations	235	229	245	239	245	239	245	239	245	239	245	239
Adj. R-squared	-0.0043	0.2922	0.0205	0.3014	0.1473	0.3572	0.0881	0.3219	0.0514	0.2989	0.0864	0.3342
Industry FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Table 10. Threat of the Virus: Transmission Rates and Fatalities

The table presents regressions of vaccination rate on store visits. In Panel A, we estimate OLS regressions, where Models 1 and 2 control for county level weekly COVID-19 transmission rates, and models 3 and 4 control for county level weekly COVID-19 related fatalities. In Panel B, we estimate seemingly-unrelated regressions (SUR). In (1), we regress *LNVISITS* on *VRATE* and store fixed effects, and in (2) we simultaneously regress *TRANSMISSIONS* on county-level demographic characteristics.

Panel A: Store Visits and Transmission Rates: OLS Model

VARIABLES	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(4) <i>LNVISITS</i>
<i>VRATE</i>	0.4376*** (0.0137)	0.1313*** (0.0191)	0.6146*** (0.0129)	0.1361*** (0.0185)
<i>TRANSMISSIONS</i>	-29.2377*** (1.4100)	-7.3400*** (0.8026)		
<i>FATALITIES</i>			-369.1978*** (31.2661)	-63.3655*** (15.8946)
<i>ALLOCATION</i>				
Observations	8,173,983	8,173,983	8,173,983	8,173,983
Adjusted R-squared	0.9387	0.9403	0.9378	0.9403
Store FE	YES		YES	
Store FE, Time FE		YES		YES

Panel B: Store Visits and Transmission Rates: SUR Model

VARIABLES	(1) <i>LNVISITS</i>	(2) <i>TRANSMISSIONS</i>
<i>VRATE</i>	0.6117*** (0.0008)	
<i>PBLACK</i>		0.0507*** (0.0001)
<i>PLATINO</i>		0.0913*** (0.0001)
<i>TRUMP_BIDEN_2020</i>		0.0806*** (0.0001)
<i>POPULATION_DENSITY</i>		0.0002*** (0.0000)
<i>LNINCOME</i>		-0.0039*** (0.0000)
Observations	8,178,030	8,178,030
Adjusted R-squared	0.0837	0.2316
Store FE	YES	

Table 11. Channels of the Vaccination Effect on Store Visits: Seniors

The table presents regression of the natural logarithm of weekly store visits at establishment level (*LNVISITS*) on county-level vaccination rates (*VRATE*), and interacted variable indicating high age of the store census block group (CBG) in models 1 and 2 or customer CBG in models 3 and 4, and control variables for the period December 28, 2020-June 28, 2021. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	Store CBG		Customer CBG	
	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(4) <i>LNVISITS</i>
<i>VRATE*HIGH_AGE</i>	0.0624*** (0.0162)	0.0505*** (0.0139)	0.0819*** (0.0172)	0.0678*** (0.0159)
<i>HIGH_AGE</i>	-0.0396*** (0.0074)	0.0022 (0.0070)	-0.1486*** (0.0094)	-0.0974*** (0.0091)
<i>VRATE</i>	0.5600*** (0.0131)	0.6090*** (0.0113)	0.5721*** (0.0124)	0.6208*** (0.0111)
<i>LNSALES</i>	0.2722*** (0.0036)	0.2754*** (0.0035)	0.2628*** (0.0039)	0.2663*** (0.0038)
<i>DEBT</i>	0.0667*** (0.0218)	0.0606*** (0.0206)	0.2656*** (0.0217)	0.2534*** (0.0208)
<i>MKTBOOK</i>	-0.0818*** (0.0036)	-0.0785*** (0.0036)	-0.0668*** (0.0032)	-0.0647*** (0.0032)
<i>ROA</i>	-0.4406*** (0.0604)	-0.4989*** (0.0584)	-0.8288*** (0.0550)	-0.8682*** (0.0539)
<i>CASH</i>	2.0515*** (0.1089)	2.0049*** (0.1075)	1.7290*** (0.1147)	1.7116*** (0.1144)
<i>PBLACK</i>	0.2263*** (0.0819)		0.2771*** (0.0741)	
<i>PLATINO</i>	0.1874 (0.1251)		0.1517 (0.1185)	
<i>TRUMP_BIDEN_2020</i>	0.8872*** (0.0839)		1.0010*** (0.0757)	
Observations	8,287,701	8,287,701	7,862,956	7,862,956
Adjusted R-squared	0.3763	0.3963	0.3718	0.3902
State FE, Industry FE	YES		YES	
County FE, Industry FE		YES		YES

Table 12. Channels of the Vaccination Effect: California Zip Code Level Evidence

Panel A presents regression of the natural logarithm of weekly store visits at establishment level (*LNVISITS*) on ZIP code level vaccination rates (*VRATE*) in California. In models 1 and 2, the vaccination rate is from the store ZIP code. In models 3 and 4 the vaccination rate is from ZIP code from which the majority of the customer traffic comes from. Panel B presents regressions of source of traffic by customer vaccination rate. For each establishment in each week, *SafeGraph* provides the number of visitors from various CBGs. We classify each customer CBG into the top or bottom quintile based on its vaccination rate measured at the corresponding ZIP code in California. Next, we calculate the ratio of number of visitors coming from the highest or the lowest quintile to total store visitors for each establishment in each week (*PCT_VISITOR*). We regress *PCT_VISITOR* on the store ZIP code *VRATE* separately for the lowest (in models 1 and 2) and the highest (in models 3 and 4) quintiles. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

Panel A

VARIABLES	Store ZIP Code		Customer ZIP Code	
	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(3) <i>LNVISITS</i>
<i>VRATE</i>	0.4939*** (0.0148)	0.2644*** (0.0303)	0.5084*** (0.0156)	0.2617*** (0.0321)
Observations	793,384	793,384	755,947	755,947
Adjusted R-squared	0.9392	0.9409	0.9327	0.9348
Store FE	YES		YES	
Store FE, Time FE		YES		YES

Panel B

VARIABLES	Lowest Quintile Vaccination Rate		Highest Quintile Vaccination Rate	
	(1) <i>PCT_VISITOR</i>	(2) <i>PCT_VISITOR</i>	(3) <i>PCT_VISITOR</i>	(4) <i>PCT_VISITOR</i>
<i>VRATE</i>	-2.0645*** (0.0561)	-0.7776*** (0.0812)	0.0721*** (0.0188)	0.2017*** (0.0534)
Observations	691,643	691,643	691,643	691,643
Adjusted R-squared	0.7761	0.8585	0.1298	0.1769
Store FE	YES		YES	
Store FE, Time FE		YES		YES

Table 13. Channels of Vaccination Effect: Employment

The table presents regression of the natural logarithm of weekly number of employees at establishment level (LN_EMP) on county-level vaccination rates ($VRATE$) and control variables for the period December 28, 2020-June 28, 2021. The number of employees is obtained from *SafeGraph* data. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	(1) <i>LN_EMP</i>	(2) <i>LN_EMP</i>	(3) <i>LN_EMP</i>	(4) <i>LN_EMP</i>
<i>VRATE</i>	0.2140*** (0.0090)	0.2405*** (0.0081)	0.2728*** (0.0088)	0.0472*** (0.0155)
<i>LNSALES</i>	0.1378*** (0.0022)	0.1380*** (0.0022)		
<i>DEBT</i>	-0.1128*** (0.0175)	-0.1164*** (0.0172)		
<i>MKTBOOK</i>	-0.0080*** (0.0023)	-0.0070*** (0.0023)		
<i>ROA</i>	-0.2062*** (0.0517)	-0.2062*** (0.0516)		
<i>CASH</i>	0.1978*** (0.0651)	0.1346** (0.0650)		
<i>PBLACK</i>	-0.0503 (0.0466)			
<i>PLATINO</i>	0.1435* (0.0743)			
<i>TRUMP_BIDEN_2020</i>	0.1155*** (0.0365)			
Observations	5,751,675	5,751,674	5,742,733	5,742,733
Adjusted R-squared	0.2284	0.2410	0.7374	0.7378
State FE, Industry FE	YES			
County FE, Industry FE		YES		
Store FE			YES	
Store FE, Time FE				YES

Table 14. Cross-sectional Analyses: Establishment and Firm Characteristics

The table presents regression of the natural logarithm of weekly store visits at establishment level, *LNVISITS*, on county-level vaccination rates, *VRATE*, and interacted variables. In Panel A, the interacted variables indicate high drop in establishment visits at the onset of COVID-19 in models 1 and 2, non-essential nature of business in models 3 and 4, or low-online percentage of establishment sales in models 5 and 6. We report coefficient estimates with standard errors in parentheses. In Panel B, the interacted variables indicate high decrease in sales in models 1 and 2, high decrease in net income in models 3 and 4, high decrease in free cash flows in models 5 and 6, and poor risk-adjusted returns in models 7 and 8, all measured over the last three quarters of 2020 on firm level. The interacted variables indicate that the change in the firm characteristic falls in the bottom quintile. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

Panel A: Establishment Characteristics

VARIABLES	High Drop in Visits		Non-essential Business		Low Online Sales	
	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(4) <i>LNVISITS</i>	(5) <i>LNVISITS</i>	(6) <i>LNVISITS</i>
<i>VRATE*Variable</i>	0.1276*** (0.0185)	0.1854*** (0.0171)	0.2086*** (0.0113)	0.2241*** (0.0112)	0.0890*** (0.0091)	0.0682*** (0.0099)
<i>VRATE</i>	0.6310*** (0.0120)	0.0758*** (0.0169)	0.6024*** (0.0106)	0.0760*** (0.0180)	0.5802*** (0.0134)	0.1130*** (0.0187)
Observations	8,267,278	8,267,278	7,694,900	7,694,900	5,564,371	5,564,371
Adjusted R-squared	0.9374	0.9401	0.9387	0.9411	0.9410	0.9445
Store FE	YES		YES		YES	
Store FE, Time FE		YES		YES		YES

Table 14, Panel B: Firm Characteristics

VARIABLES	<i>LOW SALES</i>		<i>LOW NI</i>		<i>LOW FCF</i>		<i>LOW RETURNS</i>	
	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(4) <i>LNVISITS</i>	(5) <i>LNVISITS</i>	(6) <i>LNVISITS</i>	(7) <i>LNVISITS</i>	(8) <i>LNVISITS</i>
<i>VRATE*Variable</i>	0.3903*** (0.0111)	0.4126*** (0.0106)	0.3463*** (0.0144)	0.3770*** (0.0141)	0.3176*** (0.0116)	0.3183*** (0.0111)	0.1333*** (0.0195)	0.1230*** (0.0189)
<i>VRATE</i>	0.4818*** (0.0122)	-0.1215*** (0.0166)	0.5213*** (0.0125)	-0.1027*** (0.0187)	0.4986*** (0.0110)	-0.0748*** (0.0211)	0.5286*** (0.0184)	0.0400 (0.0266)
Observations	4,706,483	4,706,483	4,551,406	4,551,406	3,698,661	3,698,661	2,861,013	2,861,013
Adjusted R-squared	0.9371	0.9402	0.9297	0.9330	0.9295	0.9327	0.9480	0.9505
Store FE	YES		YES		YES		YES	
Store FE, Time FE		YES		YES		YES		YES

Table 15. Vaccination Limitations: Delta Variant Surge

The table presents regression of the natural logarithm of weekly store visits at establishment level (*LNVISITS*) on county-level vaccination rates (*VRATE*), and interacted variable indicating the period of the “delta” variant surge (July 1, 2020 to September 30, 2021). We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county-week level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

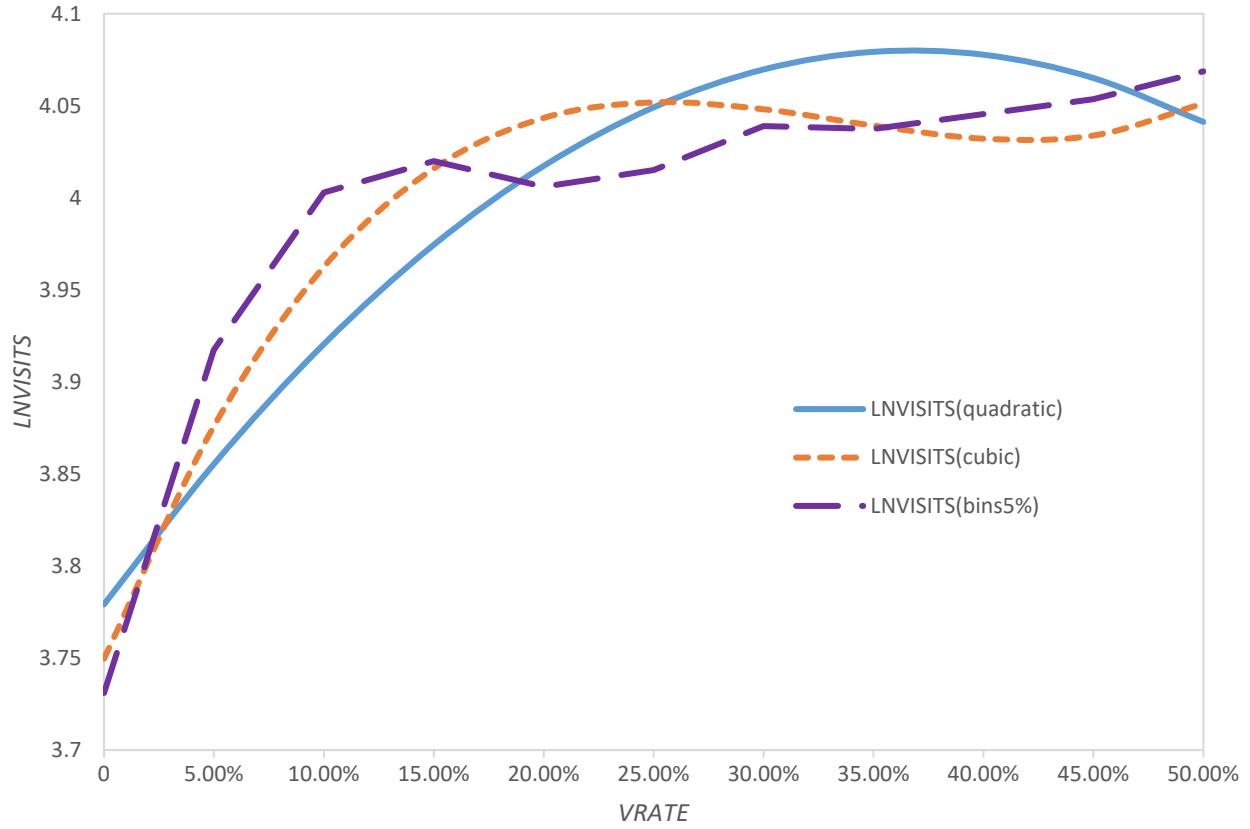
VARIABLES	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>
<i>VRATE*DELTA_VARIANT</i>	-0.4565*** (0.0223)	-0.0405*** (0.0139)
<i>VRATE</i>	0.6362*** (0.0114)	0.1277*** (0.0180)
<i>DELTA_VARIANT</i>	0.1266*** (0.0087)	
Observations	12,528,024	12,528,024
Adjusted R-squared	0.9296	0.9313
Store FE	YES	
Store FE, Time FE		YES

Internet Appendix (IA) for
COVID-19 Vaccinations, Business Activity, and Firm Value

- IA Figure 1: Non-linearity in the Effect of Vaccination Rates on Visits
- IA Table 1: Restrictions Excluding the Top Five Counties in Each State
- IA Table 2: Higher-Dimension Fixed Effects
- IA Table 3: Interaction of Restrictions and Vaccination Rates
- IA Table 4: Percentage Change in Visits
- IA Table 5: Poisson Regressions of Visits and Vaccination Rates
- IA Table 6: First Doses and State Allocation of Vaccines
- IA Table 7: The Effect of Vaccination Rates on Store Visits: US versus California
- IA Table 8: Non-linearity in the Effect of Vaccination Rates on Visits

IA Figure 1. Non-Linearity in the Effect of Vaccination Rates on Visits

This figure provides a quadratic model, a cubic model, and piece-wise linear model with bins increasing in 5 percent intervals for *VRATE*. *LNVISITS* is projected up to 50% *VRATE* which corresponds to the 97th percentile of the variable. We calculate the predicted *LNVISITS* based on the equations in IA Table 8.



IA Table 1. Restrictions excluding the Top Five Counties in Each State

The table presents regression of the natural logarithm of weekly store visits at establishment level, *LNVISITS*, on county-level cumulative vaccination rates, *VRATE*, and control variables, including restrictions, for the period December 28, 2020-June 28, 2021. We exclude the five most populous counties in each state. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>
<i>VRATE</i>	0.5677*** (0.0258)	0.6357*** (0.0190)	0.7091*** (0.0162)	0.7473*** (0.0166)	0.1131*** (0.0261)	0.4569*** (0.0335)	0.5598*** (0.0254)	0.6484*** (0.0201)	0.6851*** (0.0206)	0.0977*** (0.0265)
<i>LNSALES</i>		0.2876*** (0.0041)	0.2918*** (0.0040)				0.2876*** (0.0041)	0.2918*** (0.0040)		
<i>DEBT</i>		0.1576*** (0.0283)	0.1549*** (0.0266)				0.1574*** (0.0282)	0.1548*** (0.0266)		
<i>MKTBOOK</i>		-0.1101*** (0.0047)	-0.1063*** (0.0047)				-0.1101*** (0.0047)	-0.1063*** (0.0047)		
<i>ROA</i>		-0.1836** (0.0907)	-0.2456*** (0.0895)				-0.1836** (0.0906)	-0.2456*** (0.0895)		
<i>CASH</i>		2.5717*** (0.0920)	2.4927*** (0.0889)				2.5706*** (0.0919)	2.4928*** (0.0889)		
<i>PBLACK</i>		0.2374*** (0.0887)					0.2173** (0.0884)			
<i>PLATINO</i>		0.3508*** (0.1162)					0.3384*** (0.1144)			
<i>TRUMP_BIDEN_2020</i>		0.7734*** (0.0788)					0.7505*** (0.0777)			
<i>OPEN2</i>	0.0498 (0.0415)	0.0410 (0.0515)	0.1288*** (0.0287)	0.1435*** (0.0274)	0.0255 (0.0235)	-0.0013 (0.0333)	0.0008 (0.0444)	0.0712** (0.0310)	0.0834*** (0.0300)	0.0073 (0.0243)
<i>OPEN3</i>	0.1977*** (0.0593)	0.1500*** (0.0551)	0.0338 (0.0280)	0.0389 (0.0300)	0.0276 (0.0182)	0.1646*** (0.0515)	0.1168** (0.0483)	0.0113 (0.0303)	0.0136 (0.0324)	0.0240 (0.0189)
<i>OPEN4</i>	-0.0097 (0.0128)	-0.0231 (0.0142)	-0.0180** (0.0082)	-0.0211** (0.0085)	0.0162*** (0.0058)	-0.0317** (0.0138)	-0.0418*** (0.0146)	-0.0340*** (0.0075)	-0.0384*** (0.0078)	0.0111* (0.0057)
<i>STAY-AT-HOME ORDER</i>						-0.0631*** (0.0090)	-0.0688*** (0.0093)	-0.0599*** (0.0077)	-0.0659*** (0.0079)	0.0137** (0.0062)

<i>STATE OF EMERGENCY</i>						-0.0248 (0.0211)	-0.0194 (0.0182)	-0.0041 (0.0071)	-0.0024 (0.0073)	-0.0175*** (0.0058)
<i>NO NURSING HOME VISITS</i>						-0.0864* (0.0481)	-0.0877** (0.0434)	-0.0347 (0.0212)	-0.0400* (0.0221)	-0.0096 (0.0181)
<i>EMPLOYEES MASKS</i>						0.0458 (0.0374)	0.0821 (0.0552)	-0.0811 (0.0706)	-0.0865 (0.0733)	-0.0550 (0.0518)
<i>MASKS RECOMMENDED</i>						-0.0781** (0.0392)	-0.0886 (0.0564)	0.0850 (0.0705)	0.0925 (0.0731)	0.0687 (0.0521)
<i>BEACHES OR PARKS CLOSED</i>						-0.0070 (0.0220)	0.0314 (0.0271)	0.0212 (0.0520)	0.0177 (0.0473)	0.0114 (0.0388)
<i>NO ELECTIVE PROCEDURES</i>						0.0845 (0.0875)	0.0677 (0.0687)	-0.0330** (0.0145)	-0.0387** (0.0152)	0.0010 (0.0106)
<i>RESTAURANTS CLOSED</i>						0.0463* (0.0262)	0.0366 (0.0307)	0.0766*** (0.0268)	0.0790*** (0.0289)	0.0306* (0.0184)
<i>GYM CLOSED</i>						0.0007 (0.0208)	0.0055 (0.0175)	-0.0060 (0.0089)	-0.0081 (0.0092)	0.0009 (0.0071)
<i>SPAS CLOSED</i>						0.0803** (0.0348)	0.0689** (0.0342)	0.0395 (0.0262)	0.0441 (0.0283)	-0.0071 (0.0173)
<i>GATHERINGS LIMITED TO 10</i>						-0.1045*** (0.0114)	-0.0842*** (0.0122)	-0.0818*** (0.0090)	-0.0859*** (0.0094)	-0.0240*** (0.0060)
<i>REOPENINGS REVERSED</i>						-0.0936*** (0.0136)	-0.0809*** (0.0130)	-0.0573*** (0.0080)	-0.0583*** (0.0082)	-0.0189*** (0.0071)
Observations	4,017,765	4,017,765	4,017,765	4,017,765	4,017,765	4,017,765	4,017,765	4,017,765	4,017,765	4,017,765
Adjusted R-squared	0.3262	0.3875	0.4142	0.9349	0.9377	0.3269	0.3880	0.4146	0.9353	0.9378
State FE, Industry FE	YES	YES				YES	YES			
County FE, Industry FE			YES					YES		
Store FE				YES					YES	
Store FE, Time FE					YES					YES

IA Table 2. Higher-Dimension Fixed Effects

The table presents regression of the natural logarithm of weekly store visits at establishment level, *LNVISITS*, on county-level cumulative vaccination rates, *VRATE*, and control variables for the period December 28, 2020-June 28, 2021 using several fixed effects specifications. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(4) <i>LNVISITS</i>	(5) <i>LNVISITS</i>	(6) <i>LNVISITS</i>	(7) <i>LNVISITS</i>
<i>VRATE</i>	0.4006*** (0.0165)	0.4016*** (0.0166)	0.4045*** (0.0166)	0.4048*** (0.0165)	0.4085*** (0.0166)	0.6232*** (0.0115)	0.1279*** (0.0172)
<i>LNSALES</i>		0.1946*** (0.0019)		0.2843*** (0.0042)			
<i>DEBT</i>		1.1977*** (0.0167)		0.1329*** (0.0241)			
<i>MKTBOOK</i>		0.1175*** (0.0061)		-0.0723*** (0.0041)			
<i>ROA</i>		-2.9523*** (0.1080)		-0.7771*** (0.0650)			
<i>CASH</i>		-0.4210*** (0.0812)		1.7818*** (0.1236)			
Observations	8,287,701	8,287,701	8,287,701	8,287,701	8,287,701	8,287,701	8,287,701
Adjusted R-squared	0.0652	0.1254	0.4069	0.4611	0.6334	0.5000	0.5022
County-Time FE	YES	YES					
County-Industry-Time FE			YES	YES			
County-Brand-Time FE					YES		
Firm FE, County FE						YES	
Firm FE, County FE, Time FE							YES

IA Table 3. Interaction of Restrictions and Vaccination Rates

The table presents regression of the natural logarithm of weekly store visits at establishment level, *LNVISITS*, on county-level cumulative vaccination rates, *VRATE*, and control variables, including restrictions, for the period December 28, 2020-June 28, 2021. We interact each dummy variable *OPEN2-OPEN4* with *VRATE*. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(4) <i>LNVISITS</i>	(5) <i>LNVISITS</i>	(6) <i>LNVISITS</i>	(7) <i>LNVISITS</i>	(8) <i>LNVISITS</i>	(9) <i>LNVISITS</i>	(10) <i>LNVISITS</i>
<i>VRATE</i>	0.3043*** (0.0723)	0.4114*** (0.0524)	0.4073*** (0.0132)	0.4765*** (0.0105)	0.0477*** (0.0178)	0.0701 (0.0815)	0.2264*** (0.0525)	0.2997*** (0.0162)	0.3591*** (0.0158)	0.0138 (0.0201)
<i>OPEN2 * VRATE</i>	0.2983*** (0.0841)	0.2191*** (0.0605)	0.2144*** (0.0327)	0.1824*** (0.0333)	0.0324 (0.0253)	0.4109*** (0.0893)	0.3316*** (0.0559)	0.2728*** (0.0304)	0.2479*** (0.0311)	0.0712*** (0.0245)
<i>OPEN3 * VRATE</i>	-0.0706 (0.0615)	-0.0413 (0.0458)	0.0856** (0.0354)	0.0953** (0.0371)	0.0683** (0.0272)	-0.2428*** (0.0726)	-0.1865*** (0.0544)	-0.0255 (0.0325)	-0.0259 (0.0341)	0.0210 (0.0281)
<i>OPEN4 * VRATE</i>	-0.0586 (0.0442)	-0.0480 (0.0324)	-0.1285*** (0.0238)	-0.1391*** (0.0245)	-0.0602*** (0.0188)	0.1147* (0.0589)	0.1193*** (0.0448)	0.0205 (0.0270)	0.0255 (0.0283)	-0.0323* (0.0195)
<i>LNSALES</i>		0.2714*** (0.0037)	0.2746*** (0.0036)				0.2715*** (0.0037)	0.2746*** (0.0036)		
<i>DEBT</i>		0.0699*** (0.0226)	0.0621*** (0.0214)				0.0697*** (0.0225)	0.0620*** (0.0214)		
<i>MKTBOOK</i>		-0.0809*** (0.0037)	-0.0777*** (0.0037)				-0.0809*** (0.0037)	-0.0777*** (0.0037)		
<i>ROA</i>		-0.4320*** (0.0622)	-0.4873*** (0.0603)				-0.4328*** (0.0622)	-0.4873*** (0.0603)		
<i>CASH</i>		1.9950*** (0.1123)	1.9473*** (0.1107)				1.9948*** (0.1127)	1.9472*** (0.1107)		
<i>PBLACK</i>		0.2398*** (0.0898)					0.2182** (0.0877)			
<i>PLATINO</i>		0.1874 (0.1268)					0.2065 (0.1262)			
<i>TRUMP_BIDEN_2020</i>		0.8484*** (0.0895)					0.8108*** (0.0830)			
<i>OPEN2</i>	0.1166** (0.0579)	0.0348 (0.0371)	0.0758*** (0.0187)	0.1000*** (0.0169)	-0.0013 (0.0121)	0.0703 (0.0628)	0.0026 (0.0387)	0.0321 (0.0249)	0.0552** (0.0244)	-0.0213 (0.0133)

<i>OPEN3</i>	0.0738 (0.0475)	0.0723** (0.0289)	0.0186 (0.0123)	0.0219* (0.0130)	0.0143 (0.0113)	0.0893* (0.0470)	0.0838*** (0.0289)	0.0138 (0.0160)	0.0142 (0.0171)	0.0199 (0.0121)
<i>OPEN4</i>	0.0122 (0.0228)	-0.0063 (0.0138)	0.0027 (0.0079)	0.0026 (0.0080)	0.0158 (0.0119)	-0.0262 (0.0274)	-0.0427** (0.0184)	-0.0319*** (0.0105)	-0.0358*** (0.0110)	0.0089 (0.0116)
<i>STAY AT HOME ORDER</i>						-0.0268** (0.0112)	-0.0417*** (0.0091)	-0.0475*** (0.0081)	-0.0519*** (0.0086)	0.0141*** (0.0050)
<i>STATE OF EMERGENCY</i>						-0.0373** (0.0157)	-0.0235 (0.0146)	0.0021 (0.0064)	0.0050 (0.0066)	-0.0145*** (0.0053)
<i>NO NURSING HOME VISITS</i>						-0.0024 (0.0299)	0.0054 (0.0281)	-0.0149 (0.0139)	-0.0227 (0.0142)	0.0045 (0.0088)
<i>EMPLOYEES MASKS</i>						0.0396 (0.0469)	0.0583 (0.0512)	-0.0380** (0.0179)	-0.0345* (0.0187)	-0.0358*** (0.0130)
<i>MASKS RECOMMENDED</i>						-0.0788* (0.0475)	-0.0560 (0.0512)	0.0495*** (0.0174)	0.0484*** (0.0182)	0.0465*** (0.0129)
<i>BEACHES OR PARKS CLOSED</i>						0.0451 (0.0378)	0.0416 (0.0397)	0.0014 (0.0535)	-0.0015 (0.0478)	-0.0024 (0.0423)
<i>NO ELECTIVE PROCEDURES</i>						-0.0909 (0.0901)	-0.0526 (0.0776)	-0.0510*** (0.0102)	-0.0555*** (0.0106)	-0.0199*** (0.0068)
<i>RESTAURANTS CLOSED</i>						0.0499 (0.0366)	0.0283 (0.0303)	0.0470* (0.0245)	0.0517* (0.0276)	0.0239** (0.0117)
<i>GYM CLOSED</i>						-0.0542*** (0.0152)	-0.0441*** (0.0136)	-0.0329*** (0.0103)	-0.0373*** (0.0110)	-0.0082 (0.0064)
<i>SPAS CLOSED</i>						0.0857*** (0.0227)	0.0683*** (0.0180)	0.0261 (0.0195)	0.0277 (0.0215)	-0.0188** (0.0095)
<i>GATHERINGS LIMITED TO 10</i>						-0.1279*** (0.0152)	-0.0924*** (0.0128)	-0.0634*** (0.0149)	-0.0668*** (0.0157)	-0.0244*** (0.0066)
<i>REOPENINGS REVERSED</i>						-0.1059*** (0.0126)	-0.0828*** (0.0098)	-0.0613*** (0.0068)	-0.0651*** (0.0071)	-0.0161*** (0.0045)
Observations	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850	7,775,850
Adjusted R-squared	0.3161	0.3750	0.3950	0.9373	0.9399	0.3171	0.3756	0.3953	0.9378	0.9399
State FE, Industry FE	YES	YES				YES	YES			
County FE, Industry FE			YES					YES		
Store FE				YES					YES	
Store FE, Time FE					YES					YES

IA Table 4. Percentage Change in Visits

The table presents regression of the percent change in weekly store visits at establishment level relative to the same calendar month in 2019 (pre-COVID), *PVISITS*, on county-level weekly cumulative vaccination rates, *VRATE*, and store and time fixed effects for the period December 28, 2020-June 28, 2021. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	(1) <i>PVISITS</i>	(2) <i>PVISITS</i>	(3) <i>PVISITS</i>	(4) <i>PVISITS</i>
<i>WEEKLY VRATE</i>	1.6022*** (0.0674)	0.6872*** (0.0939)		
<i>VRATE</i>			0.0484*** (0.0081)	0.1258*** (0.0160)
Observations	7,980,554	7,980,554	7,980,554	7,980,554
Adjusted R-squared	0.7149	0.7238	0.7141	0.7239
Store FE	YES		YES	
Store FE, time FE		YES		YES

IA Table 5. Poisson Regressions of Visits and Vaccination Rates

The table presents regression of the raw weekly visits as a count variable on county-level weekly cumulative vaccination rates, *VRATE*, and store and time fixed effects for the period December 28, 2020-June 28, 2021. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	(1) <i>VISITS</i>	(2) <i>VISITS</i>
<i>VRATE</i>	0.5890*** (0.0113)	0.1311*** (0.0174)
Observations	8,283,489	8,283,489
Store FE	YES	
Store FE, Time FE		YES
Pseudo R-squared	0.909	0.909

IA Table 6. First Doses and State Allocation of Vaccines

The table presents regressions of vaccination rate on store visits. All models are based on first dose of COVID vaccines only. Models 3 and 4 control for the state allocation of vaccines.

VARIABLES	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(4) <i>LNVISITS</i>
<i>VRATE</i>	0.6072*** (0.0115)	0.0861*** (0.0167)	0.4358*** (0.0124)	0.1851*** (0.0212)
<i>ALLOCATION</i>			0.1054*** (0.0030)	0.0483*** (0.0042)
Observations	8,283,489	8,283,489	8,287,701	8,287,701
Adjusted R-squared	0.9383	0.9404	0.9387	0.9405
Store FE	YES		YES	
Store FE, Time FE		YES		YES

IA Table 7. The Effect of Vaccination Rates on Store Visits: US versus California

The table replicates our benchmark regressions from Table 2 for US excluding California and California itself. We report coefficient estimates with standard errors in parentheses. Variable definitions are provided in the Appendix. Standard errors are clustered at county level. We use ***, **, and * to indicate statistical significance at the 1, 5, and 10% levels, respectively.

VARIABLES	EXCLUDING CALIFORNIA					CALIFORNIA				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>	<i>LNVISITS</i>
<i>VRATE</i>	0.5387*** (0.0143)	0.5780*** (0.0134)	0.6247*** (0.0126)	0.6635*** (0.0130)	0.1253*** (0.0195)	0.3863*** (0.0669)	0.5806*** (0.0251)	0.5893*** (0.0272)	0.6353*** (0.0285)	0.2429*** (0.0516)
<i>LNSALES</i>		0.2814*** (0.0033)	0.2843*** (0.0032)				0.2203*** (0.0057)	0.2213*** (0.0055)		
<i>DEBT</i>		0.0344 (0.0214)	0.0285 (0.0200)				0.3681*** (0.0537)	0.3577*** (0.0510)		
<i>MKTBOOK</i>		-0.0867*** (0.0043)	-0.0832*** (0.0043)				-0.0554*** (0.0045)	-0.0554*** (0.0044)		
<i>ROA</i>		-0.3281*** (0.0589)	-0.3958*** (0.0586)				-1.1834*** (0.1560)	-1.1601*** (0.1563)		
<i>CASH</i>		2.0603*** (0.1187)	2.0197*** (0.1168)				2.0880*** (0.2363)	2.0486*** (0.2327)		
<i>PBLACK</i>		0.0926 (0.0846)					2.7510*** (0.5228)			
<i>PLATINO</i>		0.0391 (0.1113)					0.1433 (0.1224)			
<i>TRUMP_BIDEN_2020</i>		0.7201*** (0.0873)					2.0596*** (0.2026)			
Observations	7,406,902	7,406,902	7,406,902	7,406,902	7,406,902	880,799	880,799	880,799	880,241	880,241
Adjusted R-squared	0.3181	0.3780	0.3984	0.9379	0.9407	0.3060	0.3740	0.3801	0.9343	0.9365
State FE, Industry FE	YES	YES				YES	YES			
County FE, Industry FE			YES					YES		
Store FE				YES					YES	
Store FE, Time FE					YES					YES

IA Table 8. Non-linearity in the Effect of Vaccination Rates on Visits

The table replicates models 4 and 5 from Table 2 under a quadratic, cubic, as well as piece-wise linear specifications with bins increasing by 5 percent for the vaccination rate.

VARIABLES	(1) <i>LNVISITS</i>	(2) <i>LNVISITS</i>	(3) <i>LNVISITS</i>	(4) <i>LNVISITS</i>	(5) <i>LNVISITS</i>	(6) <i>LNVISITS</i>
<i>VRATE</i>	1.6352*** (0.0311)	0.3221*** (0.0415)	2.9735*** (0.0522)	1.1621*** (0.0658)		
<i>VRATE</i> ²	-2.2223*** (0.0741)	-0.2928*** (0.0688)	-9.3770*** (0.3107)	-3.7800*** (0.2883)		
<i>VRATE</i> ³			9.2728*** (0.4469)	3.9351*** (0.3562)		
<i>VRATE</i> ∈ [0, 5]					3.7275*** (0.0797)	2.3722*** (0.1174)
<i>VRATE</i> ∈ (5, 10]					1.7092*** (0.0965)	0.3922*** (0.0726)
<i>VRATE</i> ∈ (10, 15]					0.3405*** (0.0722)	0.5206*** (0.0800)
<i>VRATE</i> ∈ (15, 20]					-0.2781*** (0.0686)	-0.4197*** (0.0701)
<i>VRATE</i> ∈ (20, 25]					0.1821*** (0.0692)	0.0157 (0.0682)
<i>VRATE</i> ∈ (25, 30]					0.4771*** (0.0649)	0.2822*** (0.0659)
<i>VRATE</i> ∈ (30, 35]					-0.0316 (0.1076)	-0.1195 (0.0993)
<i>VRATE</i> ∈ (35, 40]					0.3096*** (0.0976)	0.2696*** (0.0987)
<i>VRATE</i> ∈ (40, 45]					0.1624 (0.1199)	0.1612 (0.1233)
<i>VRATE</i> >45					0.3018*** (0.0709)	0.2860*** (0.0696)
Observations	8,283,489	8,283,489	8,283,489	8,283,489	8,283,489	8,283,489
Adjusted R-squared	0.9391	0.9404	0.9399	0.9405	0.9403	0.9405
Store FE	YES		YES		YES	
Store FE, Time FE		YES		YES		YES