WP/21/281

IMF Working Paper

COVID-19 Vaccines: A Shot in Arm for the Economy

by Niels-Jakob H. Hansen and Rui C. Mano

INTERNATIONAL MONETARY FUND

IMF Working Paper

Western Hemisphere Department and Research Department

COVID-19 Vaccines: A Shot in Arm for the Economy*

Prepared by Niels-Jakob H. Hansen and Rui C. Mano[1]

Authorized for distribution by Nigel Chalk and Malhar Nabar

December 2021

Abstract

We quantify the effect of vaccinations on economic activity in the United States using weekly county level data covering the period end-2020 to mid-2021. Causal effects are identified through instrumenting vaccination rates with county-level pharmacy density interacted with state-level vaccine allocations, and by including county and state-time fixed effects to control for unobserved factors. We find that vaccinations are a significant and substantial shot in the arm of the economy. Specifically, an increase of initiated vaccination rates of 1 percentage point increases weekly consumer spending by 0.6 percent and reduces weekly initial unemployment claims by 0.004 percentage points of the 2019 labor force. Vaccinations also increase work-related mobility. Importantly, we find that the effects vary with county characteristics. Specifically, urban counties and counties with initially worse socioeconomic conditions and lower education levels exhibit larger effects of vaccinations. Our results are specific to the United States, but hold important lessons for the expected economic impact of vaccinations in other countries.

JEL Classification Numbers: E52, E58, D43, L11.

Keywords: COVID-19; pandemics; vaccinations.

Author's E-Mail Address: nhansen@imf.org; rmano@imf.org

[1]The draft has benefited from very helpful discussions with Mehdi Andaloussi, Philip Barrett, John Bluedorn, Oya Celasun, Federico Diaz, Aaron Flaaen, Deniz Igan, Francesco Grigoli, Gita Gopinath, Prachi Mishra, Ippei Shibata, and Yannick Timmer. We are very grateful to Dima Mazen Qato for sharing her data on U.S. pharmacies. We also thank participants of various internal IMF seminars and the 22nd Jacques Polak Annual Research Conference for their helpful suggestions. Shan Chen and Lin Yunhui provided superb research assistance.

1 Introduction

Around the world, COVID vaccines are currently being rolled out. The aim of these vaccination programs is to counter the spread of COVID-19 and put an end to the pandemic. This will ultimately save millions of lives. At the same time, vaccination programs can allow economies to restart as consumers and workers feel confident to return to their previous routines. This has led some observers to conjecture the return of the "roaring twenties" as consumers go back to the shops and workers to their offices.[1] A first order question currently facing economists is thus how powerful vaccines are in helping relaunch the economy.

This paper asks the question, "What is the economic effect of vaccines?". Vaccines are proven to reduce the transmission of COVID-19, which can affect economic activity both directly, as consumers and workers feel confident they can shop and go to work without catching COVID-19, or indirectly, by allowing governments to relax restrictions that hamper economic activity. An perceived end to the pandemic could also raise spending through increased confidence. If vaccines are successful in restarting the economy, it is likely to show up in higher spending, higher mobility, and lower unemployment claims. We estimate the effect of higher vaccination rates on these variables using high-frequency data at the county level in the United States.

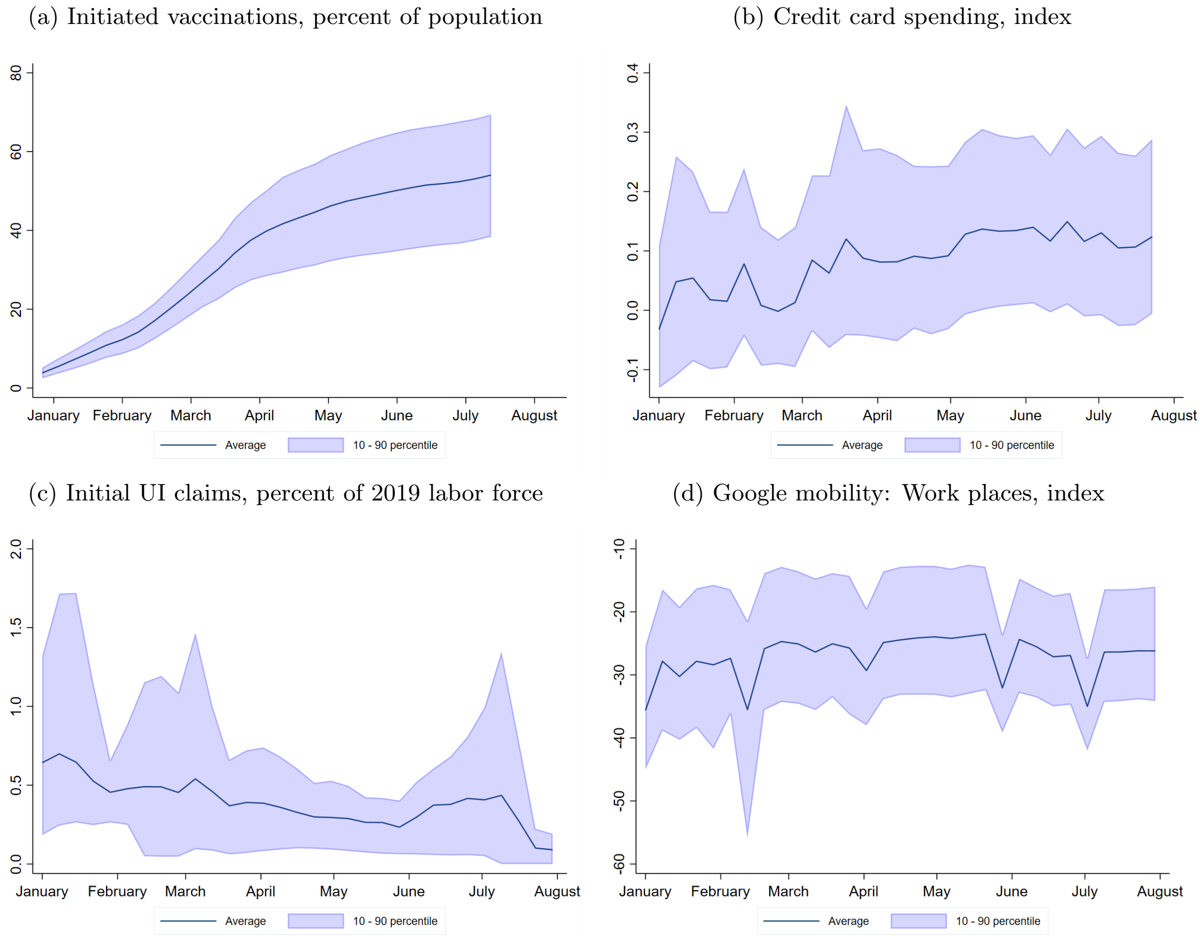
We tackle this question using U.S. county variation across time and space. In the United States, the vaccination roll-out started in December 2020 and accelerated over the winter and spring of 2021 before decelerating in the early-summer. By August 13, 2021, the average US county had a share of initiated vaccinations (i.e. first doses taken) of 56.0 percent (Panel A, Figure 1). There was, however, substantial variation around this average, with the 10th and 90th percentile standing at 40.4 and 71.7 percent initiated vaccination rates, respectively.[2] During the same period, the economy continued rebounding. Panel B of Figure 1 shows how average credit card spending increased during the same period, while Panel C illustrates how new unemployment insurance claims declined further. Finally, Panel D depicts how workplace mobility also rose in the same period.

We rely on an instrumental variable approach to identify the causal effect of vaccinations. Specifically, we instrument county-level vaccination rates with pre-determined pharmacy densities at the county level (number of pharmacies per square mile) interacted with weekly allocated vaccines at the state level. That way, the approach exploits variation in whether economic activity picks up more in counties with higher pharmacy density when vaccines are allocated to the given state. We believe this is a good instru-

[1] See for example VOXEU "The 'Roaring Twenties': Revisiting the evidence for Europe".

[2] This point is further highlighted in Figure 2 showing the full distribution of vaccination rates across counties within the U.S. on August 19, 2021.

Figure 1: Vaccinations and economic activity, 2021



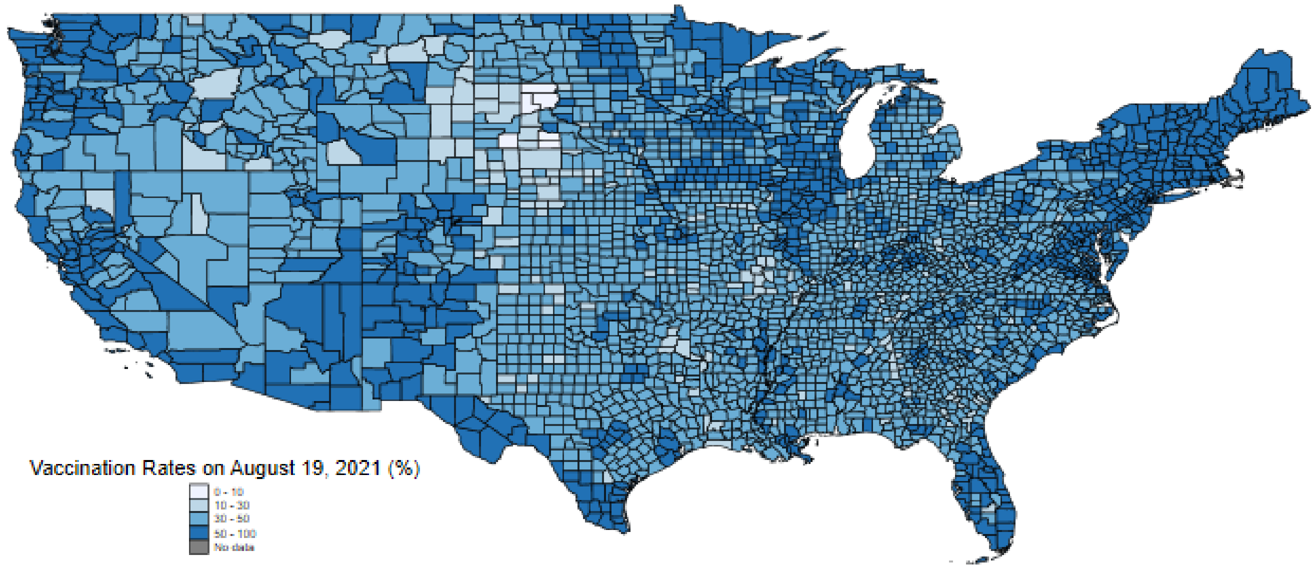
Source: Authors' calculations.

Notes: Initiated vaccinations are first doses of vaccines taken. Spending is seasonally adjusted credit/debit card spending expressed relative to Jan 4–31, 2020. Workplace mobility is compared to its median value for the same weekday in the period of Jan 3 – Feb 6, 2020. UI claims is initial unemployment insurance claims in percent of the 2019 labor force. See Section 2 for more details.

ment for two reasons. First, counties with higher pharmacy densities can better push vaccines to their population when more vaccines are allocated to the state. Empirically, this is reflected in a strong first stage. Second, our instrument arguably also satisfies the exclusion restriction as the pharmacy density is pre-determined and with no direct impact on economic activity besides through vaccination. Indeed, we show that the relationship of vaccines with the level of pre-vaccination spending is insignificant.

We find that vaccinations are a significant and substantial shot in the arm for the economy. Specifically, an increase of initiated vaccination rates by 1 percentage point increases credit card spending by 0.6 percent and reduces weekly initial unemployment claims by 0.004 percentage points of the 2019 labor force. We also find evidence that vaccination increases work-related mobility. Importantly, these effects seem to vary across

Figure 2: Vaccination rates across US counties



Source: Authors' calculations.

counties, with larger effects of vaccinations in urban counties and in counties with worse social-economic conditions. This way, vaccinations are also a *fair* shot in the arm for the economy, which highlights that equitable distribution of vaccines is important to reduce inequality.

Our results are specific to the United States but also hold important lessons for other countries. First, the United States rolled out vaccines early and at a large scale. The U.S. case thus holds important lessons for the economic impact that other countries can expect from rolling out vaccines. Second, our results highlight that ensuring an equitable distribution of vaccines is critical to reducing inequality, either pre-existing or pandemic-induced.

Literature review. Our paper contributes to the emerging literature assessing the economic impact of COVID-19 vaccination programs. Sandmann et al., 2021 studies the health and economic impact of mass vaccination in the United Kingdom using an epidemiological model. They measure the impact of vaccines on COVID-19 epidemiological outcomes and then convert those into economic costs. Deb et al., 2021 investigates the effect of COVID-19 vaccinations on economic activity as measured by high-frequency emissions and mobility. They use a comprehensive cross-country sample and identify effects based on unexpected increases in vaccinations. Ganslmeier et al., 2021 studies the impact on economic activity, as measured by nighttime lights, emissions, and mobility using 326 regions in 17 countries. They employ an instrumental variable approach using previous vaccine procurement interacted with region-time fixed effects.

We make a conceptual, methodological, and data contribution to the existing literature. Conceptually, we contribute by studying more direct measures of economic activity — credit/debit card spending and unemployment claims — unlike existing papers that use more indirect measures such as emissions, nighttime lights, and mobility. Methodologically, we exploit the pre-determined and arguably exogenous variation in pharmacy density to identify the causal effects of vaccines. We also use more granular county level data. This strengthens the identification strategy and allows us to go beyond the estimation of average effects. Indeed, we show how the impact of vaccination differs across urban-rural counties and other socioeconomic variables that vary significantly within U.S. states.

This paper is organized as follows: Section 2 introduces our data, Section 3 details our approach, and Section 4 discusses results. Finally, Section 5 concludes.

2 Data

Our dataset covers 2808 counties in the 50 U.S. states and the District of Columbia at the weekly frequency spanning end-December 2020 to early-July 2021. The dataset includes county-level data for vaccinations and economic activity (Table 1).

Let us describe each variable in more detail. Initiated and completed vaccinations (in percent of county population) are collected from the Centers for Disease Control and Prevention (CDC). Allocated vaccine doses (in percent of county population) include Pfizer and Moderna vaccines and are also collected from the CDC. Data on credit/debit card spending seasonally adjusted relative to Jan 4–31, 2020, are obtained from the Opportunity Insights Economic Tracker compiled by Chetty et al., 2020, which relies on data from Affinity Solutions. The data covers spending on all merchant category codes. Mobility is from Google and includes workplace mobility only, compared to its median value for weekdays in the period of Jan 3 – Feb 6, 2020. Our data set also includes initial unemployment claims (in percent of 2019 county labor force). This data is also obtained via the Opportunity Insights Economic Tracker, which relies on data from individual state agencies. Our dataset also includes the number of pharmacies from the NCPDP dataset aggregated to the county level in July 2020 from Guadamuz et al., 2020 kindly updated and provided by Dima Mazen Qato. Finally, county areas are from from the U.S. Census Bureau.

Table 1: Descriptive statistics

	Mean	Std.Dev.	# Obs	# Counties	# Weeks
Initiated vaccinations, percent of population	27.60	14.74	65,632	2808	26
Completed vaccinations, percent of population	20.80	14.33	65,125	2808	26
Two-week lagged allocated doses, percent of population	2.10	0.56	65,632	2808	26
Credit/debit card spending, relative to Jan2020	0.11	0.21	41,169	1728	26
Mobility: Work places	-19.66	8.93	64,284	2755	25
Initial claims, percent of 2019 labor force	0.39	0.31	14,073	610	26

Source: Authors' calculations.
Note: These statistics include at most the 2808 counties and 28 weeks from December-2020 to early-July 2021 covered in our analysis.

3 Methodology

This section lays out our empirical strategy and crucially discusses our approach to instrumenting for vaccines.

3.1 Baseline specification

Our baseline specification is as follows:

$$y_{c,t+k} = \beta \hat{v}_{c,t} + \tau_{s,t} + \tau_c + \epsilon_{c,t+k} \tag{1}$$

$$v_{c,t} = \gamma z_{c,t-2} + \delta_{s,t} + \delta_c + \xi_{c,t} \tag{2}$$

where $y_{c,t+k}$ denotes an economic outcome of interest in county c, state s, week $t+k$, including (i) weekly credit/debit card spending relative to Jan 4–31, 2020 ($k=1$), (ii) weekly unemployment claims in percent of county-level 2019 labor force ($k=6$), and (iii) mobility relative to Jan 3–Feb 6, 2020 ($k=1$). $v_{c,t}$ are initiated vaccinations in percent of the population at the county level.[3] The hat on $v_{c,t}$ denotes the fitted value of vaccinations from equation (2). $\tau_{s,t}$ and $\delta_{s,t}$ are state-time fixed effects, controlling for common state level shocks, like the incidence of the pandemic. τ_c and δ_c are county fixed effects capturing time-invariant specifics in a given county, such as geography, population density, or industrial structure, that could affect the outcome. Finally, $z_{c,t-2}$ is an instrument for vaccines explained in the next subsection.

3.2 Instrumentation

The specification in equation (1) is subject to endogeneity concerns. First, a critical worry is reverse causality bias. For example, imagine that a county is hosting an event and thus facilitating vaccination in the run up to the event. If so, the causality would run in the opposite direction — activity generated vaccines —- but equation (1) would mistakenly

[3] For Johnson & Johnson doses, initiated vaccinations are also completed.

ascribe economic activity to vaccines. Second, the relationship may be spurious if a third underlying factor is driving both vaccination rates and economic activity.

We propose an instrumental variables approach to address these concerns. Specifically, we instrument county-level vaccination rates with pharmacy densities at the county level (number of pharmacies per square mile) interacted with weekly allocated vaccines at the state level.[4] Thus, $z_{c,t-2}$ in equation (2) is such that:

$$z_{c,t-2} = p_c \times va_{s,t-2} \tag{3}$$

Here p_c denotes the number of pharmacies per square mile in county c within state s, while $va_{s,t-2}$ denotes the number of statewide allocated vaccines in percent of state population at time $t-2$.[5] The former variable varies across counties (Figure 3a), while the latter varies across time and states (Figure 3b).

Our identification strategy exploits whether activity within each state picks up more in counties with higher pharmacy densities when more vaccines are allocated to the state. We show this formally in Annex B. As such, this instrument is reminiscent of a Bartik instrument in the sense that the identification is coming from geographic cross-sectional variation as discussed in Goldsmith-Pinkham et al., 2020.[6] To understand our identification strategy better, consider a single state at a given time. Here our instrument simply exploits the variation in pharmacy density. Time variation is then introduced into the instrument by interacting with the change in the supply of vaccines at the state level.

For our instrument to be valid it needs to (i) be relevant, that is strongly related to vaccination (the first stage), and (ii) only affect economic activity through vaccines (the exclusion restriction). This is illustrated in Figure 4. Relevance is judged by how strongly correlated the instrument is with the endogenous variable. On the other hand the exclusion restriction is not directly testable.

We assess instrument validity through the relationship with initiated vaccination rates. Table 2 shows that this relationship is is positively and highly significant. This is witnessed by the coefficient estimates and F-statistic.

We assess the plausibility of the exclusion restriction by relating the density of pharmacies to changes in pre-vaccine roll-out spending.[7] If the instrument is valid we should not see a significant relationship to spending before the vaccination campaign began. Table 3 shows that this relationship is indeed insignificant. Note that for the exclusion restriction

[4]Vaccine doses administered in retail pharmacies represented 35 percent of total doses administered by October 6, 2021.

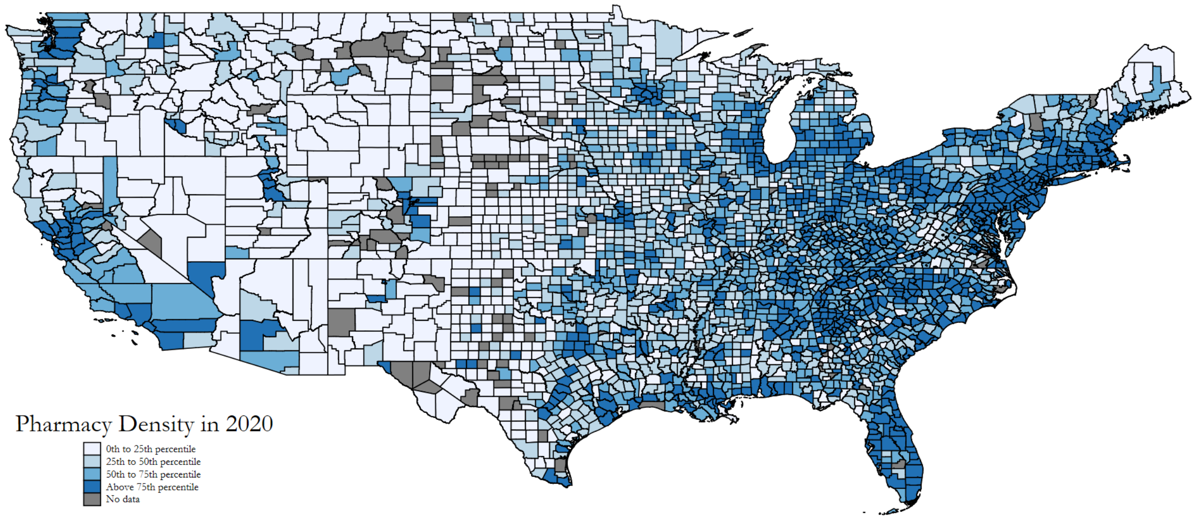
[5]A two-week lag is chosen to maximize the explanatory power in the first stage regression.

[6]However, in a strict sense, our instrument is not a Bartik, as it is not the internal product of shares and growth rates across another sub-grouping that is not geographic, like industries.

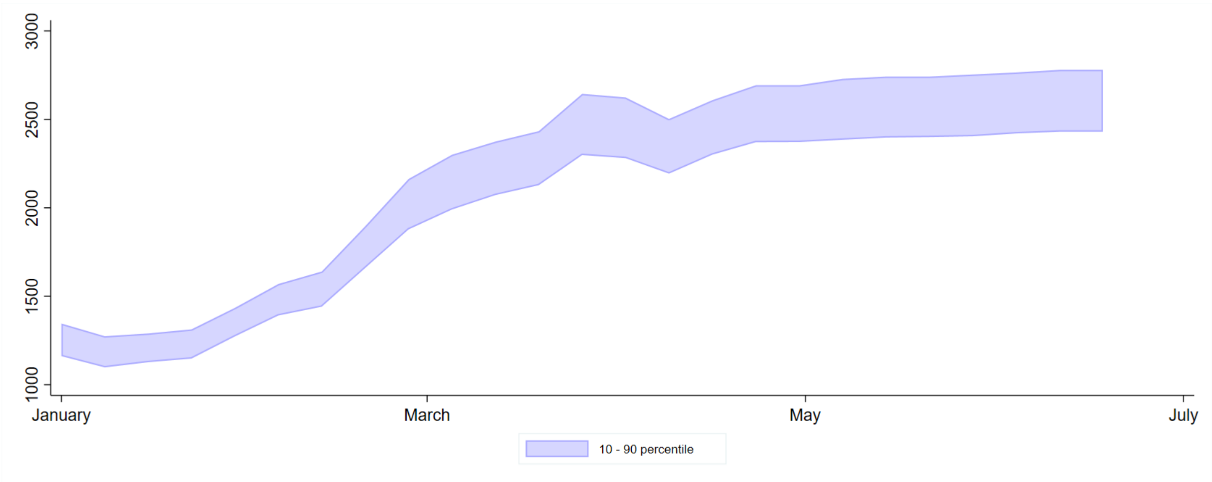
[7]This is akin to the test of pre-trends advised in Goldsmith-Pinkham et al., 2020

Figure 3: The two components of our instrument

(a) Pharmacies per square mile



(b) Weekly vaccine supplies per 100,000 inhabitants



Source: Authors' calculations.

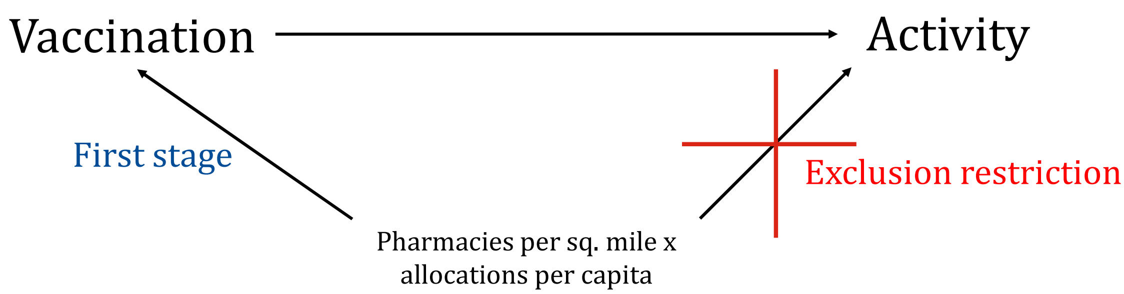
to be valid, vaccine supply to states does not need to be exogenous to economic activity over time. Instead, our identifying assumption is that the *interaction* between pharmacy densities and vaccine supplies only affects economic activity through vaccination. Thus, it suffices that the differences in the effect of a higher vaccine supply between counties with different pharmacy densities only run via vaccinations.

4 Results

This section reports and discusses our estimates of the effect of vaccines on credit card spending, mobility, and initial unemployment claims.

Table 4 shows our baseline results for spending, workplace mobility, and initial unemployment insurance (UI) claims. For each variable, we show results from (i) the un-

Figure 4: Judging instrument validity



Note: A good instrument has a strong relationship to the studied independent variable, i.e. is relevant (the first stage), and does not affect the outcome variable through other channels (the exclusion restriction).

Table 2: First stage regression

	(1) Initiated vaccinations
Pharmacies per sq. mile x allocations per capita	1.6894*** [0.2036]
Observations	40984
County FE	Yes
State-time FE	Yes
F-stat	68.9

Source: Authors' calculations.
Notes: The estimates are based on data for 1727 counties over 25 weeks. Robust standard errors are reported. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

instrumented fixed effects regression, estimating equation (1) where $\hat{v}$ is the initiated vaccination rate, and (ii) the instrumented fixed effects regression, estimating the full system in equations (1) and (2). We note that both methods yield similar results across all three variables but that the point estimates and standard errors are also larger under the instrumented regressions.[8] Overall, the instrumentation strengthens our results.

Spending rises by 0.59 percentage points for each percentage point increase in initiated vaccination rates (column 2). Column 1 shows the un-instrumented estimates, which are slightly smaller. Mobility is an index and thus harder to interpret, but our results show that for each percentage point of initiated vaccines, workplace mobility rises by 0.29 percentage points (column 4). Finally, columns 5-6 show the results for initial unemployment claims. Vaccination decreases initial unemployment claims, again with a stronger relationship when instrumenting. Specifically, we find that a one percentage point increase in initial vaccination rates decreases new unemployment claims by 0.004 percent of the 2019 labor force. Overall these results show that vaccination has a causal and immediate

[8]Standard errors are corrected for the presence of heteroskedasticity.

Table 3: Validity of exclusion restriction

	(1) Spending, 2020M12 over 2020M1
Pharmacies per sq. mile	-0.0048 [0.0060]
Constant	0.0049 [0.0041]
Observations	1730

Source: Authors' calculations.

Notes: The estimates are based on data for spending from 2012M1 to 2012M12 for 1730 counties. Spending is seasonally adjusted credit/debit card spending. The regression is purely cross-sectional (one observation per county) who no fixed effects are included. The reported result is robust to inclusion of state fixed effects. Robust standard errors are reported. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table 4: Effect of vaccination on economic activity at the county level

	(1) Spending	(2) Spending	(3) Mobility: Work	(4) Mobility: Work	(5) UI claims	(6) UI claims
Initiated vaccinations	0.0020*** [0.0001]	0.0059*** [0.0008]	0.0995*** [0.0051]	0.2860*** [0.0270]	-0.0015*** [0.0004]	-0.0035*** [0.0008]
Instrumented	No	Yes	No	Yes	No	Yes
Observations	40984	40984	64251	64251	11811	11811
Weeks	25	25	25	25	23	23
Counties	1727	1727	2741	2741	606	606
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat		68.9		84.8		277.2

Source: Authors' calculations.
Notes: Spending is seasonally adjusted credit/debit card spending expressed relative to Jan 4–31, 2020. Workplace mobility is compared to its median value for the same weekday in the period of Jan 3 – Feb 6, 2020. UI claims is initial unemployment insurance claims in percent of the 2019 labor force. We lead spending and mobility by 1 week and UI claims by 6 weeks relative to initiated vaccinations. All specifications include state-time and county fixed effects. In the IV regression initiated vaccinations are instrumented with the previous 2 week's allocation of vaccines (Pfizer and Moderna) at the state level (in percent of total population) interacted with pharmacy density at the county-level. Robust standard errors are reported. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

effect on economic activity.

These baseline results are robust to a range of robustness checks. First, we replace initiated with completed vaccinations (Appendix Table A1). Second, we vary the lag of time between vaccinations and the economic activity variables from 0 to 6 weeks for spending and workplace mobility, and 3-8 weeks for unemployment insurance claims (Appendix Table A2). Third, we vary the lags of the instrument from 0 to 6 weeks (Appendix Table A3). Fourth, we run panel regressions with only time and county fixed effects (Appendix Table A4). Our results are robust across these checks. Two exceptions are unemployment claims that become insignificant at leads of 3 to 4 weeks and mobility that becomes insignificant in the specification with time and county fixed effects.[9] We also explored

[9]The coefficients for both spending and UI claims are larger when controlling for time rather than

"within" nonlinearities by adding quadratic terms of demeaned vaccinations and the instrument, but we found no evidence of significant nonlinear effects in that specification. Finally, we note that using national supply instead of state-level supply does not affect our results meaningfully (Table A5).

Our baseline results reflect averages across all counties, which may mask important cross-geographic heterogeneity. In what follows, we study whether these effects are heterogeneous across counties.

Effects of vaccines on economic activity appear larger in counties with worse initial socioeconomic conditions (Table 5, Panel A). To proxy for initial socioeconomic conditions, we use county-level unemployment in 2019. The conditional effects are measured through an interaction of initiated vaccines with a dummy for whether a county's initial unemployment is high relative to the median. We find that this interaction is positive for spending and mobility and negative for unemployment claims, and significantly so for the latter two. This shows that the economic effect of vaccines was largest in counties with worse pre-existing socioeconomic conditions.

Counties with lower education levels also seem to have experienced larger effects of vaccines (Table 5, Panel B). In this case, our interaction with vaccines uses a dummy if the share of people with a bachelor's degree in a given county is below the median across all counties. This interaction is positive for spending and mobility and negative for unemployment claims, and significant for all three variables. This suggests that the vaccination roll-out provides larger benefit to counties with comparatively less educated inhabitants.

Finally, the effect of vaccines is strongest in urban counties (Table 5, panel C). In this table, we include an interaction for whether a county is urban. We see that this is positive and significant for spending and negative and significant for unemployment claims. Workplace mobility has the opposite sign as spending, though.

state-time fixed effects. This could reflect either omitted variable bias in the former specification, for example, concurrent state-level restrictions on economic activity, or that vaccines prompt such statewide policy responses, which themselves have an economic effect. If the former, then it is preferable to control for state-time effects as done in the baseline. If the latter, our baseline specification would underestimate the full extent of the economic effect of vaccines.

Table 5: Conditional results

Panel A: Results conditional on county-level initial unemployment

	(1) Spending	(2) Mobility: Work	(3) UI claims
Initiated vaccinations	0.0062*** [0.0009]	0.3580*** [0.0402]	-0.0031*** [0.0008]
High(Unemployment) x initiated vaccinations	0.0002 [0.0003]	0.0702*** [0.0160]	-0.0028*** [0.0004]
Instrumented	Yes	Yes	Yes
Observations	40984	64251	11963
Weeks	25	25	23
Counties	1727	2741	609
County FE	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes
F-stat	13.3	19.6	90.2

Panel B: Results conditional on county-level educational attainment

	(1) Spending	(2) Mobility: Work	(3) UI claims
Initiated vaccinations	0.0068*** [0.0010]	0.3459*** [0.0395]	-0.0103*** [0.0016]
Low(below BA degree) x initiated vaccinations	0.0010** [0.0004]	0.0483*** [0.0126]	-0.0048*** [0.0009]
Instrumented	Yes	Yes	Yes
Observations	40984	64251	11963
Weeks	25	25	23
Counties	1727	2741	609
County FE	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes
F-stat	40.2	41.2	76.1

Panel C: Results conditional on rural-urban status

	(1) Spending	(2) Mobility: Work	(3) UI claims
Initiated vaccinations	0.0049*** [0.0009]	0.3770*** [0.0313]	-0.0024*** [0.0009]
Urban county x initiated vaccinations	0.0009** [0.0003]	-0.0729*** [0.0088]	-0.0008** [0.0004]
Instrumented	Yes	Yes	Yes
Observations	40984	64251	11963
Weeks	25	25	23
Counties	1727	2741	609
County FE	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes
F-stat	34.6	42.9	139.0

Source: Authors' calculations.
Notes: Spending is seasonally adjusted credit/debit card spending expressed relative to Jan 4–31, 2020. Workplace mobility is compared to its median value for the same weekday in the period of Jan 3 – Feb 6, 2020. UI claims is initial unemployment insurance claims in percent of the 2019 labor force. We lead spending and mobility by 1 week and UI claims by 6 weeks relative to initiated vaccinations. All specifications include state-time and county fixed effects. In the IV regression initiated vaccinations are instrumented with the previous 2 week's allocation of vaccines (Pfizer and Moderna) at the state level (in percent of total population) interacted with pharmacy density at the county-level. Robust standard errors are reported. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

5 Conclusion

We conclude by answering the question we posed in the beginning: Yes, vaccinations *are indeed* an important shot in the arm for the economy. Specifically, we find evidence that a 1 percentage points increase in initiated vaccination rates increases spending by 0.6 percent and reduces the weekly inflow to unemployment by 0.004 percentage points of the labor force. Consistent with these, we also find that vaccinations increase work-related mobility.

Importantly, these effects seem to vary across counties, with larger effects in urban counties and in counties with more vulnerable populations as measured by lower levels of education and higher pre-COVID-19 unemployment rates. What explains this heterogeneity? First, urban and vulnerable counties were likely harder affected by the pandemic, owing to sectoral employment patterns and the uneven impact of lockdown and social distancing rules. Thus, it makes sense that these counties respond the most, as vaccines become widely available. This way, vaccinations are also a *fair* shot in the arm for the economy, which highlights that equitable distribution of vaccines is important to reduce inequality.

References

Chetty, Raj, John N Friedman, Nathaniel Hendren, Michael Stepner, et al. (2020). *The economic impacts of COVID-19: Evidence from a new public database built using private sector data*. Tech. rep. National Bureau of Economic Research.

Deb, Pragyan, Davide Furceri, Daniel Jimenez, Siddharth Kothari, Jonathan D. Ostry, and Nour Tawk (2021). "The Effects of COVID-19 Vaccines on Economic Activity". In: *IMF Working Papers* 2021.248.

Ganslmeier, Michael, Pragyan Deb, Davide Furceri, Jonathan Ostry, and Nour Tawk (2021). *Vaccinate Early and Vaccinate Broadly: On the health and Economic Effects of COVID-19 Vaccines*.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2020). "Bartik instruments: What, when, why, and how". In: *American Economic Review* 110.8, pp. 2586–2624.

Guadamuz, Jenny S., G. Caleb Alexander, Shannon N. Zenk, and Dima M. Qato (Jan. 2020). "Assessment of Pharmacy Closures in the United States From 2009 Through 2015". In: *JAMA Internal Medicine* 180.1, pp. 157–160.

Sandmann, Frank G, Nicholas G Davies, Anna Vassall, W John Edmunds, Mark Jit, Fiona Yueqian Sun, C Julian Villabona-Arenas, Emily S Nightingale, Alicia Showering, Gwenan M Knight, et al. (2021). "The potential health and economic value of SARS-CoV-2 vaccination alongside physical distancing in the UK: a transmission model-based future scenario analysis and economic evaluation". In: *The Lancet Infectious Diseases*.

A Robustness

Table A1: Effect of *completed* vaccinations on economic activity at the county level

	(1) Spending	(2) Spending	(3) Mobility: Work	(4) Mobility: Work	(5) UI claims	(6) UI claims
Completed vaccinations	0.0022*** [0.0002]	0.0105*** [0.0014]	0.1178*** [0.0052]	0.5480*** [0.0651]	-0.0006 [0.0005]	-0.0062*** [0.0014]
Instrumented	No	Yes	No	Yes	No	Yes
Observations	40601	40601	63827	63827	11483	11483
Weeks	25	25	25	25	23	23
Counties	1727	1727	2741	2741	601	601
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat		55.8		58.4		201.4

Source: Authors' calculations.
Notes: Spending is seasonally adjusted credit/debit card spending expressed relative to Jan 4–31, 2020. Workplace mobility is compared to its median value for the same weekday in the period of Jan 3 – Feb 6, 2020. UI claims is initial unemployment insurance claims in percent of the 2019 labor force. We lead spending and mobility by 1 week and UI claims by 6 weeks relative to initiated vaccinations. All specifications include state-time and county fixed effects. In the IV regression initiated vaccinations are instrumented with the previous 2 week's allocation of vaccines (Pfizer and Moderna) at the state level (in percent of total population) interacted with pharmacy density at the county-level. Robust standard errors are reported. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table A2: Varying the lead in the outcome variable

Panel A: Spending

	(1) Lead 1 week	(2) Lead 2 weeks	(3) Lead 3 week	(4) Lead 4 weeks	(5) Lead 5 weeks	(6) Lead 6 weeks
Initiated vaccinations	0.0059*** [0.0008]	0.0066*** [0.0007]	0.0073*** [0.0008]	0.0084*** [0.0009]	0.0093*** [0.0010]	0.0106*** [0.0011]
Instrumented	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40984	40980	40973	39246	37519	35792
Weeks	25	25	25	24	23	22
Counties	1727	1727	1727	1727	1727	1727
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	68.9	68.9	68.9	69.5	70.0	70.5

Panel B: Mobility: Work

	(1) Lead 1 week	(2) Lead 2 weeks	(3) Lead 3 week	(4) Lead 4 weeks	(5) Lead 5 weeks	(6) Lead 6 weeks
Initiated vaccinations	0.2860*** [0.0270]	0.3097*** [0.0273]	0.3010*** [0.0255]	0.3019*** [0.0267]	0.3176*** [0.0289]	0.3532*** [0.0308]
Instrumented	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64251	64255	64260	64266	64267	64249
Weeks	25	25	25	25	25	25
Counties	2741	2741	2740	2739	2736	2736
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	84.8	84.8	84.8	84.8	84.8	84.9

Panel C: UI claims

	(1) Lead 3 week	(2) Lead 4 weeks	(3) Lead 5 week	(4) Lead 6 weeks	(5) Lead 7 weeks	(6) Lead 8 weeks
Initiated vaccinations	0.0001 [0.0007]	-0.0010 [0.0007]	-0.0021*** [0.0007]	-0.0035*** [0.0008]	-0.0059*** [0.0008]	-0.0089*** [0.0008]
Instrumented	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13338	13145	12555	11963	11372	10771
Weeks	25	25	24	23	22	21
Counties	609	609	609	609	609	607
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	304.6	302.4	291.0	277.6	261.0	247.1

Source: Authors' calculations.

Notes: Spending is seasonally adjusted credit/debit card spending expressed relative to Jan 4–31, 2020. Workplace mobility is compared to its median value for the same weekday in the period of Jan 3 – Feb 6, 2020. UI claims is initial unemployment insurance claims in percent of the 2019 labor force. We lead spending and mobility by 1 week and UI claims by 6 weeks relative to initiated vaccinations. All specifications include state-time and county fixed effects. In the IV regression initiated vaccinations are instrumented with the previous 2 week's allocation of vaccines (Pfizer and Moderna) at the state level (in percent of total population) interacted with pharmacy density at the county-level. Robust standard errors are reported. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table A3: Varying the lag in the instrument variable

Panel A: Spending

	(1) Lag 1 week	(2) Lag 2 weeks	(3) Lag 3 week	(4) Lag 4 weeks	(5) Lag 5 weeks	(6) Lag 6 weeks
Initiated vaccinations	0.0056*** [0.0009]	0.0059*** [0.0008]	0.0060*** [0.0007]	0.0062*** [0.0007]	0.0067*** [0.0007]	0.0072*** [0.0008]
Instrumented	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40108	40984	41599	41988	40590	39168
Weeks	26	25	25	25	24	23
Counties	1727	1727	1727	1727	1727	1727
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	69.6	68.9	69.2	70.2	71.9	73.5

Panel B: Mobility: Work

	(1) Lag 1 week	(2) Lag 2 weeks	(3) Lag 3 week	(4) Lag 4 weeks	(5) Lag 5 weeks	(6) Lag 6 weeks
Initiated vaccinations	0.2693*** [0.0312]	0.2860*** [0.0270]	0.2800*** [0.0240]	0.2571*** [0.0208]	0.2429*** [0.0201]	0.2518*** [0.0204]
Instrumented	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62453	64251	65439	66178	66680	67096
Weeks	25	25	25	25	25	25
Counties	2742	2741	2742	2742	2741	2737
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	84.1	84.8	86.4	88.3	90.7	93.5

Panel C: UI claims

	(1) Lag 1 week	(2) Lag 2 weeks	(3) Lag 3 week	(4) Lag 4 weeks	(5) Lag 5 weeks	(6) Lag 6 weeks
Initiated vaccinations	-0.0024*** [0.0008]	-0.0035*** [0.0008]	-0.0046*** [0.0007]	-0.0059*** [0.0007]	-0.0064*** [0.0008]	-0.0060*** [0.0008]
Instrumented	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12183	11963	11611	11167	10678	10164
Weeks	24	23	22	21	20	19
Counties	609	609	609	609	609	609
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	274.9	277.6	320.3	361.5	337.5	307.7

Source: Authors' calculations.
Notes: Spending is seasonally adjusted credit/debit card spending expressed relative to Jan 4–31, 2020. Workplace mobility is compared to its median value for the same weekday in the period of Jan 3 – Feb 6, 2020. UI claims is initial unemployment insurance claims in percent of the 2019 labor force. We lead spending and mobility by 1 week and UI claims by 6 weeks relative to initiated vaccinations. All specifications include state-time and county fixed effects. In the IV regression initiated vaccinations are instrumented with the previous 2 week's allocation of vaccines (Pfizer and Moderna) at the state level (in percent of total population) interacted with pharmacy density at the county-level. Robust standard errors are reported. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table A4: Varying type of included fixed effects.

	(1) Spending	(2) Spending	(3) Mobility: Work	(4) Mobility: Work	(5) UI claims	(6) UI claims
Initiated vaccinations	0.0188*** [0.0061]	0.0059*** [0.0008]	0.0721 [0.1346]	0.2860*** [0.0270]	-0.0179*** [0.0026]	-0.0035*** [0.0008]
Instrumented	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40984	40984	64251	64251	11811	11811
Weeks	25	25	25	25	23	23
Counties	1727	1727	2741	2741	606	606
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No
State-time FE	No	Yes	No	Yes	No	Yes
F-stat	26.4	68.9	40.2	84.8	613.5	277.2

Source: Authors' calculations.
Notes: Spending is seasonally adjusted credit/debit card spending expressed relative to Jan 4–31, 2020. Workplace mobility is compared to its median value for the same weekday in the period of Jan 3 – Feb 6, 2020. UI claims is initial unemployment insurance claims in percent of the 2019 labor force. We lead spending and mobility by 1 week and UI claims by 6 weeks relative to initiated vaccinations. All specifications include state-time and county fixed effects. In the IV regression initiated vaccinations are instrumented with the previous 2 week's allocation of vaccines (Pfizer and Moderna) at the state level (in percent of total population) interacted with pharmacy density at the county-level. Robust standard errors are reported. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

Table A5: Using the *average national* vaccine supply interacted with pharmacy density as instrument.

	(1) Spending	(2) Spending	(3) Mobility: Work
Initiated vaccinations	0.0065*** [0.0010]	0.3528*** [0.0368]	-0.0034*** [0.0008]
Instrumented	Yes	Yes	Yes
Observations	40984	64251	11963
Weeks	25	25	23
Counties	1727	2741	609
County FE	Yes	Yes	Yes
State-time FE	Yes	Yes	Yes
F-stat	65.9	81.3	207.5

Source: Authors' calculations.
Notes: Spending is seasonally adjusted credit/debit card spending expressed relative to Jan 4–31, 2020. Workplace mobility is compared to its median value for the same weekday in the period of Jan 3 – Feb 6, 2020. UI claims is initial unemployment insurance claims in percent of the 2019 labor force. We lead spending and mobility by 1 week and UI claims by 6 weeks relative to initiated vaccinations. All specifications include state-time and county fixed effects. In the IV regression initiated vaccinations are instrumented with the previous 2 week's allocation of vaccines (Pfizer and Moderna) at the state level (in percent of total population) interacted with pharmacy density at the county-level. Robust standard errors are reported. ***, **, and * indicate statistical significance at 1, 5, and 10 percent, respectively.

B Details on the instrumentation

We create an instrument, $z_{c,t-2}$, for vaccines that proxies for the exogenous supply of vaccines from an individual county's perspective and is defined as:

$$z_{c,t-2} = \frac{\#pharmacies_c}{area_c} \times \frac{vaccineallocations_{s,t-2}}{population_s} \equiv p_c \times \omega_{s,t-2} \tag{4}$$

where $p_c = \frac{\#pharmacies_c}{area_c}$ is the density of pharmacies per county in 2020 and $\omega_{s,t-2} = \frac{vaccineallocations_{s,t-2}}{population_s}$ is the per capita number of state-level allocated vaccines (Pfizer and Moderna) for state s in week $t-2$. In terms of identification, this instrument has the appeal that: (i) the number of allocated vaccines are largely exogenous to county s, and (ii) the number of pharmacies in 2020 is largely pre-determined.

Take equation (2), the first stage in our framework:

$$v_{c,t} = \gamma z_{c,t-2} + \delta_{s,t} + \delta_c + \xi_{c,t}$$

This county and state-time fixed effects regression above is equivalent to running:

$$\tilde{v}_{c,t} = \gamma \tilde{z}_{c,t-2} + \tilde{\xi}_{c,t}$$

where

$$\tilde{v}_{c,t} = v_{c,t} - \sum_t \frac{v_{c,t}}{T} - v_{s,t}$$
$$\tilde{z}_{c,t-2} = z_{c,t-2} - \sum_t \frac{z_{c,t-2}}{T} - z_{s,t-2}$$
$$\tilde{\xi}_{c,t} = \xi_{c,t} - \sum_t \frac{\xi_{c,t}}{T} - \xi_{s,t}$$

Note that for any variable w, $w_{s,t} = \sum_{c \text{ in state s}} w_{c,t}/(\#\text{ counties in state s})$ denotes the average state-level w at time t. Denote $N_s = \#$ counties in state s

Using our instrument, and recalling that p_c denotes pharmacy density and $\omega_{s,t} =$

$\sum_{c \text{ in state s}} \omega_{c,t}$ denotes vaccine allocations:

$$\tilde{z}_{c,t-2} = z_{c,t-2} - \sum_t \frac{z_{c,t-2}}{T} - z_{s,t-2}$$
$$\tilde{z}_{c,t-2} = p_c \sum_{c \text{ in state s}} \omega_{c,t-2} - \sum_t \frac{p_c \sum_{c \text{ in state s}} \omega_{c,t-2}}{T} - \sum_{c \text{ in state s}} \frac{p_c \sum_{c \text{ in state s}} \omega_{c,t-2}}{N_s}$$
$$\tilde{z}_{c,t-2} = p_c \sum_{c \text{ in state s}} \omega_{c,t-2} - p_c \sum_t \frac{\sum_{c \text{ in state s}} \omega_{c,t-2}}{T} - \sum_{c \text{ in state s}} \omega_{c,t-2} \sum_{c \text{ in state s}} \frac{p_c}{N_s}$$
$$\tilde{z}_{c,t-2} = p_c \omega_{s,t-2} - p_c \omega_s - \omega_{s,t-2} \bar{p}_s$$

where $\omega_{s,t-2} = \sum_{c \text{ in state s}} \omega_{c,t-2}$; $\omega_s = \sum_t \frac{\sum_{c \text{ in state s}} \omega_{c,t-2}}{T}$ and $\bar{p}_s = \sum_{c \text{ in state s}} \frac{p_c}{N_s}$ And thus

$$\tilde{z}_{c,t-2} = (p_c - \bar{p}_s)\, \omega_{s,t-2} - p_c \omega_s$$
$$\tilde{z}_{c,t-2} = (p_c - \bar{p}_s)\, \omega_{s,t-2} - p_c \omega_s + \bar{p}_s \omega_s - \bar{p}_s \omega_s$$
$$\tilde{z}_{c,t-2} = (p_c - \bar{p}_s)\, (\omega_{s,t-2} - \omega_s) - \bar{p}_s \omega_s$$

The above means that identification focuses on whether activity picked up most in counties with where pharmacies are densest as state level allocations of vaccines picked up relative to counties with lower pharmacy density *within* each state.[10]

[10]Note in our formulation of the instrument, we could have demeaned pharmacy density at the state level, which would make the last term in the equation above drop out.